Sustainable Cities and Society 114 (2024) 105721

Contents lists available at ScienceDirect

Sustainable Cities and Society

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

A new methodology for reducing carbon emissions using multi-renewable energy systems and artificial intelligence

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ARTICLE INFO

Keywords:
DSM
HEMS
HBA
WOA
IAROA
PV
WT

ABSTRACT

Microgrid cost management is a significant difficulty because the energy generated by microgrids is typically derived from a variety of renewable and non-renewable sources. Furthermore, in order to meet the requirements of freed energy markets and secure load demand, a link between the microgrid and the national grid is always preferred. For all of these reasons, in order to minimize operating expenses, it is imperative to design a smart energy management unit to regulate various energy resources inside the microgrid. In this study, a smart unit idea for multi-source microgrid operation and cost management is presented. The proposed unit utilizes the Improved Artificial Rabbits Optimization Algorithm (IAROA) which is used to optimize the cost of operation based on current load demand, energy prices and generation capacities. Also, a comparison between the optimization outcomes obtained results is implemented using Honey Badger Algorithm (HBA), and Whale Optimization Algorithm (WOA). The results prove the applicability and feasibility of the proposed method for the demand management system in SMG. The price after applying HBA is 6244.5783 (ID). But after applying the Whale Optimization Algorithm, the cost is found 4283.9755 (ID), and after applying the Artificial Rabbits Optimization Algorithm, the cost is found 1227.4482 (ID). By comparing the proposed method with conventional method, the whale optimization algorithm saved 31.396 % per day, and the proposed artificial rabbit's optimization algorithm saved 80.3437 % per day. From the obtained results the proposed algorithm gives superior performance.

1. Introduction

Customers can engage in wholesale electricity markets and make money by purchasing their energy needs from many suppliers and taking part in demand response (DR) programs thanks to the widespread adoption of smart energy technology at client locations. In reaction to price swings, a prudent customer may lower their overall electricity expenditures by proactively modifying and obtaining their energy consumption profile from available resources. In addition to improving the power network's efficiency, efficient usage of consumption control programs also makes the system more adaptable to a range of operating situations. The ability of an electric power system to adapt to variations in the supply and demand for electricity while preserving grid stability and dependability is referred to as flexibility. It has a variety of features and functionalities that allow the system to adjust to changing operating environments, integrate renewable energy sources, and maximize resource use (Sarsabahi et al., 2024).

Microgrids are compact power networks that consist of electrical loads, energy storage devices, and distributed energy resources (DERs). They can be used in both islanded and grid-connected modes. Numerous advantages come from the extensive integration of microgrids into the electrical system, including improved voltage profiles, increased system

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https://doi.org/10.1016/j.scs.2024.105721
Received 24 March 2024; Received in revised form 28 July 2024; Accepted 28 July 2024
Available online 3 August 2024

Table 1
Contributions and limitations of the greatest recent studies concerning demand-side management systems.

Reference	Contributions	limitations
(Hussain et al., 2023)	A multi-stage optimization for energy management and trading for smart homes was given by the authors, taking into account the operational limitations of a distribution network.	The best and most cost-effective approach to operate an IAROA-based energy management system was not explored by the authors, nor was WOA.
(Cruz et al., 2024)	Authors outlined and analyzed datasets' capabilities to leverage data-driven decision-making for more efficient deployments of demand-side management (DSM) systems.	IAROA for UC is not considered.
(Abdelsalam et al., 2021)	The authors presented a metaheuristic Harris Hawk optimization technique for coordinating energy management control in microgrids with distributed generation.	The best and most cost-effective approach to operate an IAROA-based energy management system was not explored by the authors, nor was WOA.
(Čech et al., 2023)	The authors introduced an Architecture-Oriented Agent-Based Simulations and Machine Learning Solution	More computational time
(Ali et al., 2023)	The authors presented a reinforcement-learning-based level controller for separator drum unit in refinery system	Peak to average ratio is not taken into account.
(Asghar et al., 2022)	A novel approach to optimized energy management systems including an ac/dc hybrid microgrid system for industries was given by the authors.	PAR is disregarded, increasing system complexity
(Bilal Naji Alhasnawi et al., 2022)	The authors presented a method for achieving MPPT for SCADA systems based on photovoltaic systems.	The best and most cost-effective approach to operate an IAROA-based energy management system was not explored by the authors, nor was WOA.
(Jasim et al., 2023)	The authors introduced a demand-side management program based on effective optimization techniques for smart grid home load.	longer computing time
(Iqbal et al., 2019)	In order to optimize the scheduling of domestic appliances in a grid exchange context, the authors introduced a hybrid grey wolf genetic algorithm optimizer that accounts for energy storage and stochastically modelled photovoltaics.	The best and most cost-effective approach to operate an IAROA-based energy management system was not explored by the authors, nor was WOA.
(Fayaz & Kim, 2018)	Authors described how they used fuzzy logic and the bat algorithm to optimize energy use and manage user comfort in residential buildings.	longer computing time
(Mateen et al., 2023)	The authors suggested a smart energy management system that reduces electricity prices and peak to average ratios in residential areas by using a hybrid genetic flower pollination algorithm.	The best and most cost-effective approach to operate an IAROA-based energy management system was not explored by the authors, nor was WOA.

Table 1 (*continued*)

Reference	Contributions	limitations
(Bilal Naji Alhasnawi et al., 2020)	An introduction was given by the authors. An inventive cooperative microgrid inverter controller for intelligent hybrid AC/DC microgrid	However, it was determined that neither WOA nor IAROA was the best, most cost-effective way to operate an energy management system.
(Khalid et al., 2016)	The authors presented Demand Side Management Using Hybrid Bacterial Foraging and Genetic Algorithm Optimization Techniques.	Consumers' constraints for load shifting was not considered
(Khalid et al., 2018)	The authors demonstrated how to use multi-objective energy optimization to dynamically coordinate household appliances for demand side control in smart buildings.	The AI-based DSMS operation with the lowest cost was disregarded.
(Khalid & Javaid, 2019)	The building's game theoretic energy management system, based on the as-service-over-fog coalition, was introduced by the authors.	Consumers' constraints for load shifting was not considered
(Khalid et al., 2019)	The authors used game theory to enhance the time-of-use electricity price rate.	Pollutant emissions are not considered
(Rawa et al., 2023)	The authors described stochastic scheduling and optimal operation of a microgrid's renewable energy sources, together with the best battery size selection for cost-effectiveness.	Not compared with other techniques
(Zeng et al., 2023)	The authors presented day-ahead interval scheduling for power systems based on enhanced adaptive diffusion kernel density estimation.	Longer computing times due to the intricate system
(Xu et al., 2023)	Real-time multi-energy demand responses for highly renewable buildings were provided by the authors.	depends for fewer generations on a random number
(Suresh et al., 2023)	The authors described the application of metaheuristic optimization algorithms to microgrid energy management.	Peak to average ratio has been disregarded, and comfort issues have not been addressed.
(Mansouri et al., 2021)	The writers made a presentation. A multifaceted strategy for energy management in smart homes and microgrids	a rise in complexity
(Wang, 2023)	The authors presented the best scheduling plan for a multi-energy microgrid that takes integrated demand response into account.	Reduced ESS capacity and network loss
(J. Hu et al., 2019)	The writers made a presentation. Coordinated management of PV-wind-battery hybrid ac/dc microgrids under varying load and generation circumstances	The cost of implementation is not taken into account.
(Haq et al., 2022)	The authors described how they implemented a home energy management system based on reinforcement learning.	Only passive appliances are taken into consideration due to UC compromise.
(Han et al., 2023)	The concept, architecture, and scheduling algorithms for home energy management systems were provided by the authors.	Only passive appliances are taken into consideration due to UC compromise.

(*continued on next page*)

Table 1 (*continued*)

Reference	Contributions	limitations
(B.N. Alhasnawi et al., 2021)	Based on a consensus algorithm, the authors presented coalition game theory as a demand management strategy for smart microgrids.	ratio of peak to average is disregarded.
(Nasir et al., 2022)	An optimal energy management system for residential and industrial microgrids was provided by the authors.	Cost-cutting measures compromise UC.
(Ahmed, 2017)	Based on critical peak pricing, the authors proposed an opportunistic home energy management system for demand response.	However, neither WOA nor IAROA were examined as the optimal, most economical ways to run an energy management system.
(Abbassi et al., 2023)	Authors presented a Dandelion Optimization Algorithm-Based Accurate Key Parameter Estimation of PEMFC Models.	UC is compromised and only passive appliances is considered.
(Bilal Naji Alhasnawi & Jasim, 2020)	Authors introduced a new coordinated control of hybrid microgrids with renewable energy resources under variable loads and generation conditions	Needs more accuracy.
(Mahmood et al., 2023)	Using heuristic optimization techniques, the authors presented an efficient scheduling method for a home energy management controller (HEMC).	Ignored UC
(Mansouri et al., 2020)	The authors provided stochastic energy hub planning and operation while taking demand response programs into account using the Benders decomposition approach.	Increase operational cost
(Ma et al., 2023)	The authors provided a two-stage demand response technique for a range of scenarios, based on deviation compensation.	Execution time is high
(Dey et al., 2022)	An inventive metaheuristic approach was presented by the authors to measure the financial impacts of grid involvement on a microgrid system.	Proper implementation is not explored
(Kumar et al., 2023)	The authors presented a multi-objective control-based home energy management system that is equipped with smart energy meters.	AWA (average waiting time) is not included into account
(Coelho et al., 2023)	The authors delivered a presentation. Real-time management of distributed multi-energy resources in multi-energy networks	Mechanism is highly complex.
(Wahid et al., 2020)	The authors described how they optimize energy consumption and maximize user comfort in smart buildings using a hybrid Firefly and Genetic Algorithm technique.	However, neither WOA nor IAROA were examined as the optimal, most economical ways to run an energy management system.
(Karimulla and, Ravi)	The authors demonstrated how to minimize energy costs by using renewable energy sources and the Fire-Fly Algorithm.	Comfort of end users is disregarded.
(Yousaf et al., 2021)	The authors introduced a brand-new machine learning-based price forecasting method for energy management systems.	UC is not considered
(Ullah et al., 2021)	The authors provided an ideal energy management system using the hybrid Firefly Lion Algorithm (FLA) for a university campus.	Only passive appliances are taken into consideration due to UC compromise.
(Li et al., 2023)	The authors presented an intelligent deep learning approach for energy management in microgrids based on renewable energy sources: A realistic example of a digital twin	User comfort is compromised
(Tostado-Véliz et al., 2022)	Authors introduced EMS while taking uncertainties and efficient demand response techniques into account.	PAR, user comfort, and delay are disregarded
(B. Alhasnawi et al., 2021)	A novel internet of energy based optimal multi-agent control scheme for microgrid including renewable energy resources was presented by the authors.	System intricacy rose.
(K. Ullah et al., 2022)	The authors introduced the demand side management technique for multi-objective day-ahead scheduling taking wind energy into account in smart grids.	There was no investigation on the most efficient and economical approach to run an IAROA-based energy management system.
(Yan et al., 2023)	The writers offered a Effects of renewable energy on demand response-based energy management in microgrid environments	Cost went up as comfort level rose.
(Zhang et al., 2022)	The authors introduced an expert knowledge-based microgrid energy management system based on deep reinforcement learning.	IAROA for UC is not considered.
(Ngo et al., 2020)	Writers gave an introduction Model Predictive Control Using Particle Swarm Optimization for Microgrid Energy Management	Privacy and user comfort concerns
(Lokeshgupta & Ravivarma, 2023)	The authors demonstrated the coordinated smart house energy sharing with centralized neighborhood energy management.	System complexity increased
(B.N. Alhasnawi et al., 2021)	Writers showcased a novel decentralized microgrid control approach in the internet of energy framework	IAROA for UC is not taken into account
(Vardakas et al., 2016)	Writers gave an introduction Scenarios for power demand control in smart grid applications using a limited quantity of appliances	System complexity increased
(Li et al., 2017)	The authors presented an efficient computation for demand side management's sparse load shifting.	Real-time forecasting is not considered
(Bilal Naji Alhasnawi et al., 2022)	The authors offered a novel use of the internet of things-based bald eagle search optimization algorithm to solve day-ahead scheduling problems.	The authors did not use the IAROA, and WOA to minimize the cost.
(Vagdoda et al., 2018)	The authors provided a cloud-based multiagent system platform for home microgrids towards the smart grid community.	Authors did not investigate WOA or the optimal, most economical way to run an energy management system based on IAROA.

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Table 1 (*continued*)

Reference	Contributions	limitations
(B. Alhasnawi et al., 2021)	The authors introduced a new and robust internet of energy-based smart energy management and demand reduction for smart homes.	System complexity increased
(Wang et al., 2018)	Green energy scheduling for demand-side management in the smart grid was provided by the authors.	Calculation time is not useful.
(Alhasnawi & Jasim, 2018)	The authors presented a Raspberry Pi3-powered SCADA-controlled smart house.	The user hasn't ways of handling the constraints
(Moghaddam & Leon-Garcia, 2018)	The architecture for the fog-based internet of energy for transactive energy management systems was introduced by the writers.	Daily PAR increased
(B.N. Alhasnawi & Jasim, 2020)	Writers showcased an innovative on-grid/off-grid energy management system employing an adaptive neuro-fuzzy inference system	Cost minimization is not considered
(Hashmi et al., 2020)	Authors presented an energy management system based on the Internet of Things and cloud computing for demand-side management in smart grids.	Not applicable to different types of buildings with more appliances
(Mahapatra et al., 2017)	The internet of things-based energy management in smart cities was given by authors.	More computational time
(Witharama et al., 2024)	The authors introduced an Advanced Genetic Algorithm for Optimal Microgrid Scheduling Considering Solar and Load Forecasting, and Demand Response Dynamics	The authors did not use the IAROA, and WOA to minimize the cost.
(B. Alhasnawi et al., 2021)	The authors presented an innovative use of the internet of energy for real-time electricity scheduling for residential energy management systems.	Disregarded the cost of power and PAR
(Faruque & Vatanparvar, 2016)	Authors demonstrated an over fog computing platform for energy management-as-a-service.	System complexity increased
(Li et al., 2018)	The writers developed an Internet of Things (IoT) self-learning home management system (SHMS) for Singapore.	An extensive system considers several appliances, which adds complexity to the system.
(B.N. Alhasnawi et al., 2020)	Writers gave an introduction a novel and sturdy green energy-powered hybrid microgrid system management and control approach	They did not address the UC
(Zia Ullah et al., 2022)	The authors described a real-time monitoring interface-based advanced energy management technique for microgrids.	More computational time
(Davarzani et al., 2019)	Writers gave an introduction application of a new multi-agent system in low-voltage distribution networks for demand response management	However, it was determined that neither WOA nor IAROA was the best, most cost-effective way to operate an energy management system.
(B.N. Alhasnawi & Jasim, 2020)	Writers gave an introduction a new hierarchical energy management system for multi-microgrid utilizing optimization	costly for modestly sized residential users

Table 1 (*continued*)

Reference	Contributions	limitations
(Cortes-Arcos, 2017)	The authors presented a multi-objective demand response to real-time prices (RTP) using a task scheduling system.	authors did not investigate WOA or the optimal, most economical way to run an energy management system based on IAROA.
(Khalid, 2018)	The authors reported the energy efficiency in smart buildings via dynamic coordination between homes and appliances.	The authors did not use the IAROA, and WOA to minimize the cost.
(B.N. Alhasnawi & Jasim, 2020)	An adaptive energy management system for smart hybrid microgrids was presented by the authors.	Ignored the installation cost of RES
(Al-Ali et al., 2017)	The authors offered a big data analytics and Internet of Things strategy to create a smart home energy management system.	Daily PAR increased
(Alhasnawi & Jasim, 2021)	Writers showcased A new trust distributed demand side management system made possible by the internet of things.	More computational time
(Ahmed et al., 2017)	Using a novel binary backtracking search method, the authors demonstrated a real-time optimal scheduling controller for a home energy management system.	Neglected the UC
(Ahmadipour et al., 2022)	For an island power system with distributed energy resources, the authors proposed an ideal load shedding strategy based on the grasshopper optimization method.	depends for fewer generations on a random number
(Feroze, 2017)	The authors provided information on how to improve demand side management in smart grids through evolutionary methods.	The IAROA and WOA were not utilized by the writers to cut costs.
(Zafar Iqbal, 2018)	The authors presented a method for optimizing energy consumption in smart homes for demand side management by combining the operations of microgrids.	The writers didn't look at WOA or the best, most affordable approach to operate an IAROA-based energy management system.
(B.N. Alhasnawi et al., 2023)	The writers provided a unique economic dispatch employing an enhanced butterfly optimization method in the standalone system	An energy management system based on WOA and IAROA was not examined by the authors.
(Bui et al., 2018)	The authors introduced consensus negotiation-based decision making for networked appliances in smart home management systems.	UC is in jeopardy.
(B.N. Alhasnawi et al., 2023)	Writers showcased a novel mixed-integer linear programming communication platform for smart EMS	Authors did not investigate an energy management system based on WOA and IAROA.
(Waseem et al., 2020)	The authors proposed Optimal GWCSO-based scheduling for household appliances in order to respond to demand while taking user comfort into account.	The IAROA method was not employed by the writers to cut costs.
(Nadeem et al., Jan, 2018)	The authors described an evolutionary method for demand-side control in real-	The best and most cost-effective approach to operate an IAROA-based energy

(*continued on next page*)

Table 1 (*continued*)

Reference	Contributions	limitations
	time opportunistic energy-efficient scheduling of home appliances.	management system was not explored by the authors, nor was WOA.
(Jasim et al., 2022)	the authors presented Coordinated Control and Load Shifting-Based Demand Management of a Smart Microgrid Adopting Energy Internet	The IAROA and WOA were not utilized by the writers to cut costs.
(Balavignesh et al., 2023)	An optimization-based optimal energy management system for smart homes in smart grids was presented by the authors.	The authors did not use the IAROA, and WOA to minimize the cost.
(Bilal Naji Alhasnawi et al., 2023)	writers provided an introduction adopting the intelligent optimization approach for optimal load scheduling	The authors did not use the IAROA, and WOA to minimize the cost.
The major contributions of the paper are:	1. To develop a novel scheduling strategy with optimal energy management for smart home devices in grid-dependent HRES. 2. To design an optimization algorithm called IAROA that achieves notable benefits for preserving customer satisfaction in energy management while being more effective than earlier methods. 3. This work aimed to reducing carbon emissions, lower energy costs, and enhance user comfort. 4. Performance comparison of the proposed Improved Artificial Rabbits Optimization Algorithm (IAROA) algorithm over the Honey Badger Algorithm (HBA), and Whale Optimization Algorithm (WOA) in DSM architecture. 5. An extensive analysis was provided based on the suggested study, and the lowest value of generation cost, which was thus determined, was contrasted with some of the recently published literature.	By utilizing the prosumer's adaptability, future research can investigate the transformer's electrical and thermal constraints, perhaps enhancing its performance within the distribution network. Furthermore, the thermal models of the home, such as heat pumps and thermal energy storage, are not taken into account in this work. These models can be added in the future to expand the suggested framework by incorporating demand-side flexibilities.

dependability, less power loss, and a decrease in carbon emissions from traditional centralized thermal power plants.

For the microgrid system to run profitably, an efficient Energy Management Strategy (EMS) that meets various technical requirements and effectively schedules distributed energy resources (DERs), storage devices, exchanged power with the utility, and controllable loads based on historical and current data is required. The EMS regulates the flow of power within the Microgrid (MG) by providing reference profiles to the controllers of the MG based on predefined goals. Shifting flexible loads from times of high energy prices to times of low energy prices reduces the cost of energy use (J. Hassaballah et al., 2024).

1.1. Literature review

Energy management has been studied in the past, with applications ranging from cost reduction to demand-side issues, price-based scheduling, battery storage applications in regulated areas, and power reliability. This research presents an effective technique for energy management and decreasing the daily running cost of a grid-connected MG based on two levels: optimal day-ahead scheduling and real-time scheduling. In this study, the energy consumption of the load is maintained while the DSM mechanism, which is based on a load shifting technique, is utilized to improve the EMS. Table 1 outlines the limitations and contributions of recent studies on demand management systems in a smart grid.

2. Problem formulation

This article discusses the problem of energy management in a typical micro-grid that includes renewable energy sources (RES) and energy storage devices. The primary objective is to plan the microgrid's power supply for an entire day so that power may be supplied even in situations where there is little to no solar or wind energy. The goal is to meet a number of equity and inequality requirements, minimize operating costs, reduce emissions, and optimize the microgrid's performance (Dixit et al., 2023). The microgrid's operating expenses and emissions are given the least weight in the study's multi-objective optimization problem. These two target functions are taken into consideration when generation scheduling is done in two different scenarios. The first scenario makes use of demand response mechanisms-aware responsive loading algorithms to regulate electricity use. However, in the second scenario, demand response strategies are not considered. By combining several optimization approaches and taking into account various circumstances, the article aims to maximize the micro-grid's performance by minimizing running costs, cutting emissions, and ensuring the compliance of multiple limitations. This study offers critical insights for enhancing the efficiency and sustainability of microgrid systems, hence advancing energy management strategies in microgrids that are combined with energy storage and renewable energy sources (RES). The fundamental system model architecture for controlling energy and scheduling smart home appliances while taking the utility DR program into account is shown in Fig. 1.

2.1. Objective function

Eq. (1) shows that the optimal microgrid operations planning in grid-connected mode aims to minimize integrated costs, which comprise pollution emissions and microgrid operating expenses.

$$minF = \omega_1 \cdot f_1 + \omega_2 \cdot f_2 \tag{1}$$

If f_1 is the cost function for operations, f_2 is the cost function for pollutant emissions, and F is the microgrid's integrated cost. The weighting coefficients ω_1 and ω_2, which indicate the optimization priority for each function, are identified. Eqs. (2) and (3) establish the operating cost function f_1. Eqs. (4) and (5) define the pollutant emissions cost f_2.

The costs associated with each DER's operation as well as the microgrid's interactions with the main grid make up f_1. Eqs. (2) and (3) display their mathematical expressions (Liu et al., 2023):

$$f_1 = \sum_{t}^{T} \left(C_{grid}(t)\& + C_{BE}(t) + C_{WT}(t) + C_{PV}(t) + C_{DE}(t) + C_{FC}(t) \right) \tag{2}$$

$$\begin{cases} C_{grid}(t) = C_{buy}(t) + C_{sell}\ (t) \\ C_{buy}(t) = c_b(t)P_b(t) \\ C_{sell}(t) = c_s(t)P_s(t) \end{cases} \tag{3}$$

where $P_b(t)$ and $P_s(t)$ represent the electricity that the microgrid buys

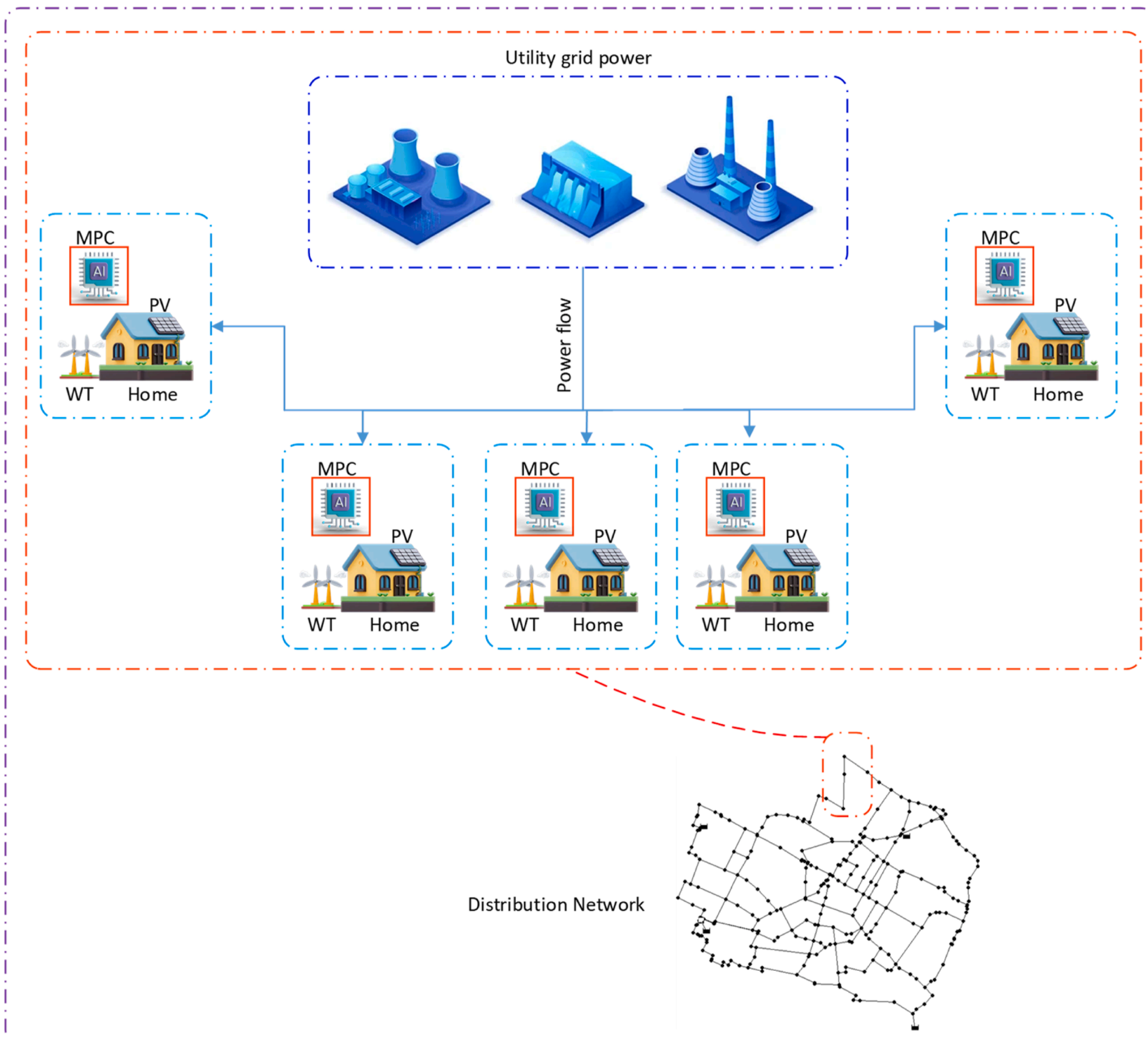

Fig. 1. Proposed EMS model.

and sells to the main grid at each time t. The costs of the electricity that the microgrid buys and sells to the larger grid at time t are denoted by the variables $C_{buy}(t)$ and $C_{sell}(t)$, respectively. The prices of the electricity that the microgrid buys and sells to the larger grid at time t are denoted by $c_b(t)$ and $c_s(t)$, respectively. It was decided to create an MG cycle dispatching model with incorporated charges and DER circumstances.

The expenses resulting from pollution of the environment yield f_2. Microgrids powered by non-renewable energy sources produce specific levels of pollutants from their generator units, such as CO_2, SO_2, CO, and NO_x. Eq. (4) provides a definition of f_2. Eq. (5) gives the average cost of all the pollutants that DEs and FCs emit.

$$f_2 = \sum_t^T (C_{DE.en}(t) + C_{FC.en}(t)) \tag{4}$$

$$\begin{cases} C_{DE.en}(t) = \left(E^{DE}_{C_O} + E^{DE}_{SO_2} + E^{DE}_{NO_x} + E^{DE}_{CO}\right) \cdot P_{DE}(t) \\ C_{FC.en}(t) = \left(E^{FC}_{C_2} + E^{FC}_{SO_2} + E^{FC}_{NO_x} + E^{FC}_{CO}\right) \cdot P_{FC}(t) \end{cases} \tag{5}$$

where $C_{DE.en}(t)$ denotes the expense of pollutant emissions from a DE at time t and $C_{DE.en}(t)$ denotes the expense of pollutant emissions from an FC at time t. $P_{DE}(t)$ and $P_{FC}(t)$ are the powers that the DE and the FC, respectively, output at time t.

2.2. Constraints

The specifications of the equipment and other components have an impact on the microgrid optimization model that each power generation unit must follow in order to ensure that the system functions safely and steadily when producing electricity.

For micro-grid to maintain regular system operation, it must satisfy power balancing limitations that arise during operation. Eq. (6) displays the constraint expression.

$$P_{\text{Load}}(t) = P_{\text{grid}}(t) + P_{BE}(t) + P_{WT}(t) + P_{PV}(t) + P_{DE}(t) + P_{FC}(t) \tag{6}$$

where $P_{\text{Load}}(t)$ is the microgrid's load power at time t. Each DER in the microgrid is limited in the amount of power it can produce by its upper and lower bounds, which are given in Eq. (7):

$$P_i^{min} \le P_i(t) \le P_i^{max} \tag{7}$$

where $P_i(t)$ is the controlled generator's output power at time t for the i_{th}

generator. The i_{th} controllable generator set's output power has upper and lower bounds, denoted as P_i^{max} and P_i^{min}, respectively.

There is a climbing constraint, or maximum power rise or decrease rate, for each DER in the microgrid. This limitation is illustrated in Eq. (8):

$$P_i(t) - P_i(t-1) \leq p_i \Delta t \tag{8}$$

where p_i is the i_{th} controlled generator unit's maximum climb rate. The increase in operation time, or Δt. Eq. (9) illustrates the limitation that governs the microgrid's interaction with the larger grid.

$$P_{\text{grid}}^{min} \leq |P_{\text{grid}}(t)| \leq P_{\text{grid}}^{max} \tag{9}$$

where P_{grid}^{max} and P_{grid}^{min} denote the maximum and minimum power thresholds for the microgrid-to-large grid interaction, respectively.

There are capacity constraints as well as power limitations for charging and discharging during normal battery usage. Eq. (10) displays these limitations:

$$\begin{cases} P_{BE}^{min} \leq P_{BE}(t) \leq P_{BE}^{max} \\ SOC_{min}(t) \leq SOC(t) \leq SOC_{max}(t) \end{cases} \tag{10}$$

where P_{BE}^{min} And P_{BE}^{max} stand for the battery's lower and maximum limits, respectively; a negative value denotes charging while a positive number denotes draining. $SOC_{max}(t)$ and $SOC_{min}(t)$, respectively, represent the battery's capacity at time t's upper and lower boundaries.

2.3. Deferrable appliances

According to this research, deferrable appliances are smart appliances that can be shifted or interrupted during the day at any moment based on the needs of the user. This class includes the dishwashing machine, spin dryer, and washing machine. Let $a_d \epsilon A_d$ represent each appliance in the deferrable class, and let A_d represent the combination of deferrable appliances. Eq. (11) uses λ_d to represent each appliance's power rating in this class. This exact formula displays the total electricity consumption (ε_d) of deferrable appliances during the day (Zafar Iqbal, 2018):

$$\varepsilon_d = \sum_{t=1}^{T} \left(\sum_{a_{ni} o' A_n d} \lambda_d \times \alpha_d(t) \right) \tag{11}$$

The hourly rate that the consumer pays overall for all deferrable appliances is as follows:

$$\sigma_{A_d}^t = \sum_{a_{ni} o' A_n d} (\lambda_d \times \rho(t) \times \alpha_d(t)) \tag{12}$$

In contrast to all deferrable appliances, the total daily electricity cost that the client pays the utility is provided by the following equation:

$$\delta_{A_d}^{Total} = \sum_{t=1}^{T} \left(\sum_{a_{ni} o' A_n d} (\lambda_d \times \rho(t) \times \alpha_d(t)) \right) \tag{13}$$

Here, OFF / ON status of deferrable devices is indicated by $\alpha_d(t)$, which can take the form of one or zero.

$$\alpha_d(t) = \begin{cases} 1 & \textit{If } a_d \textit{ is ON} \\ 0 & \textit{If } a_d \textit{ is OFF} \end{cases} \tag{14}$$

Eqs. (15) and (16) take into account the overall electricity usage and cost for numerous houses in comparison to deferrable equipment throughout a given day.

$$\vartheta_d \& = \sum_{u=1}^{\mu} (\varepsilon_d) \tag{15}$$

$$\varphi_{A_i}^{\text{Total}} \& = \sum_{u=1}^{\mu} \left(\delta_{A_i}^{\text{Total}} \right) \tag{16}$$

Eq. (15) shows the daily electricity consumption as ε_d, and Eq. (16) shows the daily cost for a single customer as $\delta_{A_d}^{\text{Total}}$.

2.4. Non-deferrable appliances

When an appliance cannot be changed or stopped while it is operating, it is regarded as non-deferrable. This equipment' requirements are the ideal window of time for their execution to conclude. It is presumed that the refrigerator and interior lighting are non-deferrable items. For any appliance in the nondeferrable appliance class, let $a_{nd} \epsilon A_{nd}$ stand for it. Each device has an electrical power rating of λ_{nd}, and the following mathematical formula shows the overall energy usage ε_{nd} per day.

$$\varepsilon_{nd} = \sum_{t=1}^{T} \left(\sum_{a_{ni} o' A_n d} (\lambda_{nd} \times \alpha_{nd}(t)) \right) \tag{17}$$

Customers bear the highest expense because the utility charges more for the requested slot of these appliances because of their non-shiftable and uninterruptible behavior. The increase in PAR is the reason for the high pricing. The utility levies higher rates to maintain perception of balance between consumption and generation. Eq. (18) can be used to get the daily electricity costs for any equipment in the nondeferrable class.

$$\delta_{A_{nd}}^{Total} = \sum_{t=1}^{T} \left(\sum_{a_{ndQ'} A_n d} (\lambda_{nd} \times \rho(t) \times \alpha_{nd}(t)) \right) \tag{18}$$

Similarly, Eq. (19) can be used to calculate the cost of non-deferrable appliances over a specific time period.

$$\sigma_{A_{nd}}^t = \sum_{a_{mj} did_n d} (\lambda_{nd} \times \rho(t) \times \alpha_{nd}(t)) \tag{19}$$

In this case, OFF/ON state of non-deferrable devices is indicated by $\alpha_{nd}(t)$.

$$\alpha_{nd}(t) = \begin{cases} 1 & \text{If } a_{nd} \text{ is } \textit{ON} \\ 0 & \text{If } a_{nd} \text{ is } \textit{OFF} \end{cases} \tag{20}$$

For a given number of users on a particular day, the total electricity consumption and cost for non-deferrable appliances are calculated using Eqs. (21) and (22), respectively.

$$\vartheta_{nd} = \sum_{u=1}^{\mu} (\varepsilon_{nd}) \tag{21}$$

$$\varphi_{A_{nd}}^{\text{Total}} = \sum_{u=1}^{\mu} \left(\delta_{A_{nd}}^{\text{Total}} \right) \tag{22}$$

3. Honey badger algorithm (HBA)

The day-ahead scheduling of sources is based on forecasts of PV power generation, wind power output, and load demand. This stage uses the meta-heuristic algorithm HBA to determine the optimal set-points of the microgrid's batteries and the Lagrange multiplier technique to get the ideal set-point of the DG. The sophisticated meta-heuristic program HBA simulates the foraging habits of honey badgers. The honey badger tracks a honeyguide bird or uses its sense of smell to find its meal. The honey badger uses its sense of smell to locate its prey. Once it has done so, it circles the target to assess the optimal spot for burrowing and hunting. HBA can maintain the proper ratio of exploration to exploitation. It also has the advantage of having fewer settings to change. The following stages can be used to summarize the HBA's mathematical model (E. Hassaballah et al., 2024):

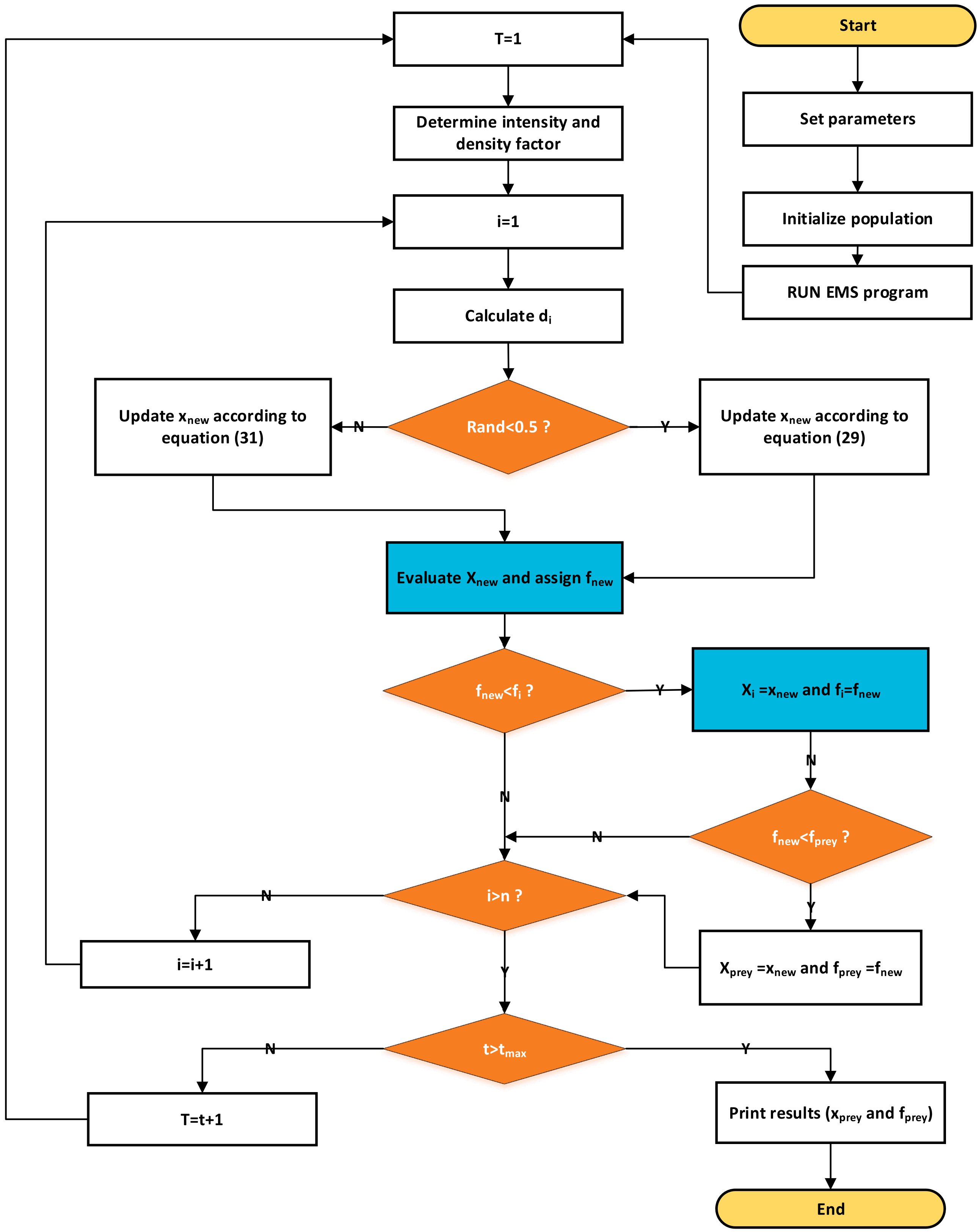

Fig. 2. Flowchart of HBA.

Step 1. Initializing the population: In a population of size n, the ith honey badger's (xi) position can be expressed as a dim-dimensional solution vector as:

$$x_i = [x_{il}, x_{i2}, x_{i3}, \ldots, x_{idim}] \tag{23}$$

dim represents the quantity of design variables.

The following equation is used to pick the initial positions of the honey badgers at random, while the initial values (x_{il}) of solution vector (x_i) are chosen based on:

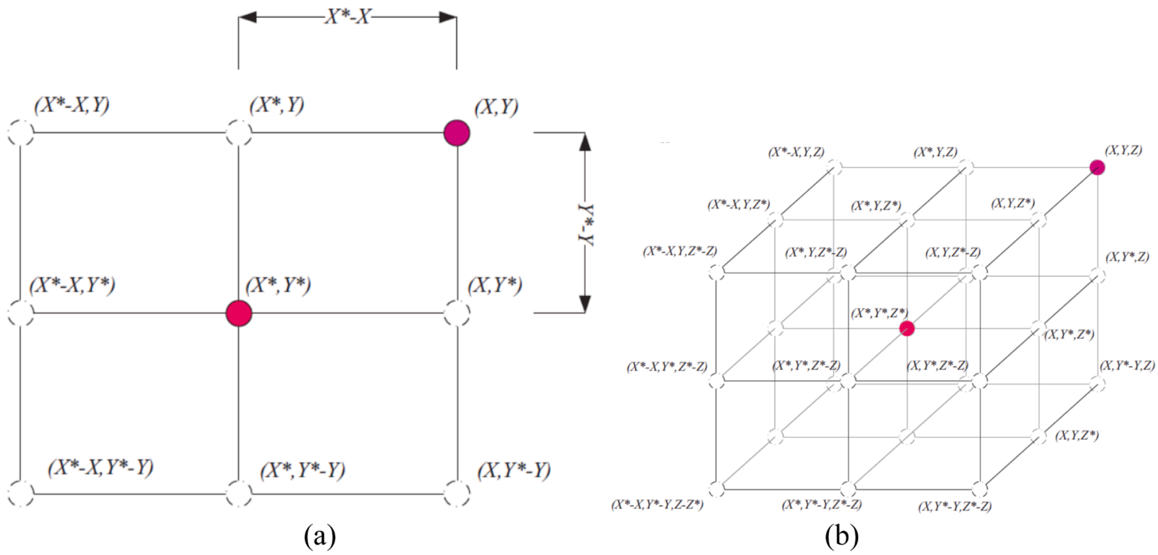

Fig. 3. (a) 2D and (b) 3D position vectors together with potential future positions (X represents the best solution found thus far).

$$x_{ij} = LB_j + r_1\left(UB_j - LB_j\right), j = 1, 2, 3, \ldots\ldots, dim \tag{24}$$

where the lower and upper search space bounds are denoted, respectively, by LB_j and UB_j. A random number in interval $(0, 1)$ is denoted by r_1.

Step 2. Using n, get the fitness of each honey badger location x_i. Next, assign fitness to f_{prey} and save the best position for x_{prey} .

Step 3. Finding intensity: The cube of the distance between the prey and the ith honey badger determines the inverse relationship between the prey's smell intensity (I_i), which can be computed as follows:

$$I_i = \frac{r_2 S}{4\pi d_i^2} \tag{25}$$

where r_2 is a randomly generated number in the range of 0 to 1.

$$S = (x_i - x_{i+1})^2 \tag{26}$$

$$d_i = \left(x_{prey} - x_i\right) \tag{27}$$

where d_i is distance between ith badger and prey, and S is source intensity or concentration intensity (prey position).

Step 4. Updating density factor: Eq. (28) updates density factor (α) over iterations to balance exploration and exploitation.

$$\alpha = C \times \exp\left(\frac{-t}{t_{max}}\right) \tag{28}$$

where t_{max} is the number of iterations and C is a constant number greater than 1 (the usual value is 2).

Step 5. Changing the locations of the honey badgers: The two stages of the HBA position update procedure (x_{new}) are the digging phase and the honeyguide phase.

Step 5–1. Phase of digging: During this stage, the honey badger approaches its prey using the following formula:

$$x_{new} = x_{prey} + F \times \beta \times I \times x_{prey} + F \times r_3 \times \alpha \times d_i \times \left|\cos(2\pi r_4) \times [1 - \cos(2\pi r_5)]\right| \tag{29}$$

where the prey's best position to date is indicated by x_{prey} . The honey badger's capacity to locate food is indicated by the constant β, which has a default value of 6. There are three distinct random numbers in the range [0, 1]: r_3,r_4, and r_5. Eq. (30) determines the value of F, a flag that alters the search direction to prevent getting trapped or stuck at the local optimum value.

$$F = \begin{cases} 1 & r_6 \leq 0.5 \\ -1 & \text{otherwise} \end{cases} \tag{30}$$

where r_6 is a chance value in the range of 0 and 1..

Step 5–2. Phase of the honeyguide: In this instance, honey badger follows honeybird and advances in direction of the meal in line with Eq. (23).

$$x_{new} = x_{prey} + F \times r_7 \times \alpha \times d_i \tag{31}$$

where, respectively, x_{new} , and x_{prey} indicate the prey's location and the honey badger's new position. The random number r_7 ranges from 0 to 1. Eqs. (28) and (30) are utilized to compute α and F, respectively.

Step 6. Find the current position's fitness value (f_{new}), or x_{new} . Update the honey badger's position (x_i) and fitness (f_i) to be x_{new} and f_{new} , respectively, if ($f_{new} \leq f_i$); if not, maintain the current values for x_i and f_i. Additionally, if its fitness value exceeds that of x_{prey} (f_{prey}), it will take the prey position.

Step 7. Examine the termination criteria: the algorithm stops and returns the best solution vector if the iteration number (t) reaches the predetermined maximum number of iterations (t_{max}); if not, move on to step 3. Fig. 2 shows the flowchart that explains the HBA's computing processes.

4. Whale optimization algorithm (WOA)

The spiral bubble-net feeding maneuver, encircling prey mathematical model, and prey search are presented first in this section.

4.1. Encircling prey

Because they can detect their prey, humpback whales may circle around it. The WOA algorithm assumes that the current best candidate solution is either the target prey or extremely close to the optimum because the position of the optimal design in the search space is unknown a priori. The other search agents will attempt to realign themselves with respect to the top search agent after it has been determined. The following equations represent this phenomenon (Mirjalili & Lewis, 2016):

$$\vec{D} = \left|\vec{C} \cdot \vec{X^*}(t) - \vec{X}(t)\right| \tag{32}$$

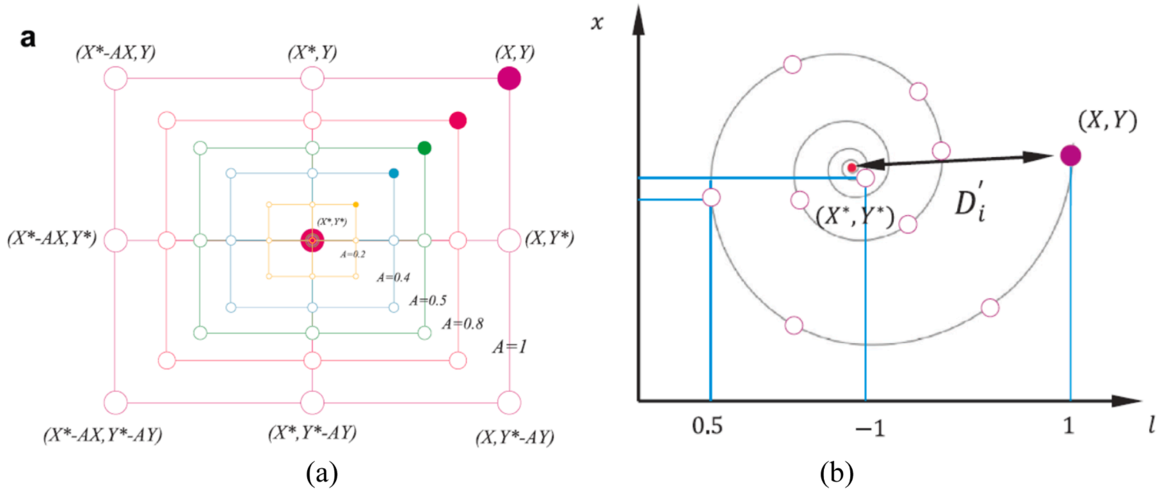

Fig. 4. The bubble-net search process used in WOA (X^* is the best result found thus far) (a) The spiral updating position and (b) the diminishing encircling mechanism.

$$\overrightarrow{X}(t+1) = \overrightarrow{X^*}(t) - \overrightarrow{A}\cdot\overrightarrow{D} \tag{33}$$

where t is the current iteration, A and C are coefficient vectors, | | is the absolute value, and ·is an element-by-element multiplication. X is the position vector of the best solution discovered thus far. It is crucial to remember that X^* needs to be changed in each cycle whenever a better option appears.

Vectors $\overrightarrow{A}$ and $\overrightarrow{C}$ are calculated as follows:

$$\overrightarrow{A} = 2\overrightarrow{a}\cdot\overrightarrow{r} - \overrightarrow{a} \tag{34}$$

$$\overrightarrow{C} = 2\cdot\overrightarrow{r} \tag{35}$$

where r is a random vector in [0,1] and $\overrightarrow{a}$ is linearly decreasing from 2 to 0 during the length of iterations (in both the exploration and exploitation phases).

Fig. 3(a) illustrates the logic underlying Eq. (33) for a 2D situation. The location of the latest best record (X^*, Y^*) can be used to change a search agent's position (X, Y). It is feasible to reach multiple places surrounding the optimal agent with respect to the current position by changing the values of the A and C vectors.

Fig. 3(b) also shows the potential updated position of a search agent in three dimensions. It should be mentioned that any position in the search space between the key points in Fig. 3 can be reached by specifying the random vector ($\overrightarrow{r}$). Eq. (33) thus allows any search agent to update its position in the area of the current optimal solution while simulating the surrounding of the prey.

Applying the same concept to an n-dimensional search space will cause the search agents to travel around the greatest solution so far discovered in hyper-cubes. As was indicated in the previous section, humpback whales use the bubble-net technique to assault their prey. The following is the method's mathematical formulation:

4.2. Bubble-net attacking method (exploitation phase)

Two methods are created in order to mathematically simulate humpback whale bubble-net behavior:

Reducing the encircling mechanism: This action is accomplished by lowering the value of an in Eq. (29). Observe that there is a corresponding drop in A's fluctuation range. Put another way, during the period of iterations, an is reduced from 2 to 0 and A is a random value in the interval [$-a$, a]. The new position of a search agent can be defined anywhere between the original position of the agent and the position of the current best agent by setting random values for A in [−1,1]. The possible positions from (X, Y) towards (X^* , Y^*) that can be attained by 0 $\leq A$ ≤ 1 in a 2D space are depicted in Fig. 4(a).

Two Spiral updating position: Using this method, which is illustrated in Fig. 4(b), the distance between the whale at (X^*, Y^*) and the prey at (X, Y) is first ascertained. Next, a spiral equation is created between the location of the whale and its prey in order to mimic the helix-shaped movement of humpback whales.

$$\overrightarrow{X}(t+1) = \overrightarrow{D'}\cdot e^{bl}\cdot\cos(2\pi l) + \overrightarrow{X^*}(t) \tag{36}$$

where is an element-by-element multiplication, b is a constant used to define the shape of the logarithmic spiral, and l is a random number in [−1,1. $\overrightarrow{D'}$ represents the distance of the i_{th} whale to the prey (best answer found thus far).

It should be mentioned that humpback whales swim around their prey in both a spiral and a decreasing circle. In order to represent this concurrent behavior, in this paper used the assumption that there is a 50 % chance of selecting the spiral model or the shrinking encircling mechanism to update the whales' positions throughout optimization. The following is the mathematical model:

$$\overrightarrow{X}(t+1) = \begin{cases} \overrightarrow{X^*}(t) - \overrightarrow{A}\cdot\overrightarrow{D} \text{ if } p < 0.5 \\ \overrightarrow{D'}\cdot e^{bl}\cdot cos(2\pi l) + \overrightarrow{X^*}(t) \text{ if } p \geq 0.5 \end{cases} \tag{37}$$

where p in [0,1] is a random number. Apart from using the bubble-net technique, humpback whales also conduct haphazard searches for food. The following is the search's mathematical model.

4.3. Search for prey (exploration phase)

One can look for prey (exploration) by using the same technique that involves changing the $\overrightarrow{A}$ vector. In actuality, humpback whales search randomly while considering one another's whereabouts. To push the search agent to travel away from a reference whale, we employ $\overrightarrow{A}$ with random values larger than 1 or less than −1. During the exploration phase, as opposed to the exploitation phase, we update the position of a search agent based on a randomly selected search agent rather than the most effective search agent to date. In order to do a worldwide search, this mechanism and $|\overrightarrow{A}\,| > 1$ place an emphasis on exploration and low the WOA algorithm. The mathematical model looks like this:

$$\overrightarrow{D} = \left|\overrightarrow{C}\cdot\overrightarrow{X_{\text{rand}}} - \overrightarrow{X}\right| \tag{38}$$

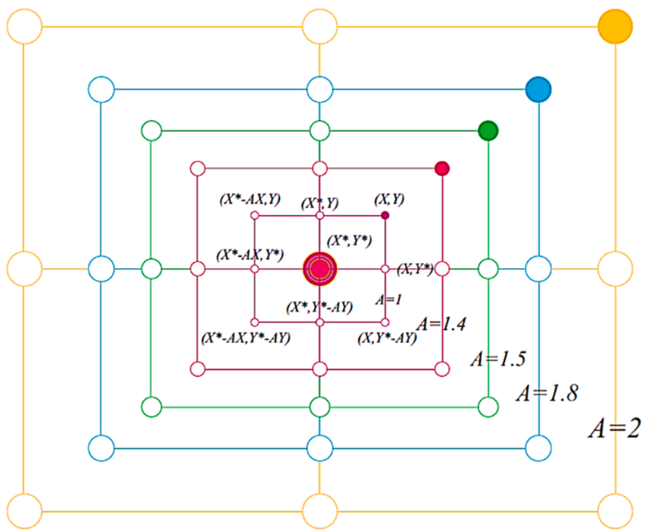

Fig. 5. Investigative technique used in WO.A

$$\overrightarrow{X}(t+1) = \overrightarrow{X_{\text{rand}}} - \overrightarrow{A}\cdot\overrightarrow{D} \tag{39}$$

where a random position vector (a random whale) selected from the present population is denoted by $\overrightarrow{X_{\text{rand}}}$. Fig. 5 shows some of the potential locations around a specific solution with $\overrightarrow{A} > 1$.

The WOA algorithm uses an initial set of random solutions. At each iteration, search agents shift their positions in relation to a randomly chosen search agent or the best solution thus far. The exploration and exploitation parameters are provided by reducing a parameter from 2 to 0. when $|\overrightarrow{A}| > 1$, a random search agent is selected; when $|\overrightarrow{A}| < 1$, the optimal solution is chosen for updating the search agent positions. The movement of WOA can be either spiral or circular, depending on the value of p. When a termination requirement is satisfied, the WOA algorithm comes to an end. Fig. 5 displays the WOA algorithm's pseudo code.

Because WOA can explore and exploit, it can be viewed as a global optimizer from a theoretical perspective. Furthermore, other search agents can take advantage of the current best record within the defined search space that the suggested hyper-cube method defines around the optimal solution. An adaptive adjustment of the search vector A allows the WOA algorithm to switch between exploration and exploitation with ease. By decreasing A, certain iterations are allocated to exploration ($|A| \geq 1$), and the remaining iterations are committed to exploitation ($|A| < 1$). Surprisingly, WOA just has two primary internal settings that need to be changed (A and C).

To fully replicate the behavior of humpback whales, mutation and other evolutionary operations might have been included in the WOA formulation. However, we chose to employ a very basic version of the WOA algorithm by reducing the number of internal parameters and rules.

5. Peak load constraint

Makes sure that the total load of the home h_j is not greater than the limit $\widehat{P}^{max}_{h_j,t}$, which is set by the local distribution companies (LDCs).

$$\sum_{i\in\Omega} P_{i,h_j} S_{i,h_j,t} + \sum_{z\in LI} P_{LI_{z,h_j}} L_{z,h_j,t} + \sum_{i\in\{B,ESD\}} P^{LDC}_{i,h_j,t} - \sum_{i\in\{R,ESD\}} P^{H}_{D_{i,h_j,t}} - P^{H}_{PV,h_j,t} \leq \widehat{P}^{max}_{h_j,t}, \forall h_j \in H \tag{40}$$

The electricity required for appliances, energy storage devices (ESD), and charging the PV panel batteries make up the residential load. Included is the net power used to use the electricity generated by the solar panel to power certain household loads.

$$\widehat{P}^{max}_{h_j,t} = P^{max}_{h_j,t} - \alpha_{h_j,t} P^{FLEX}_{j,t},\ \forall t \in \mathscr{T}; \forall h_j \in \mathscr{H}; \forall j \in \mathscr{N} \tag{41}$$

The flexibility index of the client as a percentage of the required flexibility is represented by the LDC at bus j, which is $j : \alpha_{h_j,t}$. The source of the current maximum demand in the home, $\widehat{P}^{max}_{h_j,t}$, is the maximum authorized demand, $P^{max}_{h_j,t}$. The reciprocal link between the HEMS and local distribution corporations (LDCs) is depicted in Constraint (36)

5.1. Balance power

Guarantees that, as indicated below, the entire power requirement of the household appliances is satisfied. This is accomplished by balancing the electricity that the PV system produces, the power that the grid provides, the power that the ESD and PV panel batteries discharge into household, and total power consumption of domestic devices (Alrumayh & Bhattacharya, 2019):

$$\sum_{i\in\mathscr{R}} P_{i,h_j} S_{i,h_j,t} = P^{H}_{LDC,h_j,t} + \sum_{q} P^{H}_{D_{q,h_j,t}} + P^{H}_{PV,h_j,t}, \forall t \in \mathscr{T}; \forall h_j \in \mathscr{H} \tag{42}$$

Assuming that the ESD charge level was always known is irrational. A schedule for charging and draining is shown below:

$$E_{ESD,h_j,t} = E_{ESD,h_j,t-1} + \tau\left[P^{L}_{C^{LDC}_{ESD,h_j,t}} \eta_1 - \left(P^{L}_{D^{LDC}_{ESD,h_j,t}} + P^{H}_{D_{ESD,hy,t}}\right) \Big/ \eta_2\right], \forall t \in \left\{t^{AR}_{h_j}, t^{DEP}_{h_y}\right\}; \forall h_j \in \mathscr{H} \tag{43}$$

$$E^{min}_{ESD,h_j} \leq E_{ESD,h_j,t} \leq E^{max}_{ESD,h_j}, \&\forall t \in \left\{t^{AR}_{h_j}, t^{DEP}_{h_j}\right\}; \forall h_j \in \mathscr{H} \tag{44}$$

$$P^{LDC}_{C_{EW,h_j,t}} \leq S_{C_{EW,h_j,t}} P^{max}_{C_{ESD,h_j}}, \&\forall t \in \left\{t^{AR}_{h_j}, t^{DEP}_{h_j}\right\}; \forall h_j \in \mathscr{H} \tag{45}$$

$$P^{LDC}_{D_{ESD,h_j,t}} + P^{H}_{D_{ESD,h_j,t}} \leq S_{D_{ESD,hy,t}} P^{max}_{D_{kD,h_j}},\ \forall t \in \left\{t^{AR}_{h_j}, t^{DEP}_{h_j}\right\}; \forall h_j \in \mathscr{H} \tag{46}$$

$$S_{C_{EED,h_j,t}} + S_{D_{EED,h_j,t}} \leq 1, \forall t \in \left\{t^{AR}_{h_j}, t^{DEP}_{h_y}\right\}; \forall h_j \in \mathscr{H} \tag{47}$$

$$E_{ESD,h_j,t} \geq \omega_{h_j} E^{max}_{ESD}, \forall t = t^{DEP}_{h_j}; \forall h_j \in \mathscr{H} \tag{48}$$

$$E_{ESD,h_j,t} = E^{AR}_{ESD}, \forall t = t^{AR}_{h_j}; \forall h_j \in \mathscr{H} \tag{49}$$

The power that the ESD draws and discharges to the grid and the house has an impact on how the ESD's energy level changes, as shown by Eq. (43). Constraints (45) and (46) provide limits on the ESD's charging and discharging power, respectively. The constraint ensures that the ESD energy level stays between the minimum and maximum bounds (44). The charging and discharging processes cannot take place concurrently due to a limitation (47). In addition to establishing energy level inside device at the time of arrival, $t^{AR}_{h_j}$, Constraint (49) of the ESD guarantees that stored energy in device is more than or equal to a predetermined minimum value.

5.2. Objective function

The goal of microgrid energy management is to keep running expenses as low as possible within the planned time. This is the definition of the objective function (Chen et, al.):

$$min \sum_{t\in N_T} c^{G}_{1}\left(p^{\text{DG}}_{t}\right)^2 + c^{G}_{2} p^{\text{DG}}_{t} + \lambda_t p^{\text{UG}}_{t} + b\left(p^{\text{UG}}_{t}\right)^2 \tag{50}$$

The costs of the three terms' goal functions are as follows: The objective is to lower the price of buying electricity from the external grid. The price sensitivity coefficient is represented by b in the last term,

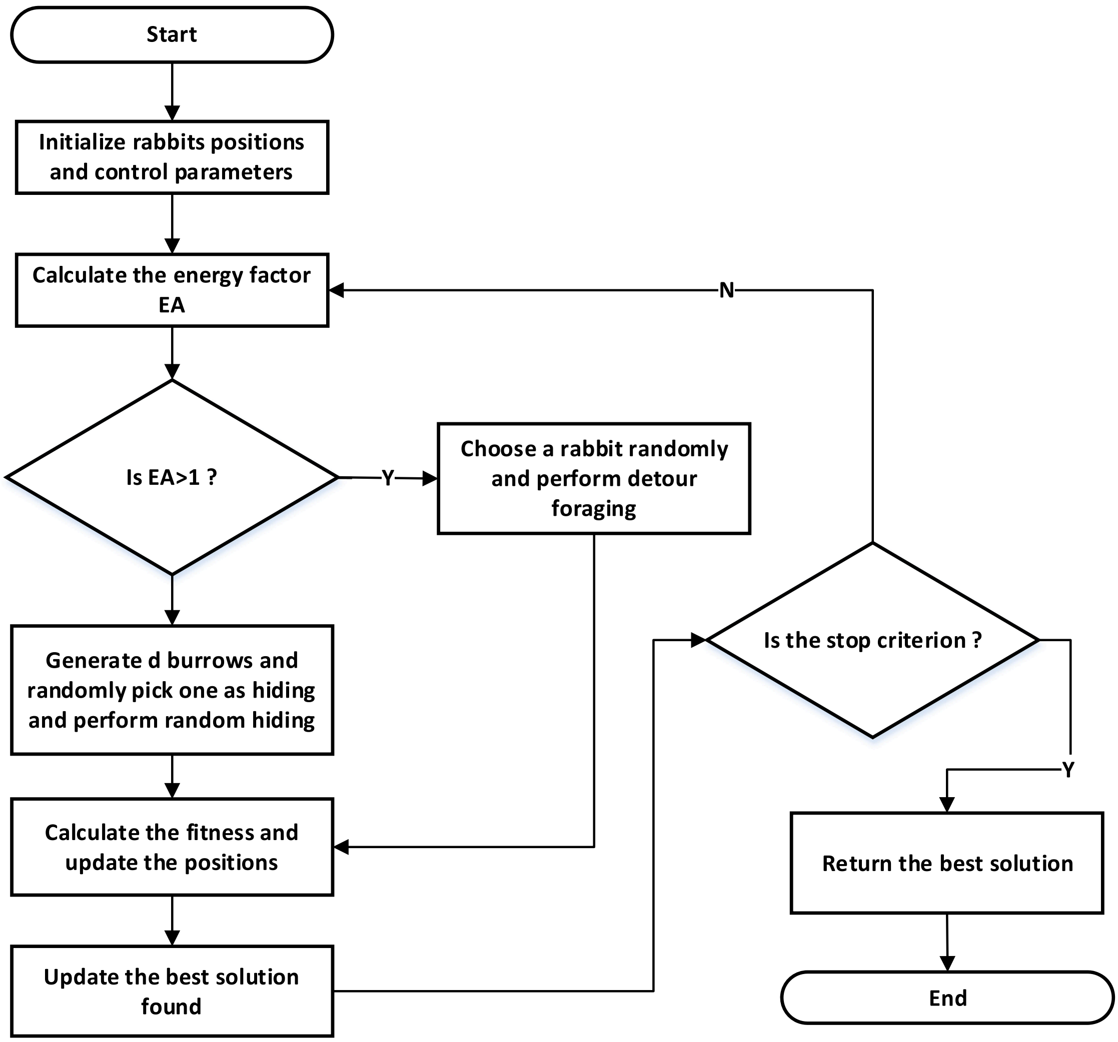

Fig. 6. Flowchart of ARO algorithm.

where p_t^{DG} is the purchased power and λ_t is the energy sport price. The first two phrases seek to reduce distributed generation's (DGs') energy expenses. Here, N_T is the set of scheduling periods, c_1^G and c_2^G are generation cost parameters, and p_t^{UG} is the DG generation.

5.3. Constraints of dg operation

$$p_t^{\mathrm{DG},min} \leq p_t^{\mathrm{DG}} \leq p_t^{\mathrm{DG},max}, \forall t \in N_T \tag{51}$$

$$\begin{cases} p_t^{\mathrm{DG,dr}} \leq p_t^{\mathrm{DG}} - p_{t-1}^{\mathrm{DG}} \leq p_t^{\mathrm{DG,ur}} \\ p_{t_1}^{\mathrm{DG,dr}} \leq p_{t_1}^{\mathrm{DG}} - p_0^{\mathrm{DG}} \leq p_{t_1}^{\mathrm{DG,ur}}, \end{cases} \forall t \in N_T \tag{52}$$

Consisting of the maximum and minimum DG active power generation constraints, denoted as $pp_t^{\mathrm{DG},max}$ and $p_t^{\mathrm{DG},min}$, respectively, restriction (51) reflects the DG capacity restriction. The upramping and downramping constraints are given by the DG ramping constraint (52) as $p_t^{\mathrm{DG,ur}}$ and $p_t^{\mathrm{DG,dr}}$, respectively.

6. Artificial rabbits optimization

The artificial rabbits optimization (ARO) algorithm was created recently and is incredibly successful. It is based on the survival techniques employed by rabbits, such as random hiding and detour foraging. To carry out the iterative searches, a mathematical model of the ARO's foraging mode is used. In this way, a rabbit tries to consume the grasses and plants next to the burrows of other rabbits. By doing this, you may be able to deceive predators and protect the rabbit burrow from harm. Put another way, rabbits seek food in distant places and disregard the easily accessible food that is close. The swarm population in the ARO method is the number of rabbits. Each rabbit has an eating area with some grass and plants, as well as a burrow. Each rabbit randomly raids the burrows of other rabbits in an effort to get food. During this phase, every rabbit tends to update its location in reference to the randomly chosen person, causing interruptions. The following is a mathematical representation of this foraging action (Rizk-Allah et al., 2023):

$$\overrightarrow{\Delta}_i(t+1) = \overrightarrow{z}_j(t) + \rho\cdot\left(\overrightarrow{z}_i(t) - \overrightarrow{z}_j(t)\right) + \mathrm{round}(0.5\cdot(0.05+g_1))\cdot n_1, i, j = 1, 2......, M \text{ and } i \neq j \tag{53}$$

$$\rho = E.c \tag{54}$$

$$E = \left(e - e^{\left(\frac{1-t}{T}\right)^2}\right)\cdot\sin(2\pi g_2) \tag{55}$$

$$c(k) = \begin{cases} 1 & if\, k == h(u) \\ 0 & else \end{cases}, k = 1, \ldots, d\&u = 1, 2, \ldots, g_3\cdot d \tag{56}$$

$$h = \text{randperm}(d) \tag{57}$$

$$n_1 \sim N(0,1) \tag{58}$$

where the following parameters are defined: rabbits population size , iterations total size, problem dimension, rounding to the nearest integer value, random permutation function ranged from 1 to problem dimension, running length during foraging, and $\vec{z}_i(t), \vec{\Delta}_i(t+1), M, T, d$, round, randperm, and E, respectively. Here, the uniform random numbers inside the interval [0, 1] are defined by g_1, g_2, g_3, and n_1 stands for the normal distribution function. Eq. (58)'s perturbation aids ARO in conducting a thorough search and avoiding local peaks and minima. Here, c is a vector that is utilized in the search process to choose a number of individuals, and ρ is a mathematical operator that simulates rabbit movement. Consequently, ARO algorithm's exploration and global search capabilities are enhanced during this foraging stage. Rabbits randomly hide in exploitation mode to evade being discovered by predators. The rabbit digs a few tunnels near to its existing burrows. It selects a burrow at random and hides there to trick predators. The formula for the *i th* rabbit with the *j th* burrow is as follows.

$$B\vec{U}_{ij}(t) = \vec{z}_i(t) + H\cdot h\cdot \vec{z}_i(t), i = 1,2......,M \text{ and } j = 1,2......,d \tag{59}$$

$$H = \frac{1-t+T}{T} g_4 \tag{60}$$

$$n_2 \sim N(0,1) \tag{61}$$

$$h(k) = \begin{cases} 1 & \text{if } k == j \\ 0 & \text{else} \end{cases}, k = 1,\ldots,d \tag{62}$$

where H and d stand for the ability to hide and, respectively, created burrows inside the rabbit's territory. A bunny's large region is mostly where holes are made. When the number of iterations increases, the neighborhood's size decreases. The options for the random concealment mode are as follows:

$$\vec{\Delta}_i(t+1) = \vec{z}_i(t) + \rho\cdot\left(g_4\cdot BU_{ir}(t) - \vec{z}_i(t)\right), i = 1,2,......M \tag{63}$$

$$h_r(k) = \begin{cases} 1 & \text{if } k == \lceil g_5\cdot d \rceil \\ 0 & \text{else} \end{cases}, k = 1,\ldots,d \tag{64}$$

$$BU_{ir}(t) = \vec{z}_i(t) + H\cdot h_r\cdot \vec{z}_i(t) \tag{65}$$

where g_4 and g_5 define random values inside the interval [0, 1], and $BU_{ir}(t)$ indicates the burrow that the rabbit chooses using the hiding mode. Following either a random concealment procedure or a detour foraging mode, the ith rabbit's position is updated as follows.

$$\vec{z}_s(t+1) = \begin{cases} \vec{z}_s(t) & f\left(\vec{z}_s(t)\right) \le f\left(\vec{\Delta}_s(t+1)\right) \\ \vec{\Delta}_s(t+1) & f\left(\vec{z}_s(t)\right) > f\left(\vec{\Delta}_s(t+1)\right) \end{cases} \tag{66}$$

Eq. (53) or Eq. (63) defines the candidate position, where the rabbit stays after leaving its current location, if the candidate fitness of the *sth* rabbit is greater than the position's existing fitness. As iteration progresses, rabbits' energy decreases, aiding in the shift from exploratory to exploitative mode, which is expressed as follows:

$$EA(t) = 4\left(1-\frac{t}{T}\right)\ln\left(\frac{1}{\alpha}\right) \tag{67}$$

where a random integer is defined by α. The method looks locally for the solution (exploitation) when $EA(t) \le 1$, and globally for the solution (exploration) when $EA(t) > 1$. Algorithm 2 presents the original ARO's pseudocode framework. Fig. 6 shows the flowchart of Artificial Rabbits Optimization (ARO) algorithm (Wang et al., 2022).

Algorithm 2. The framework of the ARO.
Initialize a set of rabbits randomly
Evaluate the fitness of each rabbit and determine the best one
While the stopping criterion not met **do**
  for $i = 1: M$
  Compute the energy of rabbit (EA) by Eq. (67)
    if $EA > 1$
      Select a rabbit randomly from the population
      Obtain ρ by Eqs. (54)-(58)
      Carry out the detour foraging phase by Eq. (53)
      Evaluate the fitness of the rabbit
      Update the rabbit' position by Eq. (66)
    else
      Create d burrows and elicit one of them randomly as hiding position by Eq. (65)
      Conduct random hiding by Eq. (63)
      Evaluate the fitness of the rabbit
      Update the rabbit' position by Eq. (66)
    End if
      Update the best so far solution (z_{best})
    End for
  End while
Output: Return z_{best}

6.1. The IARO algorithm

ARO can identify the top candidates in the search region by estimating its evolution, all the while preserving the advantages of quick convergence to workable solutions and simplicity of use. However, there are still serious faults with the algorithm that could cause signatory dilemmas and hinder it from balancing exploitative and exploratory behaviors while tackling multimodal and complicated problems. First, the rabbits carry out iterative process by randomly selecting a burrow; while this strategy can quicken pattern of convergence, it may also cause a decline in the diversity of possible solutions, trapping the rabbits in the local optimal solution. First off, throughout the iterative search, the ARO does not use any guidance strategies to approach the potential regions, which could lower the quality of the final answer. It is therefore a good task to figure out how to ensure that the new people can reach the desired location. Stated differently, there exists a chance to enhance the efficacy of the conventional ARO. Thus, this study proposes an enhanced ARO, called IARO, based on experience-based perturbed learning (EPL) method and adaptive local search (ALS) mechanism.

6.1.1. The EPL strategy's future

In the exploration phase of the IARO algorithm, the rabbits follow another rabbit in the population. This updating strategy may result in an invasive diversification trend. In order to increase the exploration search, EPL is implanted to find more potential regions inside the feasible search space.

Specifically, EPL begins by computing the mean ($\Delta^{it}_{\text{mean}}$) and deviation (Δ^{it}_{dev}) of every randomly selected solution in relation to the best solution to date (Δ_{best}).

$$\Delta^{it}_{\text{mean}} = \left(z_{\text{best}} + z^{it}_I\right)/2 \tag{68}$$

$$\Delta^{it}_{\text{dev}} = \text{abs}\left(z_{\text{best}} - z^{it}_I\right) \tag{69}$$

$$\Delta^{it}_C = \Delta^{it}_{\text{mean}} + \text{rand}_1\cdot\Delta^{it}_{\text{dev}} \tag{70}$$

$$z^{it}_{\text{new}} = \Delta^{it}_C + \text{rand}_2\cdot\left(z_{\text{best}} - \Delta^{it}_C\right) + 0.95^{it}\cdot\left(\text{rand}_3 - 0.5\right)\cdot\text{abs}\left(z_{\max\,j} - z_{\min\,j}\right), z_{\max\,j} \tag{71}$$

$$= \max_j\left\{z^{it}_i\right\}, z_{\min\,j} = \min_j\left\{z^{it}_i\right\}\forall i \tag{72}$$

where rand $_1$, rand $_2$, and rand $_3$ define three random numbers elicited according to uniform distribution inside interval [0,1], and Δ^{it}_I stands for any arbitrary solution chosen at random. In this case, the perturbed

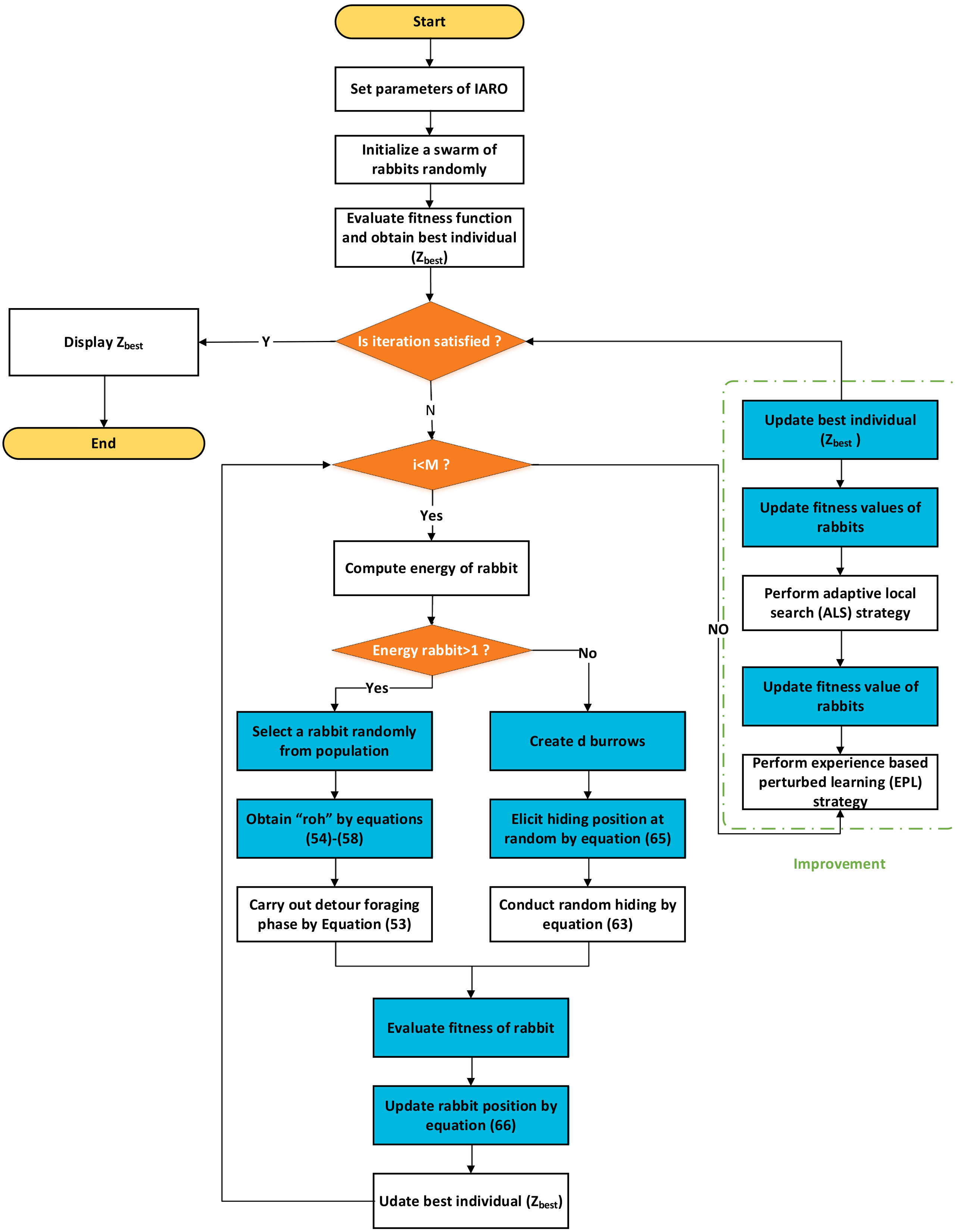

Fig. 7. IARO's flowchart.

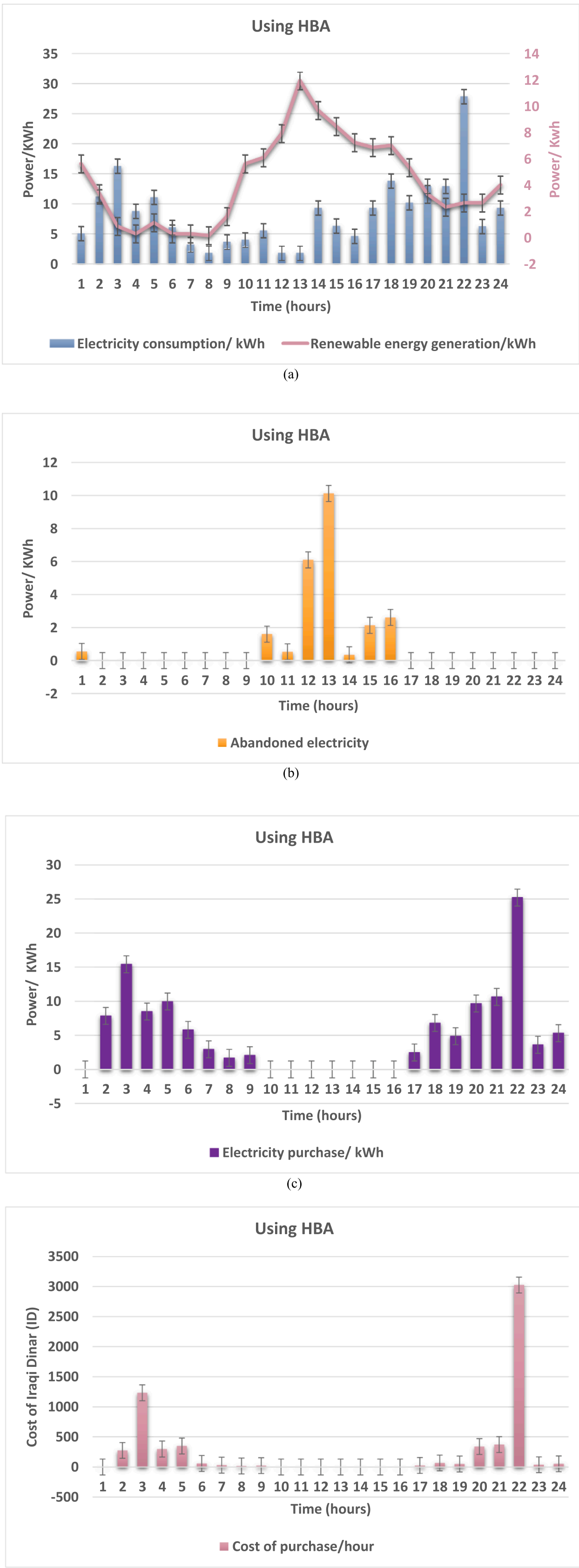

Fig. 8. Results after applying Honey Badger Algorithm (HBA) in reference (E. Hassaballah et al., 2024): (a) Comparison of renewable energy generation and usage , (b) Abandoned electricity after applying HBA, (c) Electricity purchase after applying HBA, (d) Cost of purchase after applying HBA

solution must be performed inside the dynamic bounders ($\Delta_{\max}$ and $\Delta_{\min}$) using the third term of Eq. (71).

6.1.2. *ALS approach*

To minimize the loss of accuracy during the iterative process and enhance the exploitation trend towards the promising space, an Adaptive Local Search (ALS) strategy is proposed as a guidance scheme based on shared information among the elite group within the rabbits along with their best individual (z_{best}) and worst individual (z_{worst}). Specifically, the method involves finding the poorest and best people in this group (z^P and z^W) as well as elite group based on the fitness function. The updating step is then carried out using three different sorts of movements: pushing z^W in the direction of z^P, pushing z^W in the direction of z_{best} , and pushing z^W in the direction of the average of $z^P$and z_{best} . These exercises are done in a sequential fashion, and they come to an end when a particular person achieves a higher level of fitness. This strategy's update phase can be stated as follows:

$$z_I^{it+1} = \begin{cases} z_1^{ALS} = 2 \times r_1 \times (z^P - z^W) + z^W \text{if} f(z_1^{ALS}) \le f(z_I^{it}) \\ z_2^{ALS} = 2 \times r_2 \times (z_{best} - z^W) + z^W \text{else if} f(z_2^{ALS}) \le f(z_I^{it}) \\ z_3^{ALS} = 2 \times r_3 \times ((z^P + z_{best})/2 - z^W) + z^W \text{otherwise} \end{cases} \quad (73)$$

And the current and updated solutions of *i th* solution inside the elite class are represented by the variables z_I^{it} and z_I^{it+1}. The suggested IARO's framework is shown in Fig. 7.

7. Simulation results

The suggested HEMS simulation results are shown in this section. Reducing the cost of electricity use, decreasing PAR, and raising User Comfort (UC) by cutting down on waiting times are the primary objectives of this effort. We suggest an ideal 24-hour schedule that achieves a decent balance between these objectives.

The outcomes of the Improved Artificial Rabbits Optimization Algorithm (IAROA) are compared with The Honey Badger Algorithm (HBA) and Whale Optimization Algorithm (WOA) in order to verify the accuracy of the system. The power of the recommended demand-side control at home with the Honey Badger Algorithm (HBA) corrective measure is displayed in Fig. 8. The Power of recommended home demand-side control using the WOA technique is displayed in Fig. 9. Fig. 10 illustrates the effectiveness of the AROA method's recommended residential demand-side control.

8. Discussion of results

Summertime is when renewable energy is generated at a higher rate than wintertime, and without energy storage, more electricity is wasted. As a result, an average summer day was examined. Users put the flexible load's working period in front of the electrical equipment's permitted working time when the load scheduling algorithm was not in operation. Fig. 8 illustrates how there is little correlation between the amount of power generated from renewable sources and the amount of electricity consumed by the building load. Between 10:00am and 19:30pm, a large amount of renewable energy power is wasted, and between 20:00pm and 23:30pm, as well as between 0:00am and 9:30am, home electrical equipment cannot use renewable energy generation to meet electricity demand. The demand on buildings is significant, while the generation of renewable energy is modest, especially at night. As a result, when the demand for electricity from building electrical equipment is not met, there must be an adequate supply of electricity from the grid. Iraqi Dinar (ID) 6244.5783 can be used to compute the electricity purchase cost when combined with the power grid's current electricity pricing.

Fig. 11 illustrates the results of using the Whale Optimization Algorithm (WOA). The cost of purchasing energy is 4283.9755 Iraqi Dinar (ID).

Fig. 9. Results after applying Whale Optimization Algorithm (WOA) in reference (Mirjalili & Lewis, 2016) (a) Comparison of renewable energy generation and usage, (b) Abandoned electricity after applying WOA, (c) Electricity purchase after applying WOA, (d) Cost of purchase after applying WOA, (e) The amount of improvement after applying the WOA.

The Improved Artificial Rabbits Optimization Algorithm (IAROA) has resulted in a relocation of some of the building's flexible electricity usage to the hours of 10:00am – 11:30am and 15:00pm – 19:30pm, as illustrated in Fig. 10. At the same time, during times when there is more renewable energy output, such as between 11:00am and 5:00pm, electricity demand cannot be met due to limitations in specific electrical equipment. When building load demands exceed the supply of renewable energy, building users must purchase electricity from the power grid in order to close the supply and demand gap. The cost of purchasing energy is 1227.4482 Iraqi Dinar (ID).

Fig. 9 shows the optimization outcomes of residences using load scheduling and the whale optimization technique. There is a greater match between building power use and renewable energy generation than there would be if load scheduling wasn't implemented. The majority of electrical equipment is not used during the day, due to the style of life of the locals. On the other hand, home electrical equipment can be powered by renewable energy. However, a large number of electrical devices running late into the night result in a significant power load, and the electricity generated by renewable energy sources is insufficient to supply the demand for electricity in buildings. In order to increase the rate at which renewable energy is used, load scheduling utilizing the whale optimization approach is employed in this instance to shift certain electrical equipment to a time when there is sufficient renewable energy available.

Fig. 10 shows the optimization outcomes of houses, using the Improved Artificial Rabbits Optimization Algorithm (IAROA) and load scheduling. There is a greater match between building power use and renewable energy generation than there would be if load scheduling

Fig. 10. (a) Comparison of renewable energy generation and usage after applying IAROA, (b) Abandoned electricity after applying IAROA, (c) Electricity purchase after applying IAROA, (d) Cost of purchase after applying IAROA, (e) The amount of improvement after applying the IAROA.

wasn't implemented. The majority of electrical equipment is not used during the day, due to the style of life of the locals. On the other hand, home electrical equipment can be powered by renewable energy. However, a large number of electrical gadgets running late into the night lead to a significant power load, and the amount of electricity generated by renewable energy sources is not enough to supply the demand for electricity in buildings. In order to increase the rate at which renewable energy is used, load scheduling utilizing the whale optimization approach is employed in this instance to shift certain electrical equipment to a time when there is sufficient renewable energy available.

The building's generation and consumption of renewable energy at different times are compared to illustrate the residence's rate of renewable energy utilization prior to and following load dispatching. Electricity-consuming machinery ran mostly at night before load scheduling, as above figures shows. However, during night, less renewable energy is generated. As a result, buildings might use all of the power produced at night, but during the day, additional power produced from renewable sources is wasted. The formula for the rate of renewable energy use is shown in Eq. (62) (Huang et al., 2023).

$$\omega_{RER} = \frac{E_{tot,u}}{E_{tot,g}} \tag{74}$$

where the total amount of renewable energy generated and used is denoted by $E_{tot,u}$ and the rate at which renewable energy is utilized is represented by ω_{RER}.

Construction power use increases in the afternoon, whereas renewable energy output peaks at noon. Thus, at midday, the building's electricity usage can be met by the generation of renewable energy, but not at night. Fig. 10 illustrates how actions scheduled within a specific range might raise the pace at which renewable energy is used overall.

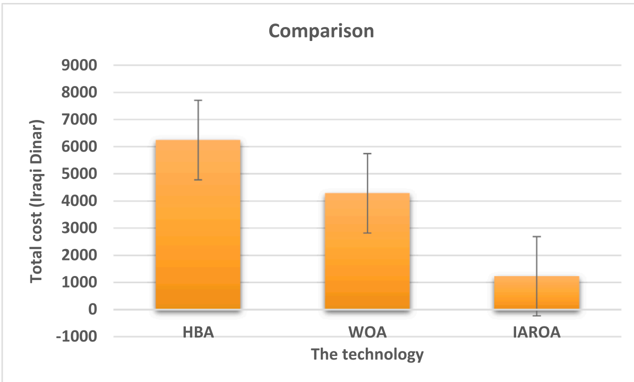

Fig. 11. The comparison of the total daily electricity bill after applying Honey Badger Algorithm (HBA) in reference (E. Hassaballah et al., 2024), after applying Whale Optimization Algorithm (WOA) in reference (Mirjalili & Lewis, 2016), and Improved Artificial Rabbits Optimization Algorithm (IAROA)

Table 2
battery storage unit specifications and initial conditions of home.

	Minimum power (kW)	Initial values (kW)	Capacity (kWh)	Maximum power (kW)
Battery home	−12.5 kW	6	47.4 kWh	12.5

Battery energy storage system is integrated to HEMS in this section to address previously listed problems. This enables the timely storing of excess power produced during the noon peak hours of renewable energy output. The additional electricity can then be used to boost the use of renewable energy sources during the nighttime peak hours. Table 2 displays the general parameters of the battery storage system. Fig. 11 compares the daily total electricity bill for the HBA, WOA, and IAROA algorithms.

The price after applying HBA optimization algorithm 6244.5783 (ID). But after applying the Whale Optimization Algorithm algorithm, the cost is found 4283.9755 (ID), and after applying the Artificial Rabbits Optimization Algorithm, cost is found 1227.4482 (ID). By comparing proposed method with conventional method, Whale Optimization Algorithm algorithm saved 31.396 % per day, and the Improved Artificial Rabbits Optimization Algorithm saved 80.3437 % per day. Table 3 shows a cost comparison of price without the corrective method, with Whale Optimization Algorithm (WOA) method and with the Improved Artificial Rabbits Optimization Algorithm (IAROA) method. Thus, the simulations suggest that HEMS, which is based on an Improved Artificial Rabbits Optimization Algorithm optimal scheduling scheme, performs well in finding solution that establishes the best trade-off between target functions.

9. Conclusion

Optimizing power generation costs is one of the primary issues that contemporary microgrids with varying energy resources and linkages must deal with. This paper provides a detailed explanation of the generation cost optimization problem with all its limitations. An extensive presentation of a novel optimization technique is made in an attempt to solve the energy management optimization problem. By contrasting it with the HBA and WOA scheduling scenario, the proposed system is assessed. In comparison scheduling case, the Improved Artificial Rabbits Optimization Algorithm decreased energy cost, PAR, and carbon emission. The price after applying HBA is 6244.5783 (ID). However after applying the Whale Optimization Algorithm algorithm, cost is found 4283.9755 (ID), and after applying Artificial Rabbits Optimization Algorithm, cost is found 1227.4482 (ID). By comparing the proposed method with HBA, the Whale Optimization Algorithm saved 31.396 % per day, and the proposed IAROA saved 80.3437 % per day. The created Improved Artificial Rabbits Optimization Algorithm is good for both utility and consumers, as evidenced by its superior performance in areas of the targeted objectives compared to the Honey Badger Algorithm (HBA) and Whale Optimization Algorithm scheduling example. The findings demonstrate that implementing the suggested plan in smart homes has a major influence on regulating energy use and containing the rising demand for electricity.

By utilizing the prosumer's adaptability, future research can investigate the transformer's electrical and thermal constraints, perhaps enhancing its performance within the distribution network. Furthermore, the thermal models of the home, such as heat pumps and thermal energy storage, are not taken into account in this work. These models can be added later to expand the suggested framework by incorporating demand-side flexibilities.

CRediT authorship contribution statement

Bilal Naji Alhasnawi: Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sabah Mohammed Mlkat Almutoki:** Writing – review & editing. **Firas Faeq K. Hussain:** Writing – review & editing. **Ambe Harrison:** Writing – review & editing. **Bahamin Bazooyar:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Funding acquisition. **Marek Zanker:** Writing – review & editing, Visualization, Validation, Supervision, Resources. **Vladimír Bureš:** Writing – review & editing, Supervision, Formal analysis, Data curation.

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.

Data availability

The data used for this research and prepatation of this article can be accessed from Brunel University of London repository at: https://doi.org/10.17633/rd.brunel.26391475.v1.

Acknowledgments

The research has been partially supported by the Faculty of Informatics and Management UHK excellence project "Methodological perspectives on modelling and simulation of hard and soft systems".

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