

Economic-Environmental Optimization of an Energy Hub with DRPs and Power-to-Gas Technology under Uncertainties with Introducing a Novel Optimization Algorithm

MEHDI AKBARPOUR¹, AMIR ABDOLLAHI^{1,2,*}, MEHRAN ABDALI¹, AND MAHDI VOSOOGH¹

¹Department of Electrical Engineering, Sirjan Branch, Islamic Azad University, Sirjan, Iran

²Department of Electrical Engineering, Shahid Bahonar University of Kerman, Iran

*Corresponding author email: a.abdollahi@uk.ac.ir

Manuscript received 10 August, 2023; revised 03 February, 2024; accepted 24 February, 2024. Paper no. JEMT-2308-1464.

In this paper, a new framework for stochastic optimal economic-environmental energy management of an energy hub (EH) is proposed. The uncertain Flexible loads, energy market prices, wind power generation and power to gas (P2G) technology are also considered in the proposed structure. Here, an innovative objective function including both operating and emissions costs is suggested and a self-adaptive hybrid algorithm of hybrid bald eagle search and mutant grey wolf optimization (hBES-MGWO) is proposed for solving such optimization problem. The simulation results indicate that flexible loads and their participation in demand response programs (DRPs) can considerably reduce the operating costs of EH. More participation of flexible loads in DRPs will cause to the lower operation cost. In this paper, an economic model of responsive loads is employed based on elasticity of demand and customer benefit function. It is shown that considering the emission cost in objective function leads to an increasement in EH' operation costs. It is also demonstrated that the proposed hBES-MGWO has higher accuracy in comparison with the other optimization algorithms.

© 2024 Journal of Energy Management and Technology

keywords: Energy Hub, Flexible Load, hBES-MOGWO Algorithm, Economic model of DRPs, Load Flexibility Index.

<http://dx.doi.org/10.22109/JEMT.2024.411002.1464>

NOMENCLATURE

A/S	Ancillary/Service	DLC	Direct load control
Bat	Battery	DP	Dynamic programming
BES	Bald eagle search algorithm	DRP	Demand response program
CAP	Capacity market Program	EDRP	Emergency Demand Response Program
CPP	Critical Peak Pricing	EH	Energy hub
CHP	Combination heat and power	hBES-MGWO	Hybrid bald eagle- modified gray wolf optimization
CO ₂	Carbon dioxide	HO	Heat only (Boiler)
CSC	Cold start-up cost	HSC	Hot start-up cost
DB	Demand bidding	IBPs	Incentive-Based Programs

I/C	Interruptible/ Curtailable service	E	Per kilowatt charging or discharging cost of HS
LFI	Load flexibility index	E_{CHP}	Emission produced by the CHP
LP	Linear programming	E_{HO}	Emission produced by the HO
MCS	Monte Carlo Simulation	E_u	Emission produced by the national network
MDT	Minimum shut down time	E_{Cost}	The cost of electrical energy
MILP	Mixed-integer linear programming	$E(t, h)$	Price elasticity during t-th hour
MGWO	Modified gray wolf optimization	EM_{Cost}	The penalty for environmental pollution
NG	Natural gas	F	HS cost coefficients
NLP	Non-linear programming	G_{Cost}	The cost of gas consumption in EH
P2G	Power to Gas	G(t)	The amount of gas consumption in EH
PDF	Probability density functions	H_{Cost}	The cost of thermal energy
PSO	Particle Swarm Optimization	H(t)	The amount of heat, which is produced by the boiler
RES	Renewable energy resources	$H_{CHP}(t)$	The heat energy produced by CHP
RTP	Real-time pricing	$H_{ch}(t)$	Amount of charged heat in the storage
SOC	The state of charge	$Hd_{ch}(t)$	Amount of discharged heat power in the storage
SUC	Time startup and shutdown cost	K	Shape parameter
TBRPs	Time-Based Rate Programs	N_k	represents the number of scenarios
TOU	Time of use	P_{best}	Best position
WT	Wind turbine	$P_{CHP}(t)$	The generation power of CHP
Parameters		$P_{Ch}(t)$	Charging power of the battery
A	WT cost coefficients	$P_{dch}(t)$	Discharging power of the battery
B	Per kilowatt cost of WT	$P_{FL}(t)$	Power reduction by the flexible load
B(D(t))	The income of customer during t Per kilowatt cost of Bat	P_{ij}	The power consumed by the load i and time interval j
C_{Bat}	The cost of power stored in the battery storage	f_{ij}	Load flexibility value
$C_{CHP}^E(t)$	CHP unit electric cost	$P_{Load}(t)$	load power
$C_{CHP}^H(t)$	CHP unit heat cost	$P_{mean}(t)$	Details of last positions
C_{FL}	Flexible load cost	$P2G(t)$	Amount of electric power converted to gas
$C_{HO}(t)$	The heat cost of a boiler	p(h)	Price during h
$C_{HS}(t)$	The cost of heat storage	$P_u(t)$	The power exchanged with national grid
$C_G(t)$	The cost of gas consumption in EH	$P_{WT}(t)$	the generation power of wind
$C_{P2G}(t)$	The P2G cost, which converts electrical energy into gas	$R_{DR}(t)$	The reduced power from participation of flexible loads in DRPs
C_u	Cost of power purchased from the national grid	S	The customer's benefit
C_{WT}	WT cost	T_{Cost}	Cost of converting electrical energy to gas by the PtG
$CG_{Storage}(t)$	The cost of gas storage	v	Per kilowatt cost of CHP
D	Bat cost coefficients	v_{th}	Wind velocity
D(t)	Electricity demand in period t	X_p	Prey position vector

$\alpha(t)$	The cost coefficient of the power exchanged
Γ	CHP cost coefficients
δ	Standard deviation of load
δ_k	HO cost coefficients
λ	CHP cost coefficients
μ	Mean load
μ_k	HO cost coefficients
η	Per kilowatt cost of CHP
ζ_k	HO cost coefficients
π_k	Probability of sth scenario
Ω	Scale parameter
ω	P2G cost coefficients
θ	Per kilowatt cost of P2G

1. INTRODUCTION

Energy hub is considered as a fundamental concept for operation of multifarious energy carrier infrastructures such as natural gas (NG) and electricity [1]. It causes to achieve various goals such as minimizing operating costs, improving reliability as well as efficiency and reducing environmental emissions [2, 3]. Indeed, optimal operation of a multi-carrier energy system can lead to different technical, economic and environmental benefits [4]. In recent years, several methods are applied for energy management system of EH. Traditional methods such as linear programming (LP) [5], non-linear programming (NLP) [6] and dynamic programming methodologies [7] are utilized for EH operation management. In reference [8], an EH' energy management system is proposed in a combined on/off and continuous operation mode with power sharing, which is solved by the linear programming and mixed-integer linear programming (MILP) methods. The authors in [9] employed the GAMS software to solve a MILP-based modular energy management system for urban multi-energy systems. Herein, DRPs are implemented to decrease the variable nature of distributed resources, improve the load factor and reduce peak load. It should be mentioned that Meta-heuristic methods such as particle swarm algorithm [10], genetic algorithm [11], living organisms search algorithm [12], bee colony algorithm [13], cuckoo search algorithm [14], multi-objective two-level optimization algorithm [15], and other algorithms [16-18] have been also considered for energy management in EH with multifarious objectives. In the past years, various uncertainties in load [19], renewable resource' generation [20] and electricity market price [21] have been appeared in EH, while considering these uncertainties will lead to more accurate operation and planning of energy hub. Although various methods are used to estimate the renewable resource generation, electricity demand and prices, inherent prediction errors can cause deviations from optimal scheduling and result in inefficient energy hub operations [22]. In [23], machine learning is utilized for managing both electrical and heat resources in an EH, where the uncertainty in electrical and heat demand is modeled by normal probability density function (PDF). The authors in [24] have considered the impact of wind and load

uncertainties on EH operation cost, while wind and load uncertainties are modeled using the Weibull and normal PDFs. In [25], an MILP approach is used with the simultaneous objective of reducing costs and emission in EH considering the uncertainties of load and renewable resources with Monte Carlo method. Load uncertainty is also modeled with a two-point estimation method in [26]. Reference [27] has been emphasized on improving the quality of both electrical and thermal power in uncertain micro grids and the particle swarm optimization (PSO) algorithm is used to solve such optimization problem. DRPs can be used as demand side option, which are divided into two main categories namely, Incentive-Based Programs (IBPs) and Time-Based Rate Programs (TBRPs). While DRPs have several economic advantages, they can create complications in the energy management of an EH [28]. Reference [29] presents an optimal scheduling in an energy hub that includes photovoltaic resources, compressed air storage and responsive loads with the aim of reducing the operating cost. Upon reviewing the research background, further studies are necessary on the utilization of power to gas technology and flexible loads in EH scheduling. Hence, the proposed EH is equipped with P2G technology, wind turbines, battery storage, boilers, heat storage and a combined heat and power (CHP). This paper investigates the impact of P2G technology and DRPs on operating cost of EH. Here, an economic model of responsive loads is extracted based on the concept of elasticity of demand and customer benefit function. A scenario-based approach is proposed for energy management and prediction of wind units and storage capacity over a 24-hour time period. The proposed method implements the PDF corresponding to each uncertainty resource and selects scenarios with appropriate dispersion using Monte Carlo simulation. The objective function of EH operation problem is consist of total operating cost as well as emission cost in different scenarios. It is notable that in each scenario, the probability of occurrence will effect on the final value of the objective function. Additionally, the lack of correct selection of coefficients in some optimization algorithms has resulted in low accuracy and being trapped in local optima, which is another significant problem highlighted in previous studies. In order to solve such optimization problem, the hybrid bald eagle search and modified gray wolf hybrid algorithm (hBES-MGWO) is proposed in this paper. The proposed algorithm combines the features of bald eagle and mutated gray wolf optimization algorithms, allowing for a wider and more precise search space while avoiding local optima. Table 1 summarizes the most recently published research on the management of the energy hub.

According to the literature review and Table 1, the main contributions of this manuscript can be summarized as follow: This study proposes several innovative approaches to energy hub (EH) management, including:

- Introducing a stochastic approach to investigate the EH' uncertainty in the presence of flexible loads and DRPs
- Recommending a weighted objective function for different scenarios with their probability of occurrence which provides a more accurate representation of the real-world scenarios
- Introducing a novel hybrid optimization algorithm the so-called hBES-MGWO to solve such EH energy management problem.
- Introducing a novel hybrid optimization algorithm the so-

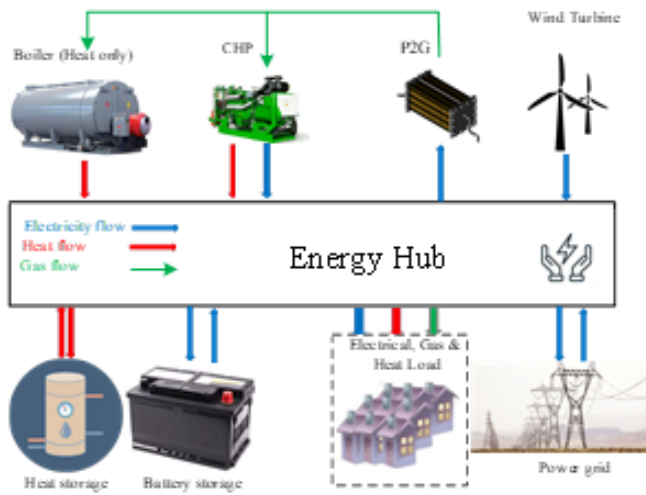


Fig. 1. Energy hub with different generation and storage units

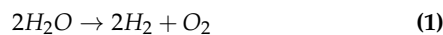
called hBES-MGWO to solve such EH energy management problem.

2. SYSTEM MODEL

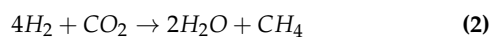
In this section, provides a primer on energy hub and the concept of P2G is briefly introduced. In the subsequent sections, a stochastic optimization problem of EH, the objective function and constraints are presented in terms of EH variables.

A. Energy Hub with P2G Storage

Energy hub encompasses various energy and storage resources along with transmission and communication lines with the aim of achieving different objectives such as reducing operational costs, improving reliability, improving power quality and reducing environmental emissions. Figure 1 provides an EH that includes wind turbine (WT), a boiler or heat only (HO), CHP, heat storage, and an electric vehicle parking as an energy storage device. Here, P2G technology is also employed to convert electrical energy into gas and use it in HO and CHP units. P2G is a novel technology that enables the conversion of surplus electrical energy of EH into natural gas in some hours. The process of converting electricity into gas by P2G includes two main steps. In the first step, P2G allows the EH to convert excess energy of an hour into natural gas, which can be utilized in generating electricity or heat in other hours. The process of water electrolysis in the first step is carried out using electricity, which converts water into oxygen and hydrogen gases as follows [30]:



In the second step, the produced hydrogen is combined with carbon dioxide (CO₂) in a process called methanation:



It should be mentioned that in addition to producing natural gas, the hydrogen in step 1 can also be used separately. It is worth noting that the hydrogen production process is much more efficient than the entire P2G process.

B. Development of Responsive Load Economic Model

Demand response resources are as the consequence of implementing DRPs which can be classified as a set of system operator-based programs that allow end users to provide interruptible load as a commodity in the electricity market. These programs are divided into two basic categories namely; Incentive-Based Programs (IBPs) and Time-Based Rate Programs (TBRPs). Each of these categories is consist of several programs. In time-based rate programs i.e. Time of Use (TOU), Real Time Pricing (RTP) and Critical Peak Pricing (CPP), the electricity price changes for different periods [31]. IBPs are designed to minimize price spikes when load demand is relatively high compared to reasonably available generation. These programs provide various incentives for end users to reduce load or use on-site generation during high price periods [31]. IBPs include Direct Load Control (DLC), Emergency Demand Response Program (EDRP), Interruptible/ Curtailable service (I/C), Capacity market Program (CAP), Demand Bidding (DB) and Ancillary Service (A/S) programs. By reducing the energy consumption during peak hours, the need for additional power generation facilities is considerably reduced, which improves the efficiency of the power system. The focus of this paper is on implementation of TBRPs. More detailed explanations about DRPs can be found in [31]. In EH, DRPs can be modeled using statistical and mathematical analysis. Appropriate modeling of DRPs causes to optimize energy consumption in EH and determines the electricity price to maintain a balance between power supply and demand. In the following, an economic model of TBRPs is derived base on price elasticity of demand and customer benefit function. Price elasticity can be determined as the sensitivity of electricity demand to price changes, which can be defined as [32]:

$$E(t, h) = \frac{P(h)\partial D(t)}{D(t)\partial P(h)} \quad (3)$$

Equation (3) expresses the consumption changes in period t according to price changes in period h . If $B(D(t))$ be the income of customer during t -th hour from the use of $D(t)$ kWh of electricity, then the customer's benefit, S for the t -th hour will be as [33,34]:

$$S = B(D(t)) - D(t)P(t) \quad (4)$$

According to the classical optimization rules, to maximize the customer's benefit, $\partial S / \partial D(t)$ should be equal to zero.

$$\begin{aligned} \frac{dS}{d(D(t))} = 0 &\rightarrow \frac{dB(D(t))}{dt} - P(t) = 0 \\ &\rightarrow \frac{dB(D(t))}{dt} = P(t) \end{aligned} \quad (5)$$

In this paper, a benefit function is used as the following [35]:

$$B(D(t)) = B_0(t) + P_0(t) [D(t) - D_0(t)] \cdot \left\{ 1 + \frac{D(t) - D_0(t)}{2E(t) \times D_0(t)} \right\} \quad (6)$$

Differentiating the above equation with respect to $D(t)$ and Substituting the result in (5) results in

$$P(t) = P_0(t) \left\{ 1 + \frac{D(t) - D_0(t)}{E(t) \times D_0(t)} \right\} \quad (7)$$

Therefore, customer's demand can be represented as equation (8), which represents the single period elastic load model

$$D(t) = D_0(t) \left\{ 1 + E(t) \frac{P(t) - P_0(t)}{P(t)} \right\} \quad (8)$$

Using the cross elasticity definition, the multi period elastic load model of customer response function can be obtained as follows [36-37]:

$$D(t) = D0(t) \left\{ 1 + \sum_{h=1, h \neq t}^{24} E(t, h) \left[\frac{P(h) - P0(h)}{P0(h)} \right] \right\} \quad (9)$$

By combining (9) and (8), the responsive load economic model can be presented as

$$D(t) = D0(t) \left\{ \begin{array}{l} 1 + E(t) \left[\frac{P(h) - P0(h)}{P0(h)} \right] + \\ \sum_{h=1, h \neq t}^{24} E(t, h) \left[\frac{P(h) - P0(h)}{P0(h)} \right] \end{array} \right\} \quad (10)$$

C. Evaluation of Load Flexibility Index

Flexibility is defined as the system's ability to face with uncertainties at an acceptable level in a reasonable time and at a reasonable cost. Load flexibility in EHs refers to the ability of an energy hub to continuously adjust its electricity demand and supply to maintain a reliable and efficient operation. This involves utilizing various fast ramp resources such as energy storages and DRPs. By optimizing the load flexibility, it is possible to increase the integration of renewable energy resources in EH. This is essential for achieving a sustainable and reliable energy system that can meet the changing demands of modern society. Equation (11) presents the scheduling of an energy hub with n flexible loads during a time interval of $t=[1 \text{ m}]$ as:

$$P^* = \begin{bmatrix} P_{11}^* & \cdots & P_{1n}^* \\ \vdots & \ddots & \vdots \\ P_{m1}^* & \cdots & P_{mn}^* \end{bmatrix} \quad (11)$$

In flexibility analysis, the main objective is determining the extent that the values of matrix arrays can be altered as well as their maximum allowable changes. According to equation (12), the positive and negative power changes are directly related to flexibility value, which is determined by using equation (13).

$$\Delta P_{ij} = P_{ij}^{new} - P_{ij}^* \quad (12)$$

$$f_{ij} = \frac{\Delta P_{ij}}{P_{ij}^{new}} \quad (13)$$

Therefore, load flexibility index (LFI) for an EH can be calculated as

$$[LFI] = \sum_{\forall i} f_{ij} \quad (14)$$

D. Uncertainties in Proposed EH Framework

The lack of precise information about parameter values, system components and measurements are represented by the uncertainty. The uncertainty issue is a significant concern in operation of EH owing to frequent changes in both load and generation. In the proposed EH framework, different supply- and demand-side uncertainties such as electrical and thermal loads, and renewable energy resource are considered. In order to effectively manage the uncertainty of electric load, the normal PDF is utilized as (15) [38]:

$$f(x) = \frac{1}{\sqrt{2\pi} \times \sigma} \exp\left(-\frac{(x - \mu)^2}{2 \times (\sigma)^2}\right) \quad (15)$$

In equation (15), μ and σ represent the mean and standard deviation of the previous data, respectively. Similarly, the electricity price is influenced by various factors such as the value of demand as well as generation, weather conditions and fuel cost. In order to model the uncertainty of electricity price, the normal PDF is commonly used as (15). In order to model the uncertainty of wind units, the Weibull PDF can be employed as (16):

$$f_{t,h}^{WT}(v) = \begin{cases} \frac{k}{\Omega} \times \left(\frac{v_{t,h}}{\Omega}\right)^{k-1} \exp\left(-\left(\frac{v_{t,h}}{\Omega}\right)^k\right), & \text{for } \Omega > 1, k > 0 \\ 0 & \text{otherwise} \end{cases} \quad (16)$$

In this paper, Monte Carlo as a stochastic simulation method has been utilized to select scenarios from PDFs. By repeating random experiments, Monte Carlo provides a means of improving and reaching an optimal state for a given problem as follows [39].

1. Defining the problem: In this step, the problem must be mathematically defined including its variables and parameters.
 2. Generating random data: Random data should be generated to be used in PDFs of uncertain parameters such as renewable resources generation and electric vehicle charging and discharging power.
 3. Running the simulation: In this step, the aforementioned random data are employed to extract the output of each scenario using PDFs.
 4. Analyzing the results: In this step, the obtained results must be analyzed. The best scenarios will be determined based on mean and variance values.
 5. Choosing the optimal scenario: In this step, the optimal scenario is chosen based on productivity or other desired criterions.
- In summary, Monte Carlo is a powerful tool for scenario selection in complex decision-making and optimization problems. This method makes it possible to identify the best scenario to achieve the desired goal by generating random data and analyzing the obtained results.

E. Objective Function and Constraints of Energy Hub Scheduling

The proposed objectives function for EH operation is defined in equation (17), while different scenarios are selected for considering uncertainty.

$$f = \min \sum_{s=1}^{N_k} \pi_k \left(\begin{array}{l} E_{Cost}(s) + H_{Cost}(s) + T_{Cost}(s) \\ + EM_{Cost}(s) + G_{Cost}(s) \end{array} \right) \quad (17)$$

The operation cost in each scenario is multiplied by its probability and the results are added together to obtain the final cost. The proposed objective function is consist of ECost as the cost of electrical energy, HCost as the cost of thermal energy, TCost as the cost of converting electric energy into gas by the P2G unit, EMCost as the penalty for environmental pollution caused by the production of electricity or heat by resources, and Gcost as the cost of gas consumption in EH. The probability of different scenarios is assumed to be equal and N_k represents the number of scenarios. ECost is formulated in (18), which is a combination of the power generation' purchased cost from the national grid, the cost of CHP unit and the compensation of flexible loads. Flexible loads can significantly contribute to operation costs reduction.

$$E_{Cost} = \sum_{t=1}^T (C_U(t) + C_{WT}(t) + C_{CHP}^E(t) + C_{Bat}(t) + C_{FL}(t)) \quad (18)$$

In (18), $C_u(t)$ represents the cost of power purchased from the national grid, $C_{WT}(t)$ is the cost of wind units, $C_{CHP}(t)$ is the cost of CHP units, $C_{Bat}(t)$ is the cost of power stored in the battery storage and $C_{FL}(t)$ is the cost of flexible loads in period t . The total scheduling period is denoted by T (i.e. $T = 1, 2, \dots, 24$). Here, the cost of purchasing energy from the national grid is presented as:

$$C_U(t) = \alpha(t) P_u(t) \quad (19)$$

Where, $P_u(t)$ represent the power exchanged in period t and $\alpha(t)$ is the cost coefficient of the power exchanged with the national network in that hour. The generation cost of wind units and CHP are formulated by equations (20) and (21), respectively.

$$C_{WT}(t) = A + BP_{WT}(t) \quad (20)$$

$$C_{CHP}^E(t) = \lambda + \eta P_{CHP}(t) \quad (21)$$

where, $P_{WT}(t)$ and $P_{CHP}(t)$ represent the generation power of wind and CHP resources, respectively. A , B , λ and η are also the cost' coefficients for the abovementioned resources. The battery storage cost is also calculated as:

$$C_{Bat}(t) = (P_{Ch}(t) + P_{dCh}(t)) \times C + D \quad (22)$$

where, $P_{Ch}(t)$ and $P_{dCh}(t)$ represents the charging and discharging power of the battery, respectively, while C and D are the cost' coefficients. The demand response resources for flexible loads can be formulated as:

$$C_{FL}(t) = \Delta P_{FL}(t) \times R_{DR}(t) \quad (23)$$

In (23), $R_{DR}(t)$ is the reduced power from participation of flexible loads in DRPs. The cost of heat energy is also presented as

$$H_{Cost} = \sum_{t=1}^T (C_{CHP}^H(t) + C_{HO}(t) + C_{HS}(t)) \quad (24)$$

Where, $C_{CHP}^H(t)$ is the heat cost of CHP unit and $C_{HS}(t)$ is the cost of heat storage. $C_{HO}(t)$ is the heat cost of a boiler, which can be formulated as

$$C_{HO}(t) = \zeta_k H^2(t) + \mu_k H(t) + \sigma_k + SUC \times |U(t) - U(t-1)| \quad (25)$$

In (25), $H(t)$ is the amount of heat, which is produced by the boiler and ζ_k , μ_k and σ_k are the cost' coefficients. SUC is also the start-up cost as follows:

$$SUC = \begin{cases} HSC & T_{off} \leq CST + MDT \\ CSC & T_{off} > CST + MDT \end{cases} \quad (26)$$

Where, HSC and CSC are the hot and cold start-up costs, respectively. CST is the required time for cold start-up and MDT is the minimum shut down time of each boiler. The heat production cost of a CHP unit is also calculated as:

$$C_{CHP}^H(t) = \Gamma + v H_{CHP}(t) \quad (27)$$

Where $H_{CHP}(t)$ is the heat energy produced by CHP. v and Γ are also CHP cost coefficients. Equation (28) presents the cost of heat storage.

$$C_{HS}(t) = (H_{Ch}(t) + H_{dCh}(t)) \times E + F \quad (28)$$

Where, $H_{Ch}(t)$ and $H_{dCh}(t)$ are the amount of charged and discharged heat of the storage, respectively, while E and F are its

cost coefficients. The cost of converting electrical energy into gas is defined as:

$$T_{Cost} = \sum_{t=1}^T (C_{P2G}(t) + C_{G-storage}(t)) \quad (29)$$

In (29), $C_{P2G}(t)$ is the P2G cost, which converts electrical energy into gas and $C_{G-storage}(t)$ is the cost of gas storage

$$C_{P2G}(t) = \omega + \theta P_{P2G}(t) \quad (30)$$

$$C_{G-storage}(t) = \zeta + \zeta G(t) \quad (31)$$

The emission cost can also calculate as follows.

$$EM_{Cost} = \sum_{t=1}^T \left\{ \begin{aligned} &(P_{CHP}(t) + H_{CHP}(t)) \times E_{CHP} \\ &+ H_{HO}(t) \times E_{HO} + P_u(t) \times E_u \end{aligned} \right\} \quad (32)$$

Where, E_{CHP} , E_{HO} and E_u are hg/MWh emission produced by the CHP, HO and national network at time t , respectively. Reducing the cost of power generation leads to an increasement in the environmental emission and vice versa. It means that both operation cost and emission cannot set in their minimum level at the same time. Finally, the cost of gas consumption in EH can be formulated as:

$$G_{Cost} = \sum_{t=1}^T (G(t)) C_G(t) \quad (33)$$

In (33), $G(t)$ and $C_G(t)$ are the amount and cost of gas consumption in EH at hour t , respectively. The objective function of EH scheduling problem is subject to the following constraints. - Electric power balance constraint: Power supplied from generation units and DRPs must satisfy the electric power consumption in each hour.

$$\begin{aligned} &P_u(t) + P_{CHP}(t) + P_{WT}(t) + P_{dCh}^{Bat}(t) \\ &= P_{Load}(t) + P_{Ch}^{Bat}(t) - P_{FL}(t) \end{aligned} \quad (34)$$

Heat power balance constraint: The amount of heat power generation and its consumption in each hour are equal as shown in (35).

$$H_{CHP}(t) + H_{HO}(t) + H_{dCh}(t) = H_{Load}(t) + H_{Ch}(t) \quad (35)$$

Power exchange with network constraint: The amount of electric power exchange with upstream network can be formulated as:

$$P_u^{Min} \leq P_u(t) \leq P_u^{Max} \quad (36)$$

CHP performance areas: The electrical and heat power produced by CHP units is subjected to constraint (37), which should be restricted between upper and lower bounds [40].

$$P_{j,t}^{CHP} - P_{j,A}^{CHP} - \frac{P_{j,A}^{CHP} - P_{j,B}^{CHP}}{H_{j,A}^{CHP} - H_{j,B}^{CHP}} \times (H_{j,t}^{CHP} - H_{j,A}^{CHP}) \leq 0 \quad (37)$$

$$\begin{aligned} &P_{j,t}^{CHP} - P_{j,B}^{CHP} - \frac{P_{j,B}^{CHP} - P_{j,C}^{CHP}}{H_{j,B}^{CHP} - H_{j,C}^{CHP}} \times (H_{j,t}^{CHP} - H_{j,B}^{CHP}) \\ &\geq - \left(1 - V_{j,t}^{CHP}\right) \times M \end{aligned} \quad (38)$$

$$\begin{aligned} &P_{j,t}^{CHP} - P_{j,C}^{CHP} - \frac{P_{j,C}^{CHP} - P_{j,D}^{CHP}}{H_{j,C}^{CHP} - H_{j,D}^{CHP}} \times (H_{j,t}^{CHP} - H_{j,C}^{CHP}) \\ &\geq - \left(1 - V_{j,t}^{CHP}\right) \times M \end{aligned} \quad (39)$$

$$0 \leq P_{j,t}^{CHP} \leq P_{j,A}^{CHP} \times V_{j,t}^{CHP} \quad (40)$$

$$0 \leq H_{j,t}^{CHP} \leq H_{j,B}^{CHP} \times V_{j,t}^{CHP} \quad (41)$$

Here, $P_{j,t}^{CHP}$ and $H_{j,t}^{CHP}$ are the output electric and heat power of the CHP j unit in hour t , respectively. - Heat only unit constraint: The HO unit heat power generation can be presented as:

$$H_{HO}^{Min} \leq H_{HO}(t) \leq H_{HO}^{Max} \quad (42)$$

Battery constraint: Charging and discharging rates as well as the charge and discharge level of batteries are considered to increase its life.

$$P_{dCh}(t) \leq P_{dCh}^{Max} \quad (43)$$

$$P_{Ch}(t) \leq P_{Ch}^{Max}$$

$$E_{Ch}(t) \leq \psi^{charge-max} \quad (44)$$

$$E_{dCh}(t) \geq \psi^{charge-min}$$

3. THE PROPOSED OPTIMIZATION ALGORITHM

Gray Wolf Optimization (GWO) is a particle-based algorithm which is modeled on how to hunt gray wolves. The gray wolves are categorized in four levels called α , β , δ and ω . The gray wolf hunting consists of three stages. The first stage includes searching space, running and approaching hunting. The second stage is comprised chasing, besieging, and boring the hunt, while attacking to the prey is encompassed in stage 3. The gray wolves hunting can be formulated as follow [41].

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(ite) - \vec{X}(ite) \right| \quad (45)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (46)$$

Where, X_p is prey position vector, X is gray wolf position vector, A and C are the vectors coefficients and ite is the algorithm current iteration number. The A and C can be calculated as

$$\vec{A} = 2\vec{\alpha} \cdot \vec{r}_1 - \vec{\alpha} \quad (47)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (48)$$

Where r_1 and r_2 are two uniform random vector and α is a component which decreases from 2 to zero. Therefore, when the A value is in rage of $[-1, 1]$, the next position of the particle will be in any paces between the current and hunting positions. The C value is in rage of $[0, 2]$ and it provides different weights for prey to show the effect of the pray on distance detection randomly as significant ($C > 1$) or insignificant ($C < 1$). In each iteration, α , β and δ wolves estimate the probable places of the prey. The hunting procedure is almost performed by α wolf and occasionally, it is fulfilled by β and δ wolves. Therefore, the three best results are accumulated and omega wolves are forced to change their positions toward best positions. Selected places tend to diverge from prey for $|A| > 1$ and tend to diverge at prey for $|A| < 1$. The wolves' position update can be formulated as follow:

$$\vec{D}_\alpha = \left| \vec{C}_1 \cdot \vec{X}_\alpha - \vec{X} \right|, \quad \vec{D}_\beta = \left| \vec{C}_2 \cdot \vec{X}_\beta - \vec{X} \right|, \quad (49)$$

$$\vec{D}_\delta = \left| \vec{C}_3 \cdot \vec{X}_\delta - \vec{X} \right|$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot (\vec{D}_\alpha), \quad \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot (\vec{D}_\beta), \quad (50)$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot (\vec{D}_\delta)$$

$$\vec{X}(ite+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (51)$$

The MGWO algorithm is consisted of two ideas. First one is

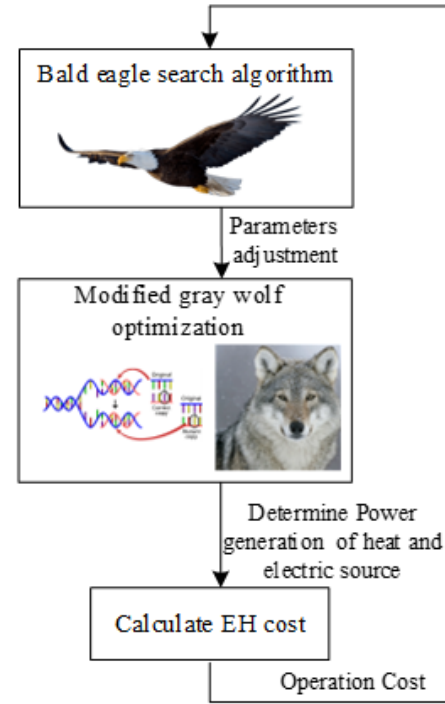


Fig. 2. Overview of the proposed hBES-MGWO algorithm

based on Pareto front and the second one is a strategy of selecting a leader which can help to select α , β and δ wolves as leaders in the hunting procedure. It is worth mentioning that for all iterations, a specific number of populations are considered for the repository. For all iterations, the dominant populations are compared with the repository populations. Three best solutions of dominant populations are segregated as α , β and δ wolves. The positions of the population are updated by the position of three leaders.

A. BES Algorithm

The BES algorithm is also a population-based optimization algorithm which is modeled on how to hunt bald eagle. The bald eagles hunt from almost high-level position and it is able to track fishes from that position. The BES algorithm is consisted of three stages such as space selection, search and swooping [42]. For space selection part, the bald eagles select the best position to search for prey, which be formulated as:

$$P_i^{new} = P_{best} + \epsilon \times rand \times (P_{mean} - P_i) \quad (52)$$

where, P_{mean} is the details of last positions, P_{best} is the best position with high number of fishes, $rand$ is a uniform distributed random number and finally, ϵ is the BES parameter in range of 1.5 and 2. For the proposed BES algorithm, the ϵ parameter is not constant and it is calculated by equation (53). Selecting the dynamic coefficient for ϵ causes that the BES algorithm finds the optimal solution with high accuracy.

$$\epsilon = \epsilon_0 (1 + (ite_{Max} - ite) / ite_{Max}) \quad (53)$$

For searching stage, the bald eagles flight in a spiral way in the search space and select the best position for prey hunting. This stage enables the BES algorithm for finding new positions and increase diversity. The search space part can be formulated as:

$$P_i, new = P_i + y(i) \times (P_i - P_{i+1}) + x(i) \times (P_i - P_{mean}) \quad (54)$$

$$x(i) = \frac{xr(i)}{\max(|xr|)} \quad (55)$$

$$y(i) = \frac{yr(i)}{\max(|yr|)} \quad (56)$$

$$xr(i) = r(i) \times \sin(\theta(i)) \quad (57)$$

$$yr(i) = r(i) \times \cos(\theta(i)) \quad (58)$$

$$\theta(i) = a \times \pi \times rand \quad (59)$$

$$r(i) = \theta(i) \times R \times rand \quad (60)$$

Where, R and a are two algorithm parameters in range of $[0.5, 2]$ and $[5, 10]$, respectively. R determines the number of cycles. Eventually, in the swooping step, eagles dive from the best position towards the prey. The swooping step can be formulated as follows.

$$P_{i, new} = rand \times P_{best} + x1(i) \times (P_i - c1 \times P_{mean}) + y1(i) \times (P_i - c2 \times P_{best}) \quad (61)$$

$$x1(i) = \frac{xr(i)}{\max(|xr|)} \quad (62)$$

$$y1(i) = \frac{yr(i)}{\max(|yr|)} \quad (63)$$

$$xr(i) = r(i) \times \sinh[\theta(i)] \quad (64)$$

$$yr(i) = r(i) \times \cosh[\theta(i)] \quad (65)$$

$$\theta(i) = a \times \pi \times rand \quad (66)$$

$$r(i) = \theta(i) \times R \times rand \quad (67)$$

The best solution can be found by multiplying the center position and current position division of polar of horizontal axis and multiplying best solution and current position division in the vertical axis. The parameters c_1 and c_2 increase the eagle search movement intensity.

B. The proposed hBES-MGWO Algorithm

The performances of all optimization algorithms are highly dependent on their parameters. If the algorithm parameters are not selected correctly, there is a possibility of non-convergence or getting trapped in local optimal points. In order to facilitate the aforementioned challenge in this paper, it is suggested that the parameters of MGWO algorithm are selected optimally by the BES algorithm. In Fig. 3, the flowchart of proposed hBES-MGWO algorithm is depicted. High accuracy as well as not getting trapped in the local optimal points can be expressed as prominent features of the proposed optimization algorithm. The correctness of this statement has been proven by performing optimization on standard benchmarks and comparing with other optimization algorithms.

4. SIMULATION RESULTS AND DISCUSSION

In this section, the proposed hBES-MGWO algorithm is evaluated based on different scenarios using the Monte Carlo simulation mechanism. The simulation is conducted on an EH that comprises CHP and boiler units, a wind power plant, electrical and heat storage systems and P2G to supply electrical, thermal and local natural gas. Fig. 4 illustrates the demand for electric, heat, and natural gas. Fig. 5 also presents the power generation of wind unit. It should be mentioned that the wind unit capacity is assumed equal to 50 kW. Here, Monte Carlo simulation is used to generate 1000 scenarios, and SCENRED is employed for

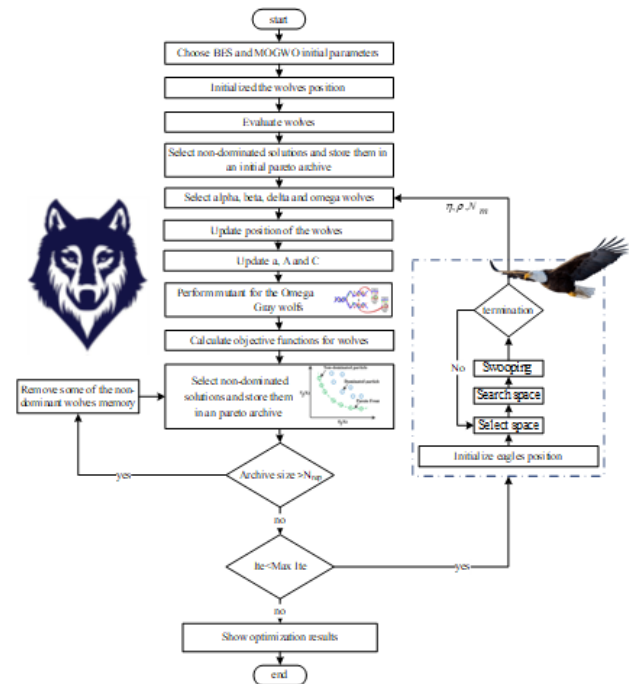


Fig. 3. The flowchart of proposed hBES-MGWO optimization algorithm

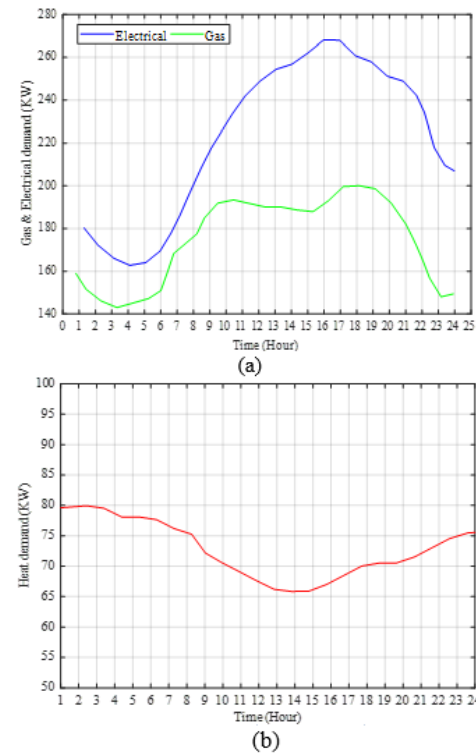


Fig. 4. (a) The electrical and gas (b) The heat EH energy consumption

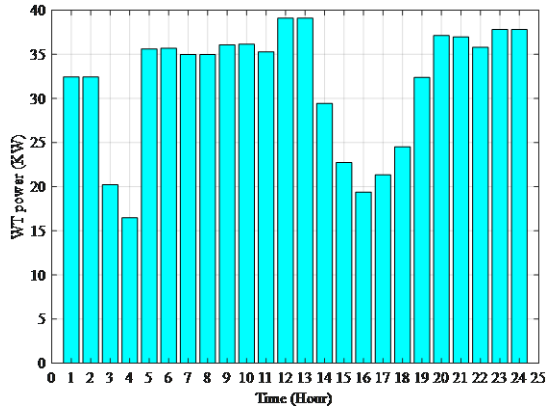


Fig. 5. The WT output power generation

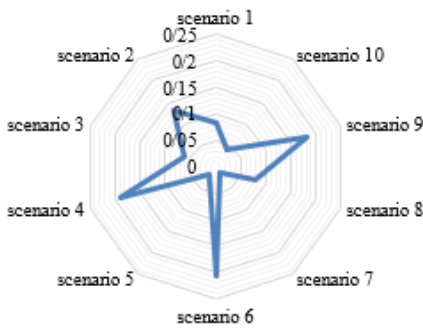


Fig. 6. Probability of selected scenarios by SCENRED

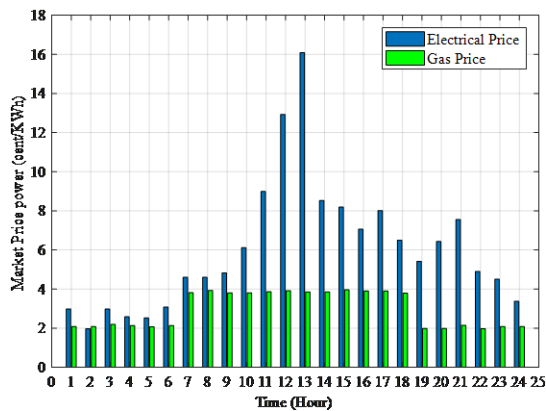


Fig. 7. Electric energy and gas prices

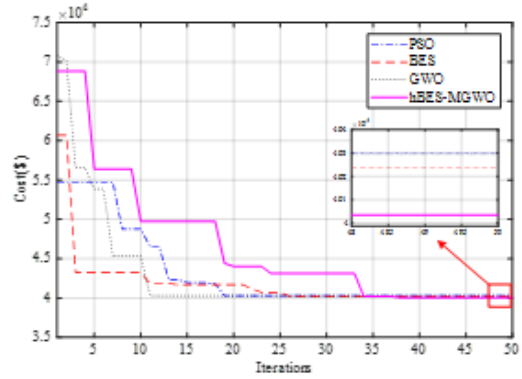


Fig. 8. The convergence curves of optimization algorithms in case study 1

Table 2. Optimization results in case study 1

Total cost (cent)	Power cost (cent)	Gas cost (cent)	Optimization Algorithm
40303.4	15118.19	25185.21	PSO
40236.31	15146.93	25089.38	BES
40293.24	15074.16	25219.08	GWO
40291.92	15104.26	25187.67	MILP[43]
40033.15	14849.88	25183.27	Proposed hBES-MGWOP

scenario reduction, while the probability of ten selected scenarios is illustrated in Fig.6. Fig. 7 also displays the market price of electricity and gas for the 24-hour period.

The simulation result is carried out in three case studies. In case study 1, the optimal scheduling of EH is evaluated considering uncertainties without flexible loads and the environmental emission penalty. In the second case study, the impact of responsive loads and DRPs on optimal energy management is assessed, while still disregards the environmental emission penalty. In case study 3, the impact of environmental emission penalty is investigated in operation of energy hub. In order to validate the results of proposed hBES-MGWO algorithm, BES, GWO, Particle Swarm Optimization (PSO), and Mixed-Integer Linear Programming (MILP) algorithms are utilized form [43] and the simulation results are compared with each other.

A. Case Study 1

In case study 1, the optimal operation of energy hub is studied without considering DRPs and environmental emission penalty. Fig. 8 illustrates the convergence process of proposed hBES-MGWO algorithm in comparison with BES, GWO and PSO, while the results are presented in Table 2. According to Table 2, operation cost of EH with the proposed hBES-MGWO algorithm is equal to 40033.15 cents, which is less than the costs of other optimization algorithms. Fig. 9 also illustrates the hourly performance of the P2G technology.

When the price of electricity decreases, the system operator purchases electricity from the national grid and converts it into natural gas using P2G. The natural gas is then stored in gas

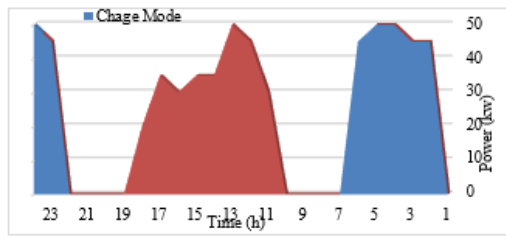


Fig. 9. P2G performance in case study 1

Table 3. Optimization results in case study 1

Total cost (cent)	Power cost (cent)	Gas cost (cent)	Optimization Algorithm
39238.01	14052.8	25185.21	PSO
39212.55	14123.17	25089.38	BES
39222.04	14002.96	25219.08	GWO
39209.36	14021.69	25187.67	MILP
39195.05	14011.78	25183.27	Proposed hBES -MGWO

tanks. Hence, when the price of natural gas increases, the P2G unit injects the stored gas into the EH. During the early hours of each day and late hours at night, when electricity price is low, electricity is converted into gas. Between 10 A.M. and 6 P.M., instead of purchasing gas from the national gas network, the stored gas is utilized to generate electricity and heat in an energy hub. According to Fig. 10-a and 10-b, it can be observed that purchasing power from the national grid is increased from 1 P.M. to 7 P.M. and from 11 P.M. when P2G unit is charged. During the discharge mode from 11 A.M. to 7 P.M., the amount of purchased natural gas from the network is also decreased. It is also worth noting that a portion of the gas produced using the P2G technology is utilized for heat production, while the remaining gas is used for electricity generation.

B. Case Study 2

In case study 2, the optimal operation of energy hub is carried out considering DRPs and without environmental emission penalty. Here, 10% of consumers are considered as responsive load. Fig. 11 illustrates the convergence process of proposed hBES-MGWO algorithm in comparison with BES, GWO and PSO, while the results are presented in Table 3 in presence of flexible loads. Table 3 demonstrates the effectiveness of the proposed hBES-MGWO algorithm in comparison with other optimization algorithms in the presence of DRPs. Specifically, the operating cost of EH using the proposed algorithm in case study 2 is found to be 39195.05 cents, which is lower than the costs obtained with PSO, BES, GWO and MILP algorithms. The results emphasize that considering flexible loads and consumers’ participation in DRPs cause to reduce cost. Fig. 12 illustrates the LFI index values considering the proposed algorithm and other ones. Fig. 13 also displays the impact of the flexible loads on the electric load profile in case study 2. Fig. 14 demonstrates the impact of flexible loads on purchasing electric power. It is shown that during peak hours, the amount of purchasing electric power

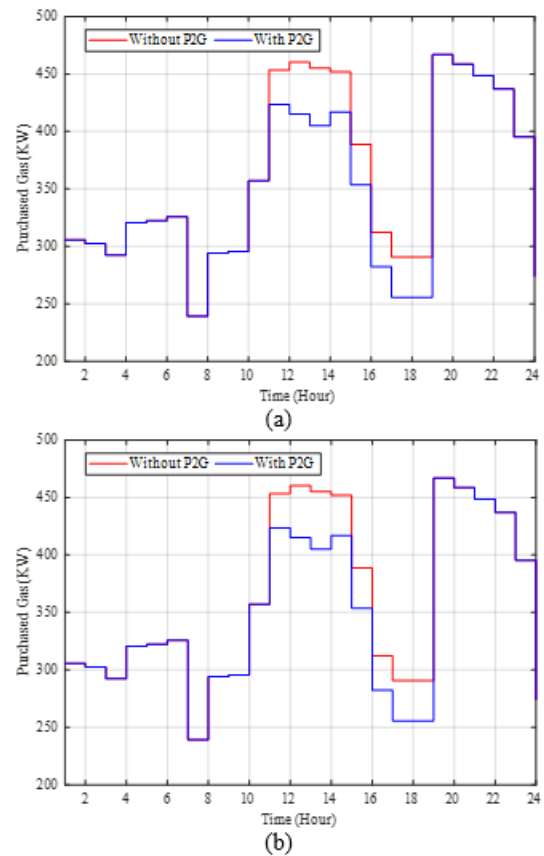


Fig. 10. (a) The electrical power purchased from the national grid in case study 1. (b) The amount of gas purchased from the national gas network in case study 1

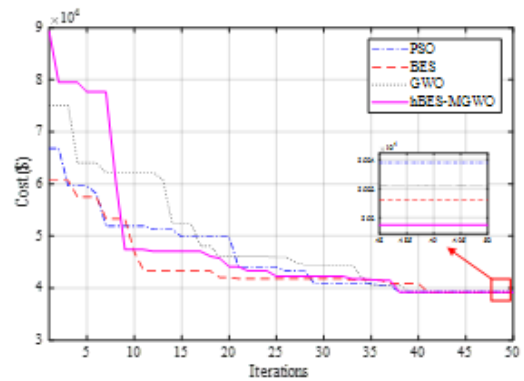


Fig. 11. The convergence curves of optimization algorithms in case study 2

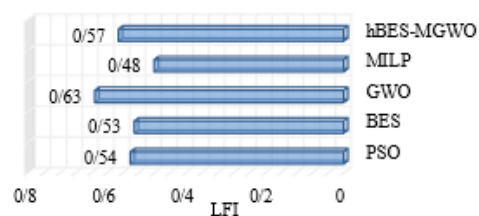


Fig. 12. The load flexibility index in case study 2

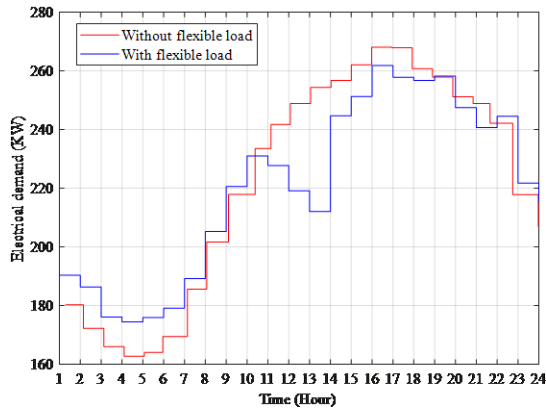


Fig. 13. The impact of flexible loads on the electric load profile in case study 2

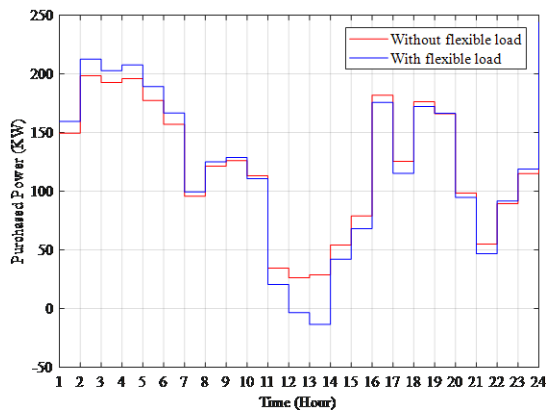


Fig. 14. The impact of flexible loads on the amount of energy exchange

is reduced in comparison with case study 1 without considering DRPs. The total operating cost in case 2 is 39195.05 cents, which indicates a considerable reduction in operating costs. According to Fig. 15, a sensitivity analysis is performed to evaluate the impact of participation rate of DRPs on operating cost. The participation rate of consumers in DRPs is considered equal to 0, 10, 15, 20, 25 and 30%. Figure 15 emphasizes that with increasing the value of DRPs' participation rate, the cost of electricity purchased from the upstream network will be decreased. The percentage of cost reduction for different levels of flexible load participation in DRPs is equal to 2.09%, 3.48%, 4.49%, 5.34%, and 5.84%, respectively.

In 10% penetration of the flexible load, the LFI index value obtained using the proposed hBES-MGWO algorithm is 0.387 p.u. While, the LFI index value for PSO, BES, GWO, and MILP algorithms are 0.378 p.u, 0.374 p.u, 0.36 p.u and 0.394 p.u respectively. As the penetration coefficient of flexible loads increases, the LFI also increases. For instance, with a penetration coefficient of 30%, the LFI index value for the hBES-MGWO reaches 0.578 p.u. and for PSO is 0.575 p.u, for BES is 0.579 p.u, for GWO is 0.576 p.u, and also for MILP algorithms is 0.583 p.u. It is worth noting that there is not a significant difference in the LFI coefficient between the permeability coefficient of 25% and 30%.

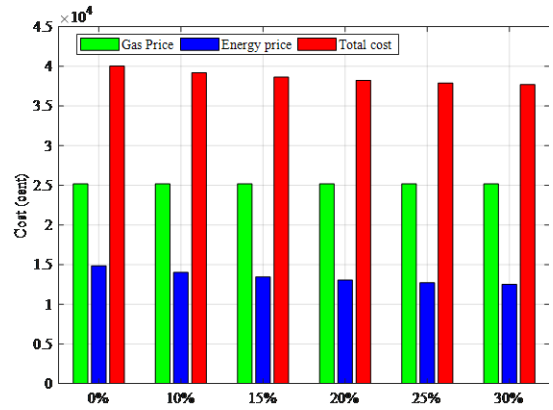


Fig. 15. EH costs for different participation rate of consumers in DRPs

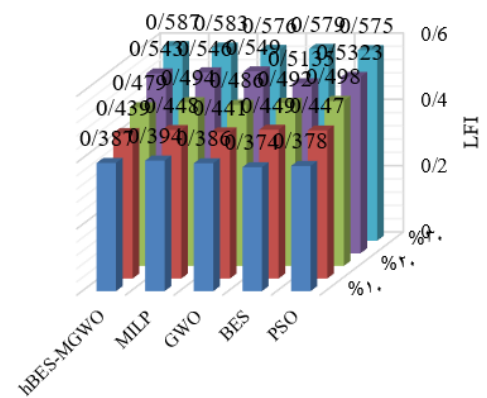


Fig. 16. The load flexible index

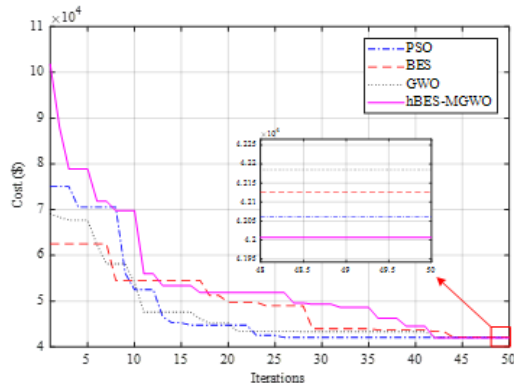


Fig. 17. The convergence curves of optimization algorithms in case study 3

Table 4. Optimization results in the third part of the simulation

Total cost (cent)	Power cost (cent)	Gas cost (cent)	Optimization Algorithm
42061.36	15135.34	25185.21	PSO
42127.11	14851.94	25089.38	BES
42184.9	15038.53	25219.08	GWO
42126.95	14939.42	25187.67	MILP
42006.36	14772.27	25183.27	Proposed hBES -MGWO

C. Case Study 3

In case study 3, the emission penalty is also considered in operation of an energy hub. In this case, the penetration rate of renewable resources is increased to reduce the pollution penalty. Fig. 17 illustrates the convergence process of proposed hBES-MGWO algorithm in comparison with BES, GWO and PSO, while the results are presented in Table 4. The results of Table 4 indicates an increase in operating costs due to consideration of pollution fines. Although the emission cost in case 3 with the proposed hBES-MGWO algorithm is higher than other algorithms, but its final cost is lower than other ones, which demonstrates higher accuracy of proposed hBES-MGWO. Fig. 18 also displays the impact of the flexible loads on the electric load profile in case study 3. DRPs shift the consumption to the hours when wind power is at its maximum level due to its zero-emission penalty in addition to low electricity price hours. This load shifting strategy helps the system operator to reduce the total operation cost and mitigating environmental pollution.

5. CONCLUSION

This paper investigates the impact of DRPs and environmental emission penalty on operation of energy hub with uncertainties. Here, the uncertainties of load, market price and wind units are evaluated. An innovative objective function based on both operation cost and emission is proposed for EH energy management. Moreover, a self-tuning hybrid hBES-MGWO algorithm is developed to solve such optimization problem. The proposed algorithm’ features include its ability to search the wide and

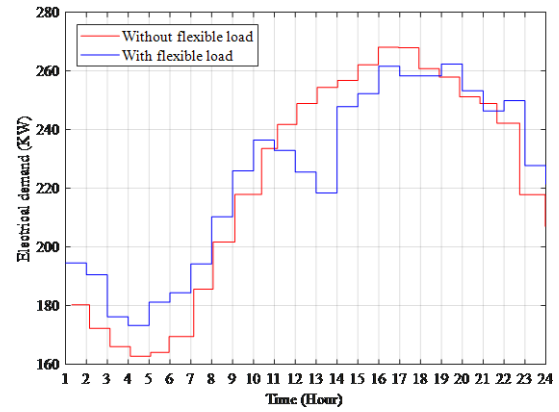


Fig. 18. The impact of flexible loads on the electric load profile in case study 3

precise search space and avoid getting trapped in local optima. Simulations are performed in MATLAB software in to demonstrate the proposed framework and algorithm. The simulation results emphasize that implementing DRPs cause to decrease the operation cost. However, the sensitivity analysis on the participation rate of DRPs demonstrates that an increasement in the permeability coefficient of flexible loads reduces the slope of cost reduction. Moreover, considering the pollution fine increased the operating costs. Future research work is needed to consider an EH energy management in the presence of electric vehicles as well as flexible heat loads.

REFERENCES

- Zhang, G., Hu, W., Cao, D., Zhang, Z., Huang, Q., Chen, Z. and Blaabjerg, F, "A multi-agent deep reinforcement learning approach enabled distributed energy management schedule for the coordinate control of multi-energy hub with gas, electricity, and freshwater, " *Energy Conversion and Management*, vol. 255, Pp.115-340,2022.
- Esapour, K., Moazzen, F., Karimi, M., Dabbaghjamesh, M. and Kavousi-Fard, A., "A novel energy management framework incorporating multi-carrier energy hub for smart city" *IET Generation, Transmission & Distribution*, 17(3), pp.655-666, 2023.
- Basu, M., "Electric, Thermal and Cooling Energy Management of a Microgrid Incorporating Renewable Energy Hub," *Electric Power Components and Systems*, 51(9), pp.915-932, 2023.
- Hammad, M.A., Elgazzar, S., Obrecht, M. and Sternad, M, "Compatibility about the concept of energy hub: A strict and visual review, " *International Journal of Energy Sector Management*, 16(1), pp.1-20., 2022.
- Ezzati, S.M., Faghihi, F., Shourkaei, H.M., Mozafari, S.B. and Soleymani, S., "Optimum operation of multi-energy carriers in the context of an energy hub considering a wind generator based on linear programming," *Journal of Renewable and Sustainable Energy*, 10(1), p.014702, 2018.
- Ahmadisedigh, H. and Gosselin, L., "Combined heating and cooling networks with part-load efficiency curves: Optimization based on energy hub concept" *Applied Energy*, 307, p.118245, 2022.

7. Bai, J., Wei, W., Chen, L. and Mei, S., "Rolling-horizon dispatch of advanced adiabatic compressed air energy storage based energy hub via data-driven stochastic dynamic programming", *Energy Conversion and Management*, 243, p.114322, 2021.
8. Rech, S., Casarin, S., Silva, C.S. and Lazzaretto, A., "University Campus and Surrounding Residential Complexes as Energy-Hub: A MILP Optimization Approach for a Smart Exchange of Solar Energy", *Energies*, 13(11), p.2919, 2020.
9. Moser, A., Muschick, D., Gölles, M., Nageler, P., Schranzhofer, H., Mach, T., Tugores, C.R., Leusbrock, I., Stark, S., Lackner, F. and Hofer, A., "A MILP-based modular energy management system for urban multi-energy systems: Performance and sensitivity analysis", *Applied Energy*, 261, p.114342, 2020.
10. Honarmand, H.A., Shamim, A.G. and Meyar-Naimi, H., "A robust optimization framework for energy hub operation considering different time resolutions: A real case study", *Sustainable Energy, Grids and Networks*, 28, pp.100526, 2021.
11. Ghorab, M., "Energy hubs optimization for smart energy network system to minimize economic and environmental impact at Canadian community", *Applied Thermal Engineering*, 151, pp.214-230, 2019.
12. Güvenç, U., Özkaya, B., Bakir, H., Duman, S. and Bingöl, O., "Energy Hub Economic Dispatch by Symbiotic Organisms Search Algorithm", *In The International Conference on Artificial Intelligence and Applied Mathematics in Engineering* (pp. 375-385). Springer, Cham, 2019, April.
13. Liu, T., Zhang, D., Dai, H. and Wu, T., "Intelligent modeling and optimization for smart energy hub. *IEEE Transactions on Industrial Electronics*", 66(12), pp.9898-9908., 2019.
14. Ghahramani, M., Nazari-Heris, M., Zare, K. and Mohammadi-Ivatloo, B., "Energy management of electric vehicles parking in a power distribution network using robust optimization method", *Journal of Energy Management and Technology*, 2(3), pp.22-30, 2018.
15. Zou, J., Yang, X., Liu, Z., Liu, J., Zhang, L. and Zheng, J., "Multiobjective Bilevel Optimization Algorithm Based on Preference Selection to Solve Energy Hub System Planning Problems", *Energy*, p.120995, 2021.
16. Sadeghi, H., Rashidinejad, M., Moeini-Aghtaie, M. and Abdollahi, A., "The energy hub: An extensive survey on the state-of-the-art", *Applied Thermal Engineering*, 161, p.114071, 2019.
17. Jadidbonab, M., Madadi, S. and Mohammadi-ivatloo, B., "Hybrid strategy for optimal scheduling of renewable integrated energy hub based on stochastic/robust approach", *Journal of Energy Management and Technology*, 2(4), pp.29-38, 2018.
18. Sharifi, V., Abdollahi, A. and Rashidinejad, M., "Flexibility Driven Generation Maintenance Scheduling in the Presence of Demand Response Resources to Attenuate Wind Output Variability Considering Gas Demand Uncertainty", *Journal of Energy Management and Technology*, 7(3), pp.142-152, 2023.
19. Li, C., Wang, N., Wang, Z., Dou, X., Zhang, Y., Yang, Z., Maréchal, F., Wang, L. and Yang, Y., "Energy hub-based optimal planning framework for user-level integrated energy systems: Considering synergistic effects under multiple uncertainties", *Applied Energy*, 307, p.118099, 2022.
20. Lu, X., Li, H., Zhou, K. and Yang, S., "Optimal load dispatch of energy hub considering uncertainties of renewable energy and demand response", *Energy*, 262, p.125564, 2023.
21. Tavakoli, A., Karimi, A. and Shafie-khah, M., "Optimal probabilistic operation of energy hub with various energy converters and electrical storage based on electricity, heat, natural gas, and biomass by proposing innovative uncertainty modeling methods", *Journal of Energy Storage*, 51, p.104344, 2022.
22. Mu, Y., Wang, C., Sun, M., He, W. and Wei, W., "CVaR-based operation optimization method of community integrated energy system considering the uncertainty of integrated demand response", *Energy Reports*, 8, pp.1216-1223, 2022.
23. Cai, Q., Luo, X., Wang, P., Gao, C. and Zhao, P., "Hybrid model-driven and data-driven control method based on machine learning algorithm in energy hub and application", *Applied Energy*, 305, p.117913, 2022.
24. Shams, M.H., Shahabi, M., MansourLakouraj, M., Shafiekhah, M. and Catalão, J.P., "Adjustable robust optimization approach for two-stage operation of energy hub-based microgrids", *Energy*, 222, p.119894, 2021.
25. Mokaramian, E., Shayeghi, H., Sedaghati, F., Safari, A. and Alhelou, H.H., "A CVaR-Robust-Based Multi-Objective Optimization Model for Energy Hub Considering Uncertainty and E-Fuel Energy Storage in Energy and Reserve Markets", *IEEE Access*, 9, pp.109447-109464, 2021.
26. Tay, Z.X., Lim, J.S., Alwi, S.R.W. and Manan, Z.A., "Optimal Planning for the Cogeneration Energy System using Energy Hub Model" *Chemical Engineering Transactions*, 88, pp.349-354, 2021.
27. Tahir, M.F., Haoyong, C. and Guangze, H., "Exergy hub-based modelling and performance evaluation of integrated energy system", *Journal of Energy Storage*, 41, p.102912, 2021.
28. Y. Li, W. Liu, M. Shahidehpour, F. Wen, K. Wang, Y. Huang, "Optimal operation strategy for integrated natural gas generating unit and power-to-gas conversion facilities", *IEEE Tran. Sustain. Energy* 9 1870–1879, 2018.
29. Jadidbonab, M., Dolatabadi, A., Mohammadi-Ivatloo, B., Abapour, M. and Asadi, S., "Risk-constrained energy management of PV integrated smart energy hub in the presence of demand response program and compressed air energy storage" *IET Renewable Power Generation*, 13(6), pp.998-1008, 2019.
30. Jalili, M., Holagh, S.G., Chitsaz, A., Song, J. and Markides, C.N., "Electrolyzer cell-methanation/Sabatier reactors integration for power-to-gas energy storage: Thermo-economic analysis and multi-objective optimization", *Applied Energy*, 329, p.120268, 2023.

31. Roukerd, S.P., Abdollahi, A. and Rashidinejad, M., "Probabilistic-possibilistic flexibility-based unit commitment with uncertain negawatt demand response resources considering Z-number method," *International Journal of Electrical Power & Energy Systems*, 113, pp.71-89, 2019.
32. Makhdoomi, H. and Moshtagh, J., "Optimal Scheduling of Electrical Storage System and Flexible Loads to Participate in Energy and Flexible Ramping Product Markets," *Journal of Operation and Automation in Power Engineering*, 11(3), pp.203-212, 2023.
33. Zeinal-Kheiri, S., Mohammadpour Shotorbani, A. and Mohammadi-Ivatloo, B., "Robust energy management of a microgrid with uncertain price, renewable generation, and load using Taguchi's orthogonal array method," *Journal of Energy Management and Technology*, 3(3), pp.1-13, 2019.
34. Vu, D.H., Muttaqi, K.M., Agalgaonkar, A.P. and Bouzerdoun, A., "Customer reward-based demand response program to improve demand elasticity and minimise financial risk during price spikes" *IET Generation, Transmission & Distribution*, 12(15), pp.3764-3771, 2018.
35. Andruszkiewicz J, Lorenc J, Weychan A., "Seasonal variability of price elasticity of demand of households using zonal tariffs and its impact on hourly load of the power system" *Energy*, 196:117175, 2020.
36. Ruan, J., Liu, G., Qiu, J., Liang, G., Zhao, J., He, B. and Wen, F., "Time-varying price elasticity of demand estimation for demand-side smart dynamic pricing" *Applied Energy*, 322, p.119520, 2020.
37. Ciarreta, A., Espinosa, M.P. and Pizarro-Irizar, C., "Pricing policies for efficient demand side management in liberalized electricity markets" *Economic Modelling*, 121, p.106215, 2023.
38. Liu, J., Tang, Z., Zeng, P.P., Li, Y. and Wu, Q., "Distributed adaptive expansion approach for transmission and distribution networks incorporating source-contingency-load uncertainties," *International Journal of Electrical Power & Energy Systems*, 136, p.107711, 2022.
39. Ghahramani, M., Nazari-Heris, M., Zare, K. and Mohammadi-Ivatloo, B., "Energy management of electric vehicles parking in a power distribution network using robust optimization method," *Journal of Energy Management and Technology*, 2(3), pp.22-30, 2018.
40. Erixno, O., Abd Rahim, N., Ramadhani, F. and Adzman, N.N., "Energy management of renewable energy-based combined heat and power systems: A review," *Sustainable Energy Technologies and Assessments*, 51, p.101944., 2022.
41. Falahzadeh, M.R., Farokhi, F., Harimi, A. and Sabbaghi-Nadooshan, R., "Deep convolutional neural network and gray wolf optimization algorithm for speech emotion recognition," *Circuits, Systems, and Signal Processing*, 42(1), pp.449-492, 2023.
42. Alsattar, H.A., Zaidan, A.A. and Zaidan, B.B., "Novel meta-heuristic bald eagle search optimisation algorithm," *Artificial Intelligence Review*, 53, pp.2237-2264., 2020.
43. Yuan, Z., He, S., Alizadeh, A.A., Nojavan, S. and Jermittiparsert, K., "Probabilistic scheduling of power-to-gas storage system in renewable energy hub integrated with demand response program," *Journal of Energy Storage*, 29, p.101393, 2020.
44. Shams, M.H., Shahabi, M., Kia, M., Heidari, A., Lotfi, M., Shafie-Khah, M. and Catalão, J.P., "Optimal operation of electrical and thermal resources in microgrids with energy hubs considering uncertainties," *Energy*, 187, p.115949, 2019.
45. Zhang, T. and Sobhani, B., "Optimal economic programming of an energy hub in the power system while taking into account the uncertainty of renewable resources, risk-taking and electric vehicles using a developed routing method," *Energy*, 271, p.126938, 2023.
46. Zheng, Y. and Shahabi, L., "Optimum operation of energy hub by considering renewable resources by considering risk tolerance and risk taking with Teaching-Learning-Based Optimization," *Journal of Cleaner Production*, 428, p.139220, 2023.