Electric Power Systems Research 214 (2023) 108859

Contents lists available at ScienceDirect

Electric Power Systems Research

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

Optimal planning and operation of energy hub by considering demand response algorithms and uncertainties based on problem-solving approach in discrete and continuous space

Asghar Iranpour Mobarakeh, Ramtin Sadeghi [*], Hadi Saghafi Esfahani, Majid Delshad

Department of Electrical Engineering, Isfahan (Khorasgan) Branch, Islamic Azad University, Isfahan, Iran

ARTICLE INFO

Keywords:
Energy hub
Two-level optimization
Demand response program
Optimal planning and operation

ABSTRACT

In this research, the two-level structure of optimal planning and operation of the energy hub (EH) based on demand uncertainty and renewable energy resources (RES) is presented. The optimal planning based on stochastic-probability models is presented at the primary and optimal operation based on stochastic-probability models is also presented at the secondary level. The proposed method is planned based on the problem-solving approach in continuous and discrete space. The optimal planning objectives include determining the optimal capacity of EH equipment and minimizing investment costs. Optimal operation objectives are also planned and formulated based on minimizing EH operation cost, reducing greenhouse gas emissions, increasing RES utilization based on stochastic-probability modelling, and examining the demand response/integrated demand response (DR/IDR) effect. The DR programs implementation causes a reduction of 14.3% of the EH total cost, and the IDR programs implementation also causes a reduction of 16.56% of the EH total cost. The use of the proposed optimal two-level model, in addition to efficiency in different operation scenarios, has also reduced the calculation time. The optimization problem is solved based on Mixed Integer Linear Programming (MILP) and Binary Real-Coded Hybrid Genetic Algorithm (HRBC-GA).

1. Introduction

In recent years, concerns about declining energy reserves have led to a greater focus on the efficient use of energy carriers and energy efficiency planning. The integrated use of different energy carriers under the concept of EH is an idea that largely responds to the concern of increasing energy demand and reducing the level of energy reserves. The use of EH ideas has not only improved the optimal distribution of energy and power but also increased the security and reliability of energy distribution systems [1]. The EH consists of various sections such as the energy input carrier, coupling section which includes converters and energy storage devices as well as energy output carriers section. Since different equipment with different characteristics is used in the EH, modelling and implementing a multi-carrier energy system will have more complexities than single-carrier power supply systems [2]. In the input energy section, energy carriers can be divided into two categories. Stochastic energy carriers and non-stochastic energy carriers. Stochastic energy carriers are like RES (wind and solar). Non-stochastic energy carriers are like fossil fuels. Therefore, renewable and non-renewable energy carriers are considered EH inputs [3]. In the coupling section, converters, different units of electrical, thermal, and cooling storage can be used. The coupling section, based on the efficiency of converters and energy storage units, is considered an interface between input and output carriers. The output of the EH also includes electrical, heating, and cooling demand [4].

The use of RES has grown significantly in recent decades. RES increase the uncertainty of optimal energy distribution in the EH structure due to their probability in power generation and energy production [5, 6]. Therefore, the use of RES increases the complexity of EH modelling and planning [7]. One of the useful and efficient methods in modelling RES is the use of probability tools. Algorithms and probability models

Abbreviations: RES, renewable energy resources; DR/IDR, demand response/integrated demand response; MILP, mixed integer linear programming; EH, energy hub; HRBC-GA, hybrid real and binary coded genetic algorithm; EVs, electric vehicles; PDF, probability distribution functions; CHP, combined heat and power; EES, electrical energy storage; TES, thermal energy storage; AC, absorption chiller; Tr, transformer; EHP, electric heat pump; EC, electric chiller.

* Corresponding author.
E-mail addresses: asghariranpour@khuisf.ac.ir (A. Iranpour Mobarakeh), r.sadeghi@khuisf.ac.ir (R. Sadeghi), h.saghafi@khuisf.ac.ir (H. Saghafi Esfahani), delshad@khuisf.ac.ir (M. Delshad).

https://doi.org/10.1016/j.epsr.2022.108859
Received 27 June 2022; Received in revised form 31 August 2022; Accepted 4 October 2022
Available online 27 October 2022
0378-7796/© 2022 Elsevier B.V. All rights reserved.

Nomenclature

$OMC_{E}^{t,s}$ operation and maintenance cost of electrical network and power exchange with upstream network ($)

$OMC_{RES}^{t,s}$ operation and maintenance cost of RES ($)

$OMC_{CHP,B}^{t,s}$ operation and maintenance cost of CHP and Boiler ($)

$OMC_{E/Th}^{t,s}$ operation and maintenance cost of electrical and thermal storages ($)

$OMC_{EM}^{t,s}$ operation and maintenance cost of emissions gas ($)

$OMC_{DR/IDR}^{t,s}$ operation and maintenance cost of DR/IDR program ($)

$OMC_{UEC}^{t,s}$ operation and maintenance cost of unsupplied energy consumers ($)

$OMC_{EV}^{t,s}$ operation and maintenance cost of EVs ($)

$TC_{EH}^{t,s}$ total cost ($)

$ICOC_{EH}^{t,s}$ investment cost and optimal capacity ($)

$OMC_{EH}^{t,s}$ operating and maintenance cost ($)

IC_{Eq}^{t} equipment investment cost ($)

ICC_{Eq}^{t} equipment installation cost based on capacity ($)

Ir equipment interest rates ($)

$\Lambda_{buy}^{grid-Hub}$ the price of electric power purchased by the hub ($/kW)

$\Lambda_{sell}^{Hub-grid}$ the price of electric power sold by the hub ($/kW)

Λ_{RES} RES generation cost ($/kW)

Λ_{g} natural gas carrier prices ($/kW)

Λ_{e}^{S} operation cost of electric energy storage ($/kW)

Λ_{Th}^{S} operation cost of thermal energy storage ($/kW)

Λ_{em} emission costs ($/kW)

$\Lambda_{z}^{DR/IDR}$ implementing cost of DR/IDR algorithms ($/kW)

Λ_{UEC} unsupplied energy of the consumer cost ($/kW)

Λ_{sell}^{Hub-EV} the selling price of electrical energy from the EH to the EV ($/kW)

Λ_{buy}^{EV-Hub} the purchase price of electrical energy from an EV by an EH ($/kW)

Λ_{e}^{OMC} operating cost due to the implementation of the DR/IDR algorithm ($/kW)

Λ_{e}^{base} base cost due to the implementation of the DR/IDR algorithm ($/kW)

$P_{Eq}^{\max,c}$ maximum equipment installation capacity (kW)

$P_{Eq}^{Install,c}$ equipment installation capacity (kW)

$P_{e}^{Hub-grid}(t,s)$ the electric power sold by the hub (kW)

$P_{e}^{grid-Hub}(t,s)$ the electric power purchased by the hub (kW)

$P_{RES}^{t,s}(t,s)$ RES power (kW)

$P_{g}^{CHP}(t,s)$ natural gas power required by the CHP unit (kW)

$P_{g}^{B}(t,s)$ natural gas power required by the boiler unit (kW)

$P_{e}^{Heater}(t,s)$ electric heater power (kW)

$P_{c}^{EHP}(t,s)$ electric heat pomp power for cooling (kW)

$P_{Th}^{EHP}(t,s)$ electric heat pump power for thermal (kW)

$P_{e}(t,s)$ electrical power demand (kW)

$P_{e}^{UEC}(t,s)$ unsupplied electrical power (kW)

$P_{e}^{RES}(t,s)$ electric power of RES (kW)

$P_{Th}(t,s)$ thermal power demand (kW)

$P_{Th}^{AC}(s,t)$ absorption chiller power (kW)

$P_{c}(t,s)$ cooling power demand (kW)

$P_{E}^{ch}(t,s)$ charge power of electric storage (kW)

$P_{E}^{dis}(t,s)$ discharge power of electric storage (kW)

$P_{Th}^{ch}(t,s)$ charge power of thermal storage (kW)

$P_{Th}^{dis}(t,s)$ discharge power of thermal storage (kW)

$P_{e,Th,c}^{Sh-up}(t,s)$ electrical, thermal and cooling demand shifted up (kW)

$P_{e,Th,c}^{Sh-down}(t,s)$ electrical, thermal and cooling demand shifted down (kW)

$P_{UEC}(t,s)$ unsupplied energy of the consumer (kW)

$P_{Hub-EV}^{t,s}(t,s)$ power injected from the EH into the EV (kW)

$P_{EV-Hub}^{t,s}(t,s)$ power injected from an EV into an energy hub (kW)

$P_{EV,ch}^{t,s}(t,s)$ EV charge power (kW)

$P_{EV,dis}^{t,s}(t,s)$ EV discharge power (kW)

$P_{e}^{\mathrm{Pr-up,down}}(t,s)$ participation of electric power in the DR/IDR price-based program (kW)

$\delta_{E/Th}^{\min}, \delta_{E/Th}^{\max}$ minimum and maximum charge and discharge index of storage units (kW)

$\delta_{E/Th}^{Loss}$ energy loss index of storage units

$b_{E/Th}^{ch}, b_{E/Th}^{dis}$ binary variables related to storage units

b_{h}^{EHP}, b_{c}^{EHP} binary variables related to EHP

$b_{e}^{Sh-up}, b_{e}^{Sh-down}$ binary variables related to DR/DR shifted demand

$b^{\mathrm{Pr-up}}, b^{\mathrm{Pr-down}}$ binary variables related to the DR/IDR price-based program

$b_{e,Th,c}^{T-up}, I_{e,Th,c}^{T-down}$ binary variable related to transmitted electrical, thermal and cooling loads

$b_{e.Th.c}^{Int-up}, b_{e.Th.c}^{Int-down}$ binary variable related to electrical, thermal and cooling cut-off loads

b_{Eq} the binary variable in the discrete approach

b_{EV} binary variable related to EV unit

$b_{e}^{buy}, b_{e}^{sell}$ binary variable related to the sale and purchase of electrical power

η_{Th-c}^{AC} absorption chiller efficiency (%)

η_{ee}^{Tr} transformer efficiency (%)

η_{ee}^{Con} efficiency of converters (%)

η_{e-Th}^{EHP} thermal efficiency of EHP unit (%)

η_{e-c}^{EHP} electric efficiency of EHP unit (%)

η_{g-Th}^{CHP} thermal efficiency of CHP unit (%)

η_{ge}^{CHP} electrical efficiency of CHP unit (%)

η_{g-Th}^{B} thermal efficiency of Boiler unit (%)

η_{e-Th}^{Heater} thermal and electrical efficiency of electric heater unit (%)

$\eta_{EV,ch}$ EV charging efficiency (%)

$\eta_{EV,dis}$ EV discharge efficiency (%)

$\eta_{E/Th}^{ch}, \eta_{E/Th}^{dis}$ charging and discharging efficiency of electrical and thermal storage units (%)

EI_{em}^{CHP} CHP emission index

EI_{em}^{B} boiler emission index

$E_{EV-\min}, E_{EV-\max}$ charging and discharging range of EV (kWh)

EV_{n} number of EVs

$E_{E/Th}^{Loss}(t,s)$ energy losses in electric and thermal storage units (kWh)

$SOC_{EV,ch}^{t,s}$ EV state of charge

DPR demand participation rate for DR/IDR

$\xi^{up,down}$ DR/IDR algorithm execution coefficient

C_1, C_2, C_3 load cut-off coefficients

$\rho(s)$ probability of scenarios

$d(se)$ days of the season

h_{Eq} equipment lifetime

t time

s season

Δ_t time changes

express the best pattern of renewable resource behaviour [8]. Therefore, by using renewable resource probability modelling, EH operators are able to provide more accurate and efficient planning of the EH. Electric vehicles (EVs) are also a unit whose use has grown significantly in recent years. Although EVs play an important role in providing a secure and efficient EH structure, the use of this equipment requires careful modelling. EVs, like RES, have uncertainties that reduce the reliability and security indicators of optimal energy distribution in the structure of the EH. Therefore, modelling and considering uncertainties caused by RES and EVs are necessary and important. Algorithms and probability models can also be used to model EV units [9].

One of the most important challenges of EH ideas is energy distribution and optimal planning. As mentioned, because the EH uses different equipment with linear, nonlinear, random and probabilistic characteristics, modelling the EH is more complex and difficult than single-carrier distribution networks [10]. In recent years, the use of stochastic-probability algorithms has been considered as an efficient tool in modelling the structure of the EH. Stochastic-probabilistic algorithms accurately describe the behaviour of EH actors. Thus, EH operators are able to obtain an optimal energy planning model. Therefore, energy management is one of the most important challenges of the EH. EH management and planning is a multidimensional issue. Optimal management of EH includes technical, economic and environmental dimensions. Therefore, in recent years, the use of different demand-side management algorithms and DR programs has grown significantly. DR algorithms have highlighted the role of consumers in the mechanism of energy distribution systems. Therefore, DR programs and demand-side management algorithms play an effective role in providing the optimal structure of the energy distribution system [11]. DR programs are basically classified into two categories: price-based and incentive-based. Because DR programs, in addition to being used in the electric carrier sector, can also be used in the thermal and cooling carrier sector, the term IDR can be used instead of DR. DR programs generally affect customer consumption patterns. Therefore, the effect of DR algorithms on the load curve and reduction of operating costs of the EH can be seen [12].

Optimal EH scheduling describes a complex nonlinear problem based on the presence of stochastic sources, energy storage units, DR / IDR programs, operating constraints, various decision variables, as well as technical and economic uncertainties. Therefore, choosing a problem-solving method is important [13].

In this paper, a two-step approach to linearize the problem of stochastic-probability optimization as well as the optimal planning and operation of EHs based on solving the optimization problem in continuous and discrete space is presented. In this study, optimization algorithms have been programmed at two primary and secondary levels. In the primary, optimal planning and determination of the optimal capacity of EH equipment have been presented. In the secondary, optimal operation of EH is provided by considering DR/IDR programs, technical, economic and environmental indicators. The proposed model based on two approaches of continuous and discrete problem solving space is calculated and its results are presented. Providing two spaces for solving discrete and continuous problems increases the freedom of action of EH users. Therefore, operators can choose EH equipment based on the results of the continuous problem solving space, or they can plan and model the EH equipment based on the security margin obtained in the results of the discrete problem solving space. On the other hand, DR/IDR programs with the goals of changing the consumption pattern of subscribers, which causes an increase in profit due to the implementation of DR/IDR algorithms, as well as improving the load curve profile due to changing the consumption pattern of subscribers and reducing investment and operation costs have been presented.

1.1. Literature review

In this section, in addition to reviewing previous research in the field of planning and optimal management of multi-carrier energy distribution systems (EH), the strengths and challenges of various research are also expressed. Finally, according to Table 1, a comparison of the proposed method with other research is presented.

In [14], a multi-carrier distribution model in the microgrid context based on DR programs to reduce operating costs and environmental hazards due to fossil fuel consumption is presented. The problem model is based on technical and environmental uncertainties. The proposed method is solved using the Modified Shuffled Frog Leaping Algorithm (MSFLA). The DR program model is also based on the TOU method. The results of this study show the efficiency of the proposed method in different operation scenarios such as reducing operating costs, reducing costs due to greenhouse gas emissions and improving the load curve based on the implementation of DR programs. The most important challenge of this research is the lack of using energy storage devices and the effect of these devices on improving the load curve. Although in the problem model, the probability algorithm is used to model the behaviour of RES, the effect of uncertainty of RES on the proposed method has not been investigated.

In [15], the EH probability model based on considering the uncertainty of power generation sources and EVs is presented. In this study, DR programs are proposed to improve the load curve profile based on changes in the price of electricity carriers. The proposed method is based on robust optimization and is solved using the mixed integer linear programming method. In order to validate, the results of this study are presented in different scenarios such as the effect of probability loads on the optimal distribution of energy and also the effect of the implementation of the DR programs on the flattening of the load curve. The results of this study show the efficiency of the proposed method in the face of various uncertainties such as uncertainty of the RES and EVs. The most important challenge of this research is the lack of analysis of the proposed method on a large scale. The larger the scale of the EH topology, the more indicators and decision-making variables and uncertainties must be considered in the optimization problem. Another challenge of this research is the lack of the DR model for thermal energy sectors.

In [16], the optimal model of EH for a coastal city with economic and environmental indicators is presented. In order to reduce the risk indicators of fossil fuels and reduce the cost of greenhouse gas emissions, RES provides part of the electrical demand. In this study, the optimization problem, which includes reducing the cost of operation and reducing the cost of greenhouse gas emissions based on the genetic algorithm (GA), has been solved. The results of this study show a significant reduction in the annual operating cost of the EH and a reduction in the cost of greenhouse gas emissions. The most important challenge of this study is the lack of consideration of RES uncertainties. Also, in this study, the probability indicators due to changes in energy carrier prices and loads have not been considered.

In [17], a stochastic EH model based on responding to various challenges such as energy demand, the uncertainty of RES, electricity prices and the interaction of energy carriers with each other is presented. The probability planning model based on considering DR programs and reducing greenhouse gas emissions with the aim of reducing operating costs is presented. The most important challenge of this research is the lack of consideration of stochastic loads and the lack of analysing the proposed method on a large scale.

In [18], a two-level EH control model is presented with the aim of reducing operating costs and improving the efficiency of energy distribution networks. At the primary level, optimization goals include minimizing the daily costs of energy distribution networks, while at the secondary level, goals such as reducing the cost of operating energy and also the optimal exchange of power and energy with distribution networks and other hubs are considered. In this study, the EH, in addition to connecting to other energy distribution networks, is also able to exchange power and energy with other hubs. The proposed method is based on the nonlinear optimization problem with the Karush – Kuhn –

Table 1
Comparison of previous research and literature.

References	Stochastic Generation	Non-Stochastic Generation	Optimization Algorithms		Uncertainties Assessment	Demand Response Assessment (DR/IDR)		Environmental Assessment	Probability Assessment	ESS	Continuous Solution Space	Discrete Solution Space	Probability Loads
			Planning	Operation		Price based	Incentive based						
Ref. [14]	*	*	–	*	–	*	*	–	–	–	*	–	–
Ref. [15]	*	*	*	*	*	*	–	*	–	*	*	–	*
Ref. [16]	*	*	–	*	*	–	*	–	*	*	*	–	–
Ref. [17]	*	*	*	*	–	*	–	*	–	*	–	*	–
Ref. [18]	*	*	*	*	*	*	*	–	–	*	*	–	–
Ref. [19]	*	*	*	*	*	–	*	*	–	*	*	*	–
Ref. [20]	*	*	*	*	*	*	*	*	*	*	*	–	–
Ref. [21]	*	*	*	–	–	*	*	–	*	*	*	–	–
Ref. [22]	*	*	*	–	–	–	–	*	–	*	*	–	–
Ref. [23]	*	*	–	*	–	*	–	–	*	*	–	*	*
Ref. [24]	*	*	–	*	–	–	*	*	*	*	–	*	–
Proposed Method	*	*	*	*	*	*	*	*	*	*	*	*	*

Tucker (KKT) optimization indices. The proposed method is analysed in different scenarios in the IEEE 33 network. The challenge of this research is the lack of consideration of renewable sources and renewable resource probability models. Uncertainties due to technical, economic and environmental indicators have not been considered in this study.

In [19], the day ahead energy planning based on electricity market exchange indicators as well as consideration of economic and environmental indicators is presented. The optimal EH model is planned based on reducing operating costs and reducing costs due to greenhouse gas emissions. The results of this study have been analysed in different scenarios and the results of this study show a 22% reduction in the operating cost of the EH and a 13% reduction in the greenhouse gas emissions cost. The most important challenge of this study is the lack of analysis of the probability RES behaviour in the structure of the EH and the effect of probability behaviour of these resources on the performance of the proposed method. Also, in this study, the uncertainty caused by changes in the prices of energy carriers has not been considered in the planning of the day ahead.

In [20], the optimal EH model based on two levels of primary and secondary optimization with economic and environmental indicators is presented. In this study, the primary objectives are planned based on reducing operating costs. The secondary objectives also include reducing greenhouse gas emissions, reducing energy losses, and optimizing the capacity and size of energy storage units. The nonlinear optimization model is programmed based on the lexicography optimization method. The proposed model includes uncertainties due to RES and the price of electricity carriers. The analysis of the proposed method in different scenarios shows the reduction of operating costs, energy losses and greenhouse gas emissions.

In [21], the EH model based on intelligent structure and Lyapunov optimization algorithm in three levels of virtual control is presented. The proposed model is modelled by considering energy distribution constraints, operating constraints, flexible loads, and energy storage indices. In this study, flexible loads have been considered as random process variables in modelling the optimization problem. In this study, part of the energy demand hub is supplied by stochastic (renewable) sources. Although the results of this research show the efficiency of the proposed method in different operation scenarios, the most important challenges of this research are the lack of analysis of resource probability behaviour and the lack of analysis of environmental indicators.

In [22], the intelligent EH structure based on the stochastic mixed-integer linear programming (SMILP) method and the goals of optimal day-ahead planning as well as increasing the influence of RES in the structure of optimal energy distribution are presented. The problem of optimization is planned by considering energy market interactions and various decision-making indicators, including economic and technical indicators. Although the results of this study show the efficiency of the proposed method in reducing the costs of operating EH and increasing the penetration of RES, the most important challenges of this study are the lack of analysis of RES stochastic behaviour and the lack of analysis the risks of greenhouse gas emissions.

In [23], optimal EH planning is presented by considering the charge and discharge threshold indicators of energy storage units and the implementation of DR programs. In this study, by analysing the charge and discharge status of energy storage units, the performance planning of energy storage units for the next day is presented. The implementation of DR programs is also planned with the aim of reducing the costs of operating the EH and increasing the security and flexibility indicators of the EH. The proposed method has been analysed in different operation scenarios. The results of this study show the optimal performance of the proposed method in short-term planning. The most important challenge of this research is the lack of analysis the greenhouse gas emissions risks and the costs associated with it.

In [24], EH planning based on the analysis of uncertainties due to RES and EVs with the aim of reducing operating costs and greenhouse gas emissions is presented. The proposed method is programmed and solved based on the robust mixed-integer linear programming (RMILP) method. In this study, uncertainties of EVs and RES have been considered as random variables in the optimization problem. The proposed method has been validated in different scenarios. The results of this study show the optimal performance and high efficiency of the proposed method in the optimal operation of the EH, taking into account various uncertainties.

1.2. Research challenges

1 In the structure of the EH, different equipment with different characteristics such as linear, nonlinear, random and probabilistic are used. The characteristics of different equipment increase the various uncertainties of operation. Therefore, it is necessary to pay attention to various uncertainties such as technical, economic and environmental uncertainty for modelling the EH.
2 The use of RES is a suitable response to the challenges of energy systems and the concerns from the reduction of fossil fuel sources. However, when using RES, it should be noted that these resources have random and probability behaviour. For this reason, RES can be called stochastic resources. Therefore, to accurately model the behaviour of renewable resources, it is better to use probability tools. The probability behaviour of renewable resources and consequently its uncertainties are well modelled using probability tools.
3 Considering that the subscribers in the EH structure have the ability to have a direct impact on the performance and optimal operation of the EH, therefore, this part of the EH can be used as a suitable opportunity to improve the operating conditions of the EH based on DR and demand side management programs. Therefore, accurate modelling of DR programs based on customer consumption patterns is another challenge of the EH.
4 Since EH optimization problems are generally presented with linearization algorithms for simplification, the use of discrete and continuous problem-solving environments provides users with a more comprehensive view of EH behaviour.
5 Given that the behaviour of the EH based on various stochastic equipment is described, the choice of stochastic-probability optimization algorithm will bring better performance. It is noteworthy that due to the range of stochastic-probability variables of EH, the optimal model of EH based on stochastic-probability algorithms has more complexities than definite methods.

1.3. Innovation and objectives

In this research, a stochastic-probability model based on optimal integrated operation and planning of EHs in discrete-continuous space is presented in two levels of optimization. At the primary level, the optimal EH planning model and the determination of the optimal capacity of the EH equipment based on the genetic algorithm (GA) are presented. Then, at the secondary level, the optimal operation of the EH is presented. The proposed method consists of two DR algorithms and three IDR algorithms. The results of these algorithms are presented in different operating scenarios. The optimization problem is presented in this study based on a multi-objective function. In the optimization problem, the reduction of the index due to greenhouse gas emissions has also been modelled and formulated. The objective function of the optimization problem is planned and formulated based on reducing investment costs and reducing the operating cost of the EH. The proposed optimization problem, based on the mixed-integer linear programming method, is solved by considering different random and probability variables in two discrete and continuous spaces, and the results are compared in different scenarios. The proposed method is programmed based on increasing the use of the RES. Therefore, the probability model of the RES has been presented in order to analyse the behaviour of these sources in detail. Also in this research, in order to analyse the performance of the proposed method in the face of uncertainties, electrical energy storage and probability loads are considered as EVs. EV is considered as a probability load at the time of connection to the EH and if it receives energy from the EH, and if EV injects power into the EH after connection to the EH, then it is considered as the energy storage source in the optimization equations.

Therefore, the **main contribution** of this article can be categorized as follows:

1 Develop and present the integrated model of optimal operation and planning of EHs, taking into account optimization objectives such as technical, economic and environmental goals.
2 Provide a model and optimization platform based on DR and IDR algorithms, taking into account uncertainties caused by RES, probability loads and storage units.
3 Develop and present the probability optimization model based on meta-heuristic algorithms with two problem-solving approaches in discrete-continuous space and present an optimal EH model by considering nonlinear, stochastic and probability indices.

1.4. Article structure

Section 2 presents the modelling, topology, equipment of the EH and the optimization problem. Section 3 presents the solution method. In Section 4, the results of different operation scenarios are presented along with discussion and comparison, and in Section 5, conclusions are presented.

2. Modelling

2.1. Energy hub equipment and stochastic-probability model of RES and EVs

As shown in Fig. 1, the framework and equipment of the EH are presented. In the proposed structure, energy input carriers include an electrical network, natural gas network, and RES. Output carriers also consist of electrical demand, cooling load, and thermal load. The RES, electrical networks, CHP units, and EV's batteries are responsible for electrical demand. While the boiler, CHP unit, electric heater, thermal storage, and electric heat pump are responsible for the thermal demand. Cooling demand is also provided by an absorption chiller and electric heat pump. The equipment model presented in the EH along with the equations and constraints of each equipment is in accordance with the reference [25] and in this section only the continuous and discrete probability model of RES along with the probability and random model of EVs are presented.

2.1.1. Stochastic-probability model of RES

Power generation by RES is a random process. The random process of power generation by RES is due to various conditions such as climate change and atmospheric conditions. Therefore, the power generated by RES is considered random. Given that the fluctuation of power generation by RES has a direct impact on the indicators of operation, maintenance and investment costs, accurate modelling of these resources behaviour is necessary. Considering the probability behaviour of RES, the use of probability algorithms to explain the behaviour of these sources is efficient and effective. Therefore, it is important to choose a probability model based on the behaviour of RES. In this study, considering that the problem-solving space is analysed in two dimensions of discrete and continuous, the probability model to describe the behaviour of RES based on continuous and discrete probability algorithms is presented. According to Fig. 2, the probability distribution functions (PDF) of beta (β), gamma (Γ) and beta-binomial distribution are presented to describe the continuous and discrete behaviour of RES [25]. The beta-binomial distribution probability function is a discrete probability distribution function with finite value support. According to Fig. 3, the beta and gamma probability distribution functions are

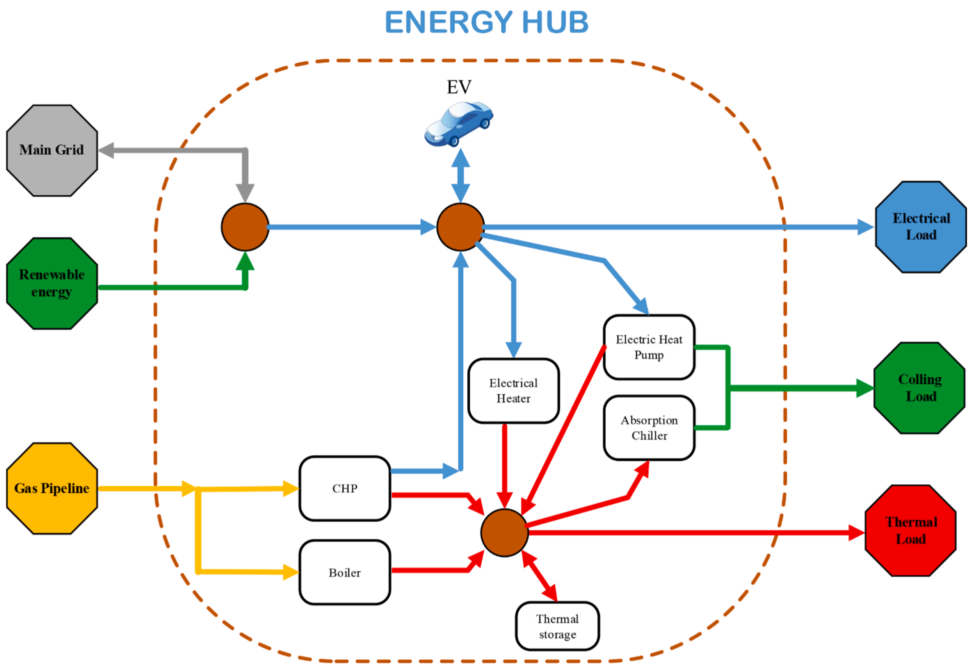

Fig. 1. Framework and structure of the EH.

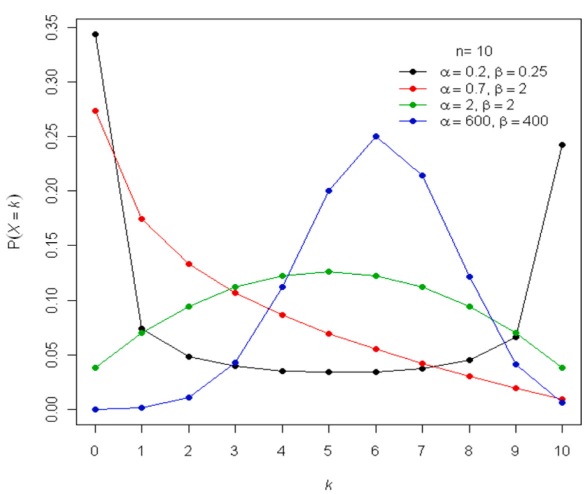

Fig. 2. Beta-binomial distribution probability distribution function.

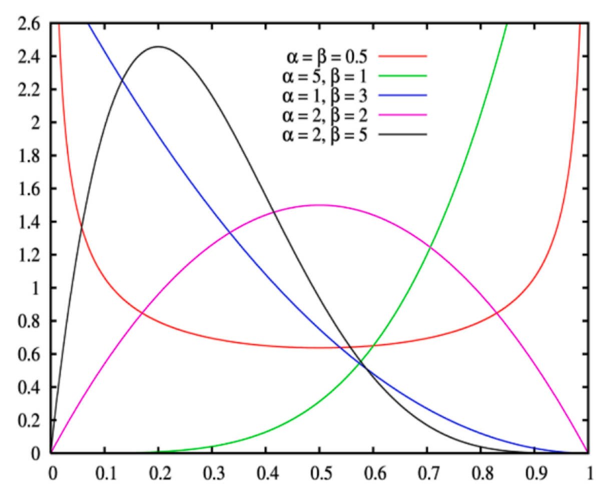

Fig. 3. Beta probability distribution function.

amongst the continuous probability distribution functions based on the limited support interval.

Equations describing the probability behaviour of RES are equal to [25]:

$$f(x|n,\alpha,\beta) = \int_0^1 Bin(x|n,p)Beta(p|\alpha,\beta)dp = \binom{n}{x}\frac{(B(x+\alpha,n-x+\beta))}{B(\alpha,\beta)} \tag{1}$$

$$f(x,\alpha,\beta) = \frac{1}{B(\alpha,\beta)}x^{\alpha-1}.(1-x)^{\beta-1}\bigg|_{B=\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha,\beta)}} \tag{2}$$

Eq. (1) is a beta-binomial discrete probability distribution function based on a rewritten continuous beta probability distribution function. Eq. (2) also presents the beta continuous probability distribution function based on the gamma probability distribution function. Indicators x, α,β are considered as decision variables in the random process and describe the behaviour of RES. In this study, wind and solar energy sources are considered as RES. The behaviour of wind and solar sources can be described according to Figs. 2 and 3 and Eqs. (1) and (2).

2.1.2. Stochastic -probability model of EVs

In the last decade, the use of EVs has increased dramatically. Due to the fact that the consumption of fossil fuels by cars have number of environmental hazards, EVs are a suitable alternative to diesel vehicles. Due to the change in the structure of electrical networks from the traditional framework to the modern framework, conditions have been provided for subscribers and consumers of energy (especially electricity) to become one of the actors and decision-makers in the energy industry. Therefore, by using demand-side management and DR algorithms, subscribers have the opportunity to play an important role in the optimal operation of the energy distribution system. EVs, due to their technical characteristics, have the ability to participate in DR programs. But it is important to note that in modelling of EVs, their operating conditions and performance must also be considered. There are two modes of operation of EV units. The first case is when the EV is connected to the EH and receives electrical power from the hub. In this case, the EV model is considered in the operating equations as the electric demand model. In the second mode, the EV connects to the EH and injects the energy stored in the batteries into the EH. In the case of EVs, in the operating equations, it is considered as a supplier of electrical energy. Therefore, the most efficient tool for modelling EVs is the use of stochastic-probability models and algorithms. In modelling EVs, the normal probability distribution function and its different types are used. This function describes and models the behaviour of EVs [25,26].

To model EV units, three models of EV behaviour are modelled.

1 EV connection time to EH and start charging or discharging process of battery (t_a)
2 The distance travelled by the EV unit in 24 h (d_h)
3 EV disconnection time from EH and finish charging or discharging process of battery (t_d)

Therefore, according to Fig. 4 (a - c), the behaviour and performance of EVs can be expressed according to the normal probability distribution function and its generalized types. Eqs. (3) to (5) express the connection time, the distance travelled, and the disconnection time of the EV unit from the EH, respectively. Table 2 also shows stochastic iterative analysis to determine indicators appropriate to the behaviour of EVs.

$$PDF\left(f_{t_a}(t)\right) = \frac{1}{\sigma_{t_a}}\left(1+k_{t_a}\frac{(d-\mu_{t_a})}{\sigma_{t_a}}\right)^{-\left(1+\frac{1}{k_{ta}}\right)} .e^{-\left(1+k_{t_a}\frac{(d-\mu_{ta})}{\sigma_{ta}}\right)^{-\left(\frac{1}{k_{ta}}\right)}} ,t>0 \tag{3}$$

$$PDF\left(f_{d_h}(t)\right) = \frac{1}{\sigma_{d_h}}\left(1+k_{d_h}\frac{(d-\mu_{d_h})}{\sigma_{d_h}}\right)^{-\left(1+\frac{1}{k_{d_h}}\right)} .e^{-\left(1+k_{d_h}\frac{(d-\mu_{d_h})}{\sigma_{d_h}}\right)^{-\left(\frac{1}{k_{d_h}}\right)}} ,t>0 \tag{4}$$

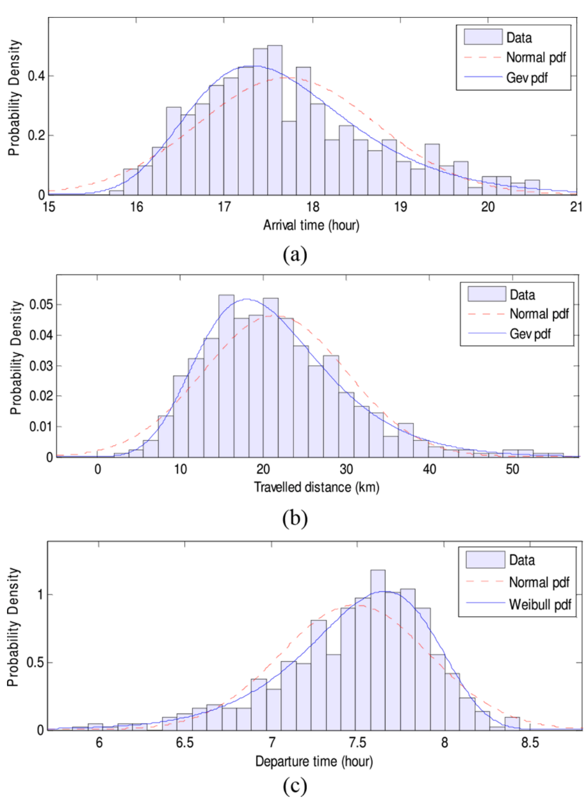

Fig. 4. Describing the behaviour of EV units based on the normal probability distribution function [24,25].

Table 2
Parameters of normal distribution functions and proposed distribution functions [25,26].

Parameter	Normal distribution	Proposed distribution
(t_d)	$\mu_{Nt_d} = 7.4843$ $\sigma_{Nt_d} = 0.4317$	$\alpha = 7.6745$ $\beta = 21.3812$
(d_h)	$\mu_{Nd_h} = 21.4150$ $\sigma_{Nd_h} = 8.5871$	$k_{d_h} = -0.0523$ $\mu_{Nd_h} = 17.6568$ $\sigma_{Nd_h} = 7.1222$
(t_a)	$\mu_{Nt_a} = 17.7170$ $\sigma_{Nt_a} = 1.0138$	$k_{t_a} = -0.0607$ $\mu_{Nt_a} = 17.27$ $\sigma_{Nt_a} = 0.8483$

$$PDF\left(f_{t_d}(t)\right) = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{(\beta-1)} .e^{-\left(\frac{t}{\alpha}\right)^{\beta}} ,t>0 \tag{5}$$

2.2. Problem modelling of optimal energy hub planning and operation

In this section, the two-level objective function of the optimization problem at the two levels of optimal energy planning and operation-maintenance of the EH is presented. At the first level, which includes the EH planning section, the main objectives include determining the optimal equipment capacity and reducing investment costs. In the second level of the objective function, the optimal operation and maintenance of the EH based on the uncertainty of RES and EV units are expressed. In this section, DR algorithms are modelled along with economic and environmental indicators. The optimization problem is planned and designed based on the MILP method [17]. Eq. (6) shows the two-level objective function of the optimization problem.

$$\min : TC^{t,s}_{EH} = ICOC^{t,s}_{EH} + OMC^{t,s}_{EH} \tag{6}$$

2.2.1. Optimal energy hub planning problem model

Eqs. (7) to (9) show the first level of the objective function and the optimal planning problem. In this section, EH planning is programed based on the optimal capacity of the equipment and the minimum investment cost. The investment cost includes various equipment, topology and structure of the EH. Eq. (7) shows the investment cost. It also expresses the investment cost of EH equipment based on the capacity of each equipment. Due to the fact that the optimal values of the capacity of the EH equipment are determined in the optimal planning problem, therefore, to solve the discrete space problem, Eq. (8), which is based on the binary index b_{Eq}, has been used [27]. Eq. (9) also shows the range of the binary index of discrete space.

$$ICOC^{t,s}_{EH} = \sum_{Eq=1}^{Eq} \frac{Ir(1+Ir)^{h_{Eq}}}{(1+Ir)^{h_{Eq}}-1}.IC^{t}_{Eq} \tag{7}$$

$$IC^{t}_{Eq} = ICC^{t}_{Eq} P^{\max,c}_{Eq} \Big|_{P^{\max,c}_{Eq} = \sum_{c=1}^{C} P^{Install,c}_{Eq}.b_{Eq}} \tag{8}$$

$$0 \le \sum_{c=1}^{C} b_{Eq} \le 1 \tag{9}$$

2.2.2. Optimal energy hub operation problem model

Optimal operation of the EH is a multidimensional technical, economic and environmental issue. In this study, three basic technical, economic and environmental indicators in the optimization of EH operation have been considered. The model of the optimal operation of the EH problem is planned over a period of one year [28]. Eq. (10) shows the objective function of the EH optimal operation.

$$OMC_{EH}^{t,s}=\sum_{s=1}^{S}\rho(s).\sum_{se=1}^{Se}d(se).\sum_{t=1}^{T=24}\left[OMC_{E}^{t,s}+OMC_{RES}^{t,s}+OMC_{CHP,B}^{t,s}+OMC_{E/TES}^{t,s}+OMC_{EM}^{t,s}+OMC_{DR/IDR}^{t,s}+OMC_{UEC}^{t,s}+OMC_{EV}^{t,s}\right] \tag{10}$$

$$OMC_{E}^{t,s}=\left(\Lambda_{buy}^{grid-Hub}.P_{e}^{grid-Hub}(t,s)-\Lambda_{sell}^{Hub-grid}.P_{e}^{Hub-grid}(t,s)\right)_{\Delta_t}^{t,s} \tag{11}$$

$$OMC_{RES}^{t,s}=(\Lambda_{RES}\times P_{RES}^{t,s}(t,s))_{\Delta_t}^{t,s} \tag{12}$$

$$OMC_{CHP,B}^{t,s}=\left(\Lambda_{g}.P_{g}^{CHP}(t,s)+\Lambda_{g}.P_{g}^{B}(t,s)\right)_{\Delta_t}^{t,s} \tag{13}$$

$$OMC_{E/Th}^{t,s}=\Lambda_{e}^{S}\left(P_{E}^{ch}(t,s)+P_{E}^{dis}(t,s)\right)_{\Delta_t}^{t,s}+\Lambda_{Th}^{S}\left(P_{Th}^{ch}(t,s)+P_{Th}^{dis}(t,s)\right)_{\Delta_t}^{t,s} \tag{14}$$

$$OMC_{EM}^{t,s}=\sum_{em=1}^{EM}\left(\Lambda_{em}EI_{em}^{CHP}.P_{g}^{CHP}+\Lambda_{em}EI_{em}^{B}.P_{g}^{B}\right)_{\Delta_t}^{t,s} \tag{15}$$

$$OMC_{DR/IDR}^{t,s}=\Lambda_{z}^{DR/IDR}\left(P_{e,Th,c}^{Sh-up}(t,s)+P_{e,Th,c}^{Sh-down}(t,s)\right)_{\Delta_t}^{t,s} \tag{16}$$

$$OMC_{UEC}^{t,s}=(\Lambda_{UEC}.P_{UEC}(t,s))_{\Delta_t}^{t,s} \tag{17}$$

$$OMC_{EV}^{t,s}=\min\sum_{s=1}^{S}\rho(s)\sum_{n=1}^{N}EV_{n}\left\{\sum_{t=1}^{T=24}\Lambda_{sell}^{Hub-EV}.P_{Hub-EV}^{t,s}(t,s)-\Lambda_{buy}^{EV-Hub}.P_{EV-Hub}^{t,s}(t,s))_{\Delta_t}^{t,s}\right\} \tag{18}$$

Where $\rho(s)$and $d(se)$ show the probability of different scenarios as well as the days of each season. Eq. (11) shows the interaction of the EH and the electricity distribution network based on electricity market indicators. Eq. (12) shows the operation cost of RES based on the uncertainty of power generation of these resources. Eq. (13) shows the operation cost of CHP and boiler units based on the power of these two units and their natural gas capacity. Eq. (14) shows the operating cost of electrical and thermal energy storage units. Eq. (15) presents the emission cost of greenhouse gases based on three hazardous gases (NOx, CO2 and SO2). Eq. (16) presents the implementing algorithm of the DR program for electrical, thermal and cooling demand. If the candidate subscribers do not implement DR programs, the penalty factor for the subscribers will be considered by the EH operator [29]. Eq. (17) shows the cost of unsupply of subscribers' demand and the penalty of unsupply of demand. Eq. (18) also shows the operation cost of the EV as well as the interaction with the EH based on electricity market indicators. According to Eq. (18), the operating conditions of EVs can be expressed according to the following equations.

$$E_{EV}^{t,s}=\left(\eta_{EV,ch}P_{EV,ch}^{t,s}(t,s)-\frac{P_{EV,dis}^{t,s}(t,s)}{\eta_{EV,dis}}\right)+E_{EV}^{t-1,s} \tag{18–1}$$

$$E_{EV-\min}\leq E_{EV}^{t,s}\leq E_{EV-\max} \tag{18–2}$$

$$P_{Hub-EV}^{t,s}(t,s)=E_{EV-\max},\forall t=DT \tag{18–3}$$

$$P_{EV,ch}^{t,s}=P_{Hub-EV}^{t,s}(t,s) \tag{18–4}$$

$$P_{EV,dis}^{t,s}=P_{EV-Hub}^{t,s}(t,s) \tag{18–5}$$

$$SOC_{\min}^{t,s}\leq SOC_{EV,ch}^{t,s}\leq SOC_{\max}^{t,s},\forall t=AT \tag{18–6}$$

$$P_{EV-\min}^{t,s}(t,s).b_{EV}\leq P_{EV,ch}^{t,s}(t,s)\leq P_{EV-\max}^{t,s}(t,s).b_{EV} \tag{18–7}$$

$$P_{EV-\min}^{t,s}(t,s).b_{EV}\leq P_{EV,dis}^{t,s}\leq P_{EV-\max}^{t,s}(t,s).b_{EV} \tag{18–8}$$

$$0\leq b_{EV}\leq 1, \tag{18–9}$$

Eq. (18–1) shows the charge status of EVs batteries in different scenarios, seasons and times. Eq. (18–2) describes the EVs battery charge range. Eq. (18–3) describes the reliability index for disconnection and exit of EV units from the parking lot at full charge and T_d time. Eqs. (18–4) and (18–5) describe the interactions of EVs and EHs based on electricity market indicators. Eq. (18–6) describes the initial charge amount of EVs connected to the EH. Eqs. (18–7), (18–8) and (18–9) show the battery charge and discharge constraints and the binary index of EV units based on the problem-solving approach in discrete space.

2.2.3. *Constraints on the two-level problem of optimal energy hub planning and operation*

In this section, two-level constraints on the planning and optimal operation of EHs due to restrictions on the exchange and supply of energy in both electricity and natural gas, as well as the limitations of energy storage units are stated.

2.2.3.1. Energy exchange and supply constraints. In the electrical sector, the operation problem is planned in such a way that the energy exchange between the EH and the electricity distribution network is bidirectional. This is while the operation model between the natural gas network and the EH is considered unidirectional from the natural gas network to the EH [29]. Eqs. (19) and (20) show the constraints of electrical power exchange between the EH and the electrical network based on electricity market indicators. Eq. (21) shows that the EH is not able to inject and absorb power from the electrical network at the same time. Eq. (22) also shows the natural gas supply constraints.

$$P_{e-\min}(t,s).b_{e}^{buy}\leq P_{e}^{grid-Hub}(t,s)\leq P_{e-\max}(t,s).b_{e}^{buy} \tag{19}$$

$$P_{e-\min}(t,s).b_{e}^{sell}\leq P_{e}^{Hub-grid}(t,s)\leq P_{e-\max}(t,s).b_{e}^{sell} \tag{20}$$

$$0\leq b_{e}^{buy}+b_{e}^{sell}\leq 1 \tag{21}$$

$$P_{g-\min}\leq P_{g}^{CHP,B}(t,s)\leq P_{g-\max} \tag{22}$$

2.2.3.2. Energy constraints of electrical and thermal storage units. Eq. (23) describes the constraints of energy and the energy stored at different hours of operation. This equation is designed based on three indicators of charge, discharge and energy loss of electrical and thermal energy storage units [30]. Eqs. (24) and (25) show the power rate of energy storage units in the first and last hour of operation. Eq. (26) shows the energy loss constraints of an energy storage unit. Eq. (27) describes the minimum and maximum storage intervals of ES units. Eqs. (28) and (29) describe the minimum and maximum charge and discharge limits of energy storage units. Eq. (30) also shows that energy storage units are not able to charge and discharge simultaneously.

$$E^{S}_{E/TES}(t,s) = E^{S}_{E/Th}(t-1,s) + P^{ch}_{E/Th}(t,s).\eta^{ch}_{E/Th} - \left(\frac{P^{dis}_{E/Th}(t,s)}{\eta^{dis}_{E/Th}} + E^{Loss}_{E/Th}(t,s)\right) \tag{23}$$

$$E^{S}_{E/Th}(t,s) = \delta^{\min}_{E/Th}.P^{\max}_{E/Th} \forall t, s=0 \tag{24}$$

$$E^{S}_{E/Th}(t,s) = \delta^{\max}_{E/Th}.P^{\max}_{E/Th} \forall t, s=24 \tag{25}$$

$$E^{Loss}_{E/Th}(t,s) = \delta^{Loss}_{E/Th}.E^{S}_{E/Th}(t,s) \tag{26}$$

$$\delta^{\min}_{E/Th}.P^{\max}_{E/Th} \le E^{S}_{E/Th}(t,s) \le \delta^{\max}_{E/Th}.P^{\max}_{E/Th} \tag{27}$$

$$\delta^{min,ch}_{E/Th}.P^{\max}_{E/Th}.b^{ch}_{E/Th} \le P^{ch}_{E/Th}(t,s) \le \delta^{\max,ch}_{E/Th}.P^{\max}_{E/Th}.b^{ch}_{E/Th} \tag{28}$$

$$\delta^{min,ch}_{E/Th}.P^{\max}_{E/Th}.b^{dis}_{E/Th} \le P^{dis}_{E/Th}(t,s) \le \delta^{\max,dis}_{E/Th}.P^{\max}_{E/Th}.b^{dis}_{E/Th} \tag{29}$$

$$0 \le b^{ch}_{E/Th} + b^{dis}_{E/Th} \le 1 \tag{30}$$

2.2.3.3. Power and energy balance constraints. Eqs. (31) to (33) show the power and energy balance in the EH structure based on different scenarios and time intervals. The stated equations show that with the implementation of DR programs, the energy injected into the EH by the energy storage units and the reduction of loads are not considered as power generation [30]. These two factors only compensate for the lack of power caused by inequality in energy generation and consumption. While increasing load at off-peak times, or charging energy storage units at off-peak times, are modelled as load consumption.

$$\begin{aligned} &P_e(t,s) + \frac{P^{Hub-grid}_{e}(t,s)}{\eta^{Tr}_{ee}} + P^{ch}_{E}(t,s) + P^{Sh-up}_{e}(t,s) + \frac{P^{EHP}_{Th}(t,s)}{\eta^{EHP}_{e-Th}} + \frac{P^{EHP}_{c}(t,s)}{\eta^{EHP}_{e-c}} + P^{Heater}_{e}(t,s) = \\ &\eta^{Tr}_{ee}P^{grid-Hub}_{e}(t,s) + \eta^{CHP}_{ge}P^{CHP}_{g}(t,s) + \eta^{Con}_{ee}P^{RES}_{e}(t,s) + P^{dis}_{E}(t,s) + P^{Sh-down}_{e}(t,s) + P^{UEC}_{e}(t,s) \end{aligned} \tag{31}$$

$$\begin{aligned} &P_{Th}(t,s) + P^{ch}_{Th}(t,s) + P^{AC}_{Th}(s,t) + P^{Sh-up}_{Th}(t,s) = \\ &\eta^{CHP}_{g-Th}P^{CHP}_{g}(t,s) + \eta^{B}_{g-Th}P^{B}_{g}(t,s) + P^{dis}_{Th}(t,s) + P^{EHP}_{Th}(t,s) + \eta^{Heater}_{e-Th}P^{Heater}_{e}(t,s) + P^{Sh-down}_{Th}(t,s) \end{aligned} \tag{32}$$

$$P_c(t,s) + P^{Sh-up}_{c}(t,s) = \eta^{AC}_{Th-c}P^{AC}_{Th}(t,s) + P^{EHP}_{c}(t,s) + P^{Sh-down}_{c}(t,s) \tag{33}$$

2.2.3.4. Constraints of equipment and structure of energy hub. Eqs. (34) to (42) describe the operating constraints of various EH equipment such as the power purchased and sold to the electrical network, the constraints of CHP unit, boiler, absorption chiller, electric heat pump and electric heater [29,30].

$$0 \le \eta^{Tr}_{ee}P^{grid-Hub}_{e}(t,s) + \frac{P^{Hub-grid}_{e}(t,s)}{\eta^{Tr}_{ee}} \le P^{Tr}_{\max} \tag{34}$$

$$0 \le \eta^{CHP}_{ge}.P^{CHP}_{g}(t,s) \le P^{CHP}_{\max} \tag{35}$$

$$0 \le \eta^{CHP}_{g-Th}P^{CHP}_{g}(t,s) \le P^{CHP}_{\max} \tag{36}$$

$$0 \le \eta^{B}_{g-Th}P^{B}_{g}(t,s) \le P^{B}_{\max} \tag{37}$$

$$0 \le \eta^{AC}_{Th-c}P^{AC}_{Th}(t,s) \le P^{AC}_{\max} \tag{38}$$

$$0 \le P^{EHP}_{Th}(t,s) \le \eta^{EHP}_{Th}.P^{EHP}_{\max}.b^{EHP}_{Th} \tag{39}$$

$$0 \le P^{EHP}_{c}(t,s) \le \eta^{EHP}_{c}.P^{EHP}_{\max}.b^{EHP}_{c} \tag{40}$$

$$0 \le b^{EHP}_{h} + b^{EHP}_{c} \le 1 \tag{41}$$

$$0 \le \eta^{Heater}_{e-Th}.P^{Heater}_{e}(t,s) \le P^{Heater}_{\max} \tag{42}$$

2.3. DR / IDR programs algorithms and modelling

As mentioned, subscribers and consumers in multi-energy systems are effective actors in the optimal operation and distribution of energy. In this section, algorithms and modelling of DR and IDR programs are presented [31]. DR algorithms are presented based on two formats: technical (shiftable demand) and economic (price-based). IDR algorithms are also based on the three formats of shiftable loads, fixed time range transferable loads and interruptible (cut-off) loads. Therefore, the equations of the DR and IDR programs are programmed based on technical and economic indicators.

2.3.1. Modelling of DR algorithm with shiftable and price-based formats

Because energy carriers have different prices during 24 h, subscribers are able to shift some of their loads to off-peak times in order to increase the profitability of the DR program executive. Thus, this algorithm not only introduces the subscribers as part of the actors in the optimal EH operation, but also, from a technical point of view, flattens the load curve at peak times [32]. Therefore, by implementing this algorithm, peak shaving of the load curve can be achieved at peak consumption. Eqs. (43) to (46) show the DR program algorithm for shiftable loads. The proposed algorithm is programmed based on shift up or shift down loads. Index $b^{Sh-up}_{e}, b^{Sh-down}_{e}$ are a binary component (discrete) that are considered in the discrete solution space of the DR algorithm.

$$\sum_{t=1}^{T=24} P^{Sh-up}_{e}(t,s) = \sum_{t=1}^{T=24} P^{Sh-down}_{e}(t,s) \tag{43}$$

$$0 \le P^{Sh-up}_{e}(t,s) \le DPR^{Sh-up}.b^{Sh-up}_{e}.P_e(t,s) \tag{44}$$

$$0 \le P^{Sh-down}_{e}(t,s) \le DPR^{Sh-down}.b^{Sh-down}_{e}.P_e(t,s) \tag{45}$$

$$0 \le b^{Sh-up}_{e} + b^{Sh-down}_{e} \le 1 \tag{46}$$

The models of price-based DR algorithms are: increase or decrease of energy consumption based on the price of energy carriers. Accordingly, the decision of subscribers to reduce or increase consumption over a period of time depends on the price of the energy carrier at that time. Eqs. (47) to (52) describe the price-based DR algorithm and its constraints. Index $b^{\text{Pr}-up}(t,s), b^{\text{Pr}-down}(t,s)$are a binary component (discrete) that are considered in the discrete solution space of the DR algorithm.

$$\sum_{t=1}^{T=24} P_e^{\text{Pr}-up}(t,s) = \sum_{t=1}^{T=24} P_e^{\text{Pr}-down}(t,s) \tag{47}$$

$$P_e^{\text{Pr}-up}(t,s) \geq \xi^{up} P_e(t,s)\left(1 - \frac{\Lambda_e^{OMC}}{\Lambda_e^{base}}\right) \tag{48}$$

$$P_e^{\text{Pr}-down}(t,s) \geq \xi^{down} P_e(t,s)\left(1 - \frac{\Lambda_e^{OMC}}{\Lambda_e^{base}}\right) \tag{49}$$

Fig. 5. Problem solving algorithm based on two discrete and continuous approaches.

$$0 \leq P_e^{\mathrm{Pr}-up}(t,s) \leq DPR^{up}.b^{\mathrm{Pr}-up}.P_e(t,s) \tag{50}$$

$$0 \leq P_e^{\mathrm{Pr}-down}(t,s) \leq DPR^{down}.b^{\mathrm{Pr}-down}.P_e(t,s) \tag{51}$$

$$0 \leq b^{\mathrm{Pr}-up} + b^{\mathrm{Pr}-down} \leq 1 \tag{52}$$

2.3.2. Modelling of IDR algorithm with shiftable, transferable format with fixed time and interruptible (Cut-Off) demands

The IDR algorithms are a suitable way to implement demand-side management programs at different loads such as electrical, thermal and cooling. This algorithm is an extended model of the DR algorithms that has the ability to manage different demands simultaneously [33, 34]. Therefore, Eqs. (53) to (56) of the IDR program based on the shiftable loads format for electrical, thermal and cooling loads are presented. Index $b_{e,Th,c}^{Sh-up}, I_{e,Th,c}^{Sh-down}$are a binary component (discrete) that are considered in the discrete solution space of the IDR algorithm.

$$\sum_{t=1}^{T} P_{e,Th,c}^{Sh-up}(t,s) = \sum_{t=1}^{T} P_{e,Th,c}^{Sh-down}(t,s) \tag{53}$$

$$0 \leq P_{e,Th,c}^{Sh-up}(t,s) \leq DPR^{Sh-up}.b_{e,Th,c}^{Sh-up}.P_{e,Th,c}^{Sh-up}(t,s) \tag{54}$$

$$0 \leq P_{e,Th,c}^{Sh-down}(t,s) \leq DPR^{Sh-down}.b_{e,Th,c}^{Sh-down}.P_{e,Th,c}^{Sh-down}(t,s) \tag{55}$$

$$0 \leq b_{e,Th,c}^{Sh-up} + I_{e,Th,c}^{Sh-down} \leq 1 \tag{56}$$

Transferable loads with a fixed period of consumption are loads that can be transferred to other hours, but provided that the time required for consumption is also provided. In other words, the consumption time for transferable loads is fixed and unchangeable. Therefore, suppliers are obliged to supply power within the required time period of such loads [35]. Eqs. (57) to (60) show the IDR algorithm for transferable loads with a fixed time interval. Index $b_{e,Th,c}^{T-up}, I_{e,Th,c}^{T-down}$are a binary component (discrete) that are considered in the discrete solution space of the IDR algorithm.

$$P_{e.Th.c}^{T-up}(t,s) = P_{e.Th.c}^{T-down}(t,s) \tag{57}$$

$$0 \leq P_{e.Th.c}^{T-up}(t,s) \leq DPR^{T-up}.b_{e.Th.c}^{T-up}.P_{e.Th.c}^{T-up}(t,s) \tag{58}$$

$$0 \leq P_{e.Th.c}^{T-down}(t,s) \leq DPR^{T-down}.b_{e.Th.c}^{T-down}.P_{e.Th.c}^{T-down}(t,s) \tag{59}$$

$$0 \leq b_{e,Th,c}^{T-up} + I_{e,Th,c}^{T-down} \leq 1 \tag{60}$$

Interruptible loads are also loads that are interrupted by the operator or subscriber at peak times. This method is designed in such a way that subscribers are not able to consume energy at certain times of the day [36, 37]. This method is generally performed by users of energy distribution systems. For example, the plug of some high-consumption equipment are disconnected at certain times of the day, and consumers are unable to receive power from the network. The IDR algorithm based on Interruptible loads is presented in Eqs. (61) to (64). Index $b_{e.Th.c}^{Int-up}, b_{e.Th.c}^{Int-down}$are a binary component (discrete) that are considered in the discrete solution space of the IDR algorithm.

$$P_{e.Th.c}^{Int,down}(t,s) = C_1 P_{e.Th.c}^{Int-up}(t,s+1) + C_2 P_{e.Th.c}^{Int-up}(t,s+2) + C_3 P_{e.Th.c}^{Int-up}(t,s+3) \tag{61}$$

$$0 \leq P_{e.Th.c}^{Int-up}(t,s) \leq DPR^{Int-up}.b_{e.Th.c}^{Int-up}.P_{e.Th.c}^{Int-up}(t,s) \tag{62}$$

$$0 \leq P_{e.Th.c}^{Int-down}(t,s) \leq DPR^{Int-down}.b_{e.Th.c}^{Int-down}.P_{e.Th.c}^{Int-down}(t,s) \tag{63}$$

$$0 \leq b_{e.Th.c}^{Cut-up} + b_{e.Th.c}^{Cut-down} \leq 1 \tag{64}$$

3. Problem solving method and algorithm

Because the optimal problem-solving space is programmed based on continuous and discrete solution space, in this study the hybrid real and binary coded genetic algorithm (HRBC-GA) method has been used [38, 39]. In this method, two categories of variables are programmed. Discrete decision variables are considered as binary values based on "0″ and "1″ values, and continuous decision variables are programmed based on real values. The algorithm for implementing the proposed method is shown in Fig. 5. The proposed algorithm is simulated simultaneously and continuously by GAMS and MATLAB software with 8 GB RAM with Core i7 CPU configuration. As mentioned in Section 2, the optimization problem is planned at two levels. The first level is the issue of optimizing the capacity of EH equipment and reducing investment costs. This level is run by MATLAB software. The second level of optimization problem includes minimizing the cost of operating the EH based on DR and IDR algorithms, which is also implemented in GAMS software. In this section, the HRBC-GA algorithm is presented in detail.

3.1. Chromosome coding process

Both binary and real approaches are used to encode the objective function variables based on the GA algorithm. The equations of the binary approach are:

$$g_1 \cdots g_l \cdots g_{(i-1)l+1} \cdots g_{il} \cdots g_{(n-1)l+1} \cdots g_{nl} \tag{65}$$

$$g_j \in \{0,1\}, \mathrm{j} = 1,\ldots,\mathrm{nl} \tag{66}$$

$$\eta_i = g_{(i-1)l+1}2^0 + g_{(i-1)l+2}2^1 + \ldots g_{il}2^{l-1} \in \{0,1,\ldots,2^{l-1}\} \tag{67}$$

$$\zeta_i = \frac{\zeta_{i,\max} - \zeta_{i,\min}}{2^l - 1}\eta_i + \zeta_{i,\min} \in [\zeta_{i,\max}, \zeta_{i,\min}], i = 1,\ldots,n \tag{68}$$

The equations of the real coding approach are:

$$g_1 \ldots g_n \tag{69}$$

$$g_i \in \{0,1,\ldots,2^{l-1}\}, \mathrm{j} = 1,\ldots,\mathrm{n} \tag{70}$$

$$\zeta_i = \frac{\zeta_{i,\max} - \zeta_{i,\min}}{2^l - 1}g_i + \zeta_{i,\min} \in [\zeta_{i,\max}, \zeta_{i,\min}], i = 1,\ldots,n \tag{71}$$

In these equations g_i, g_jshows genes and $\zeta_i$are also continuous and discrete variables of problem solving space for the objective function.

3.2. Selection operation process

The selection process is planned based on the selection of good solutions and the gradual elimination of poor solutions. Using the binary tournament selection operator, it selects two random solutions simultaneously from the initial population. Creates a temporary population (population mass) based on the best answer. This process continues until the temporary privileged population equals the initial population.

3.3. Crossover process

The task of the crossover operator in the GA algorithm is to use the optimal population generated by the selection operator, and to search the search space as well as to create new solutions. Therefore, this function is expressed by two approaches, binary and real.

3.3.1. Binary variable crossover operator

In this section, the two-point crossover operator is used to process the crossover of binary variables (U_{it}). In this operator, first two parent solutions are selected from the generated population. A predefined probability (Q_c) is then used to generate new solutions. Generating a new generation based on crossover performance is equivalent to choosing two unequal intersections and creating two child solutions by random exchange.

3.3.2. Real variable crossover operator

In this section, the simulated binary crossover operator [38,39] is used to intersect the binary variables (Q_{it}). The process of genration two solutions for a child from two parents is:

$$\begin{aligned} Q_{it}^{c_1} &= \frac{1}{2}\left[(1+\overline{\theta})Q_{it}^{d_1} + (1-\overline{\theta})Q_{it}^{d_2}\right] \\ Q_{it}^{c_2} &= \frac{1}{2}\left[(1-\overline{\theta})Q_{it}^{d_1} + (1+\overline{\theta})Q_{it}^{d_2}\right] \end{aligned} \tag{72}$$

Where c_k and d_k represent the child and the parents, respectively. The $\overline{\theta}$is also the random-probability distribution function is to implement a random intersection and are:

$$\overline{\theta} = \begin{cases} \dfrac{1}{2u^{(n+1)}} u \leq 0.5 \\ \left(\dfrac{1}{2(1-u)}\right)^{\frac{1}{n+1}} \text{otherwise} \end{cases} \tag{73}$$

Where n is a positive factor in the probability distribution function.

3.4. Mutation operator process

In order to execute the mutation operator with two approaches, binary and real variables can be done as follows.The mutation of binary variables (U_{it}) is determined by changing the state from "0″ to "1″ or vice versa.Real variable mutation (Q_{it}) is defined based on the polynomial mutation operator. For a given polynomial index $\eta > 0$, and the random variable v, which is defined in the probability range (0 and 1), the mutation of the real variable can be defined as follows:

$$Q_{it} \leftarrow Q_{it} + \left(Q_i^{\max} - Q_i^{\min}\right)\overline{\varpi}$$

$$\overline{\varpi} \begin{cases} \left[2v + (1-2v).\left(\dfrac{Q_i^{\max} - Q_{it}}{Q_i^{\max} - Q_i^{\min}}\right)\right]^{\frac{1}{\eta+1}} \quad v < 0.5 \\ 1 - \left[2(1-v) + (2v-1).\left(\dfrac{Q_{it} - Q_i^{\min}}{Q_i^{\max} - Q_i^{\min}}\right)\right]^{\frac{1}{\eta+1}} \quad \text{otherwise} \end{cases} \tag{74}$$

That the parameter$\overline{\varpi}$is determined from the probability distribution function of polynomials with the $p(\omega) = \frac{1}{2}(\eta + 1)(1-|\omega|)^{\eta}$characteristic.

4. Results and simulation

4.1. Data and executive requirements

In this section, the executive requirements, equipment specifications and topology of the EH along with the uncertainty model based on two

Table 3
Scenarios with uncertainties.

Scenario	Solution space	Uncertainties RES	Electrical demand	Thermal demand	Cooling demand
1	Continuous	–	–	–	–
2	Continuous	*	–	–	–
3	Continuous	*	*	–	–
4	Continuous	*	*	*	–
5	Continuous	*	*	*	*
6	Discrete	–	–	–	–
7	Discrete	*	–	–	–
8	Discrete	*	*	–	–
9	Discrete	*	*	*	
10	Discrete	*	*	*	*

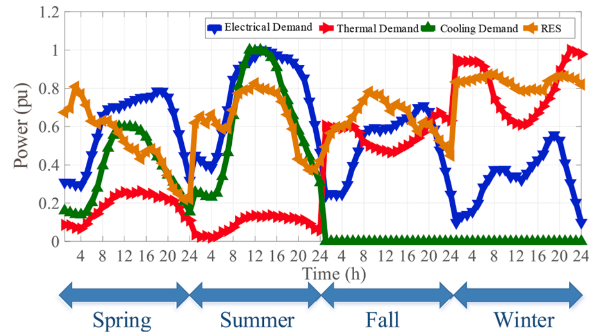

Fig. 6. Demand and RES generation profiles.

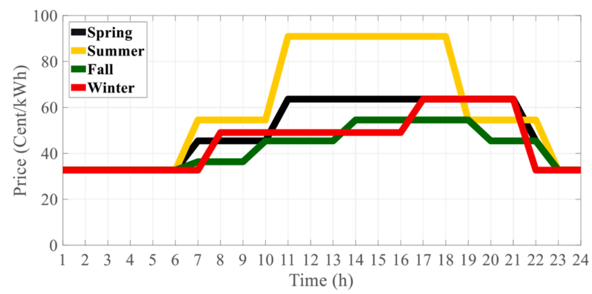

Fig. 7. Average price of electric energy carrier.

Table 4
Capacity and cost of installing EH equipment.

Equipment	Min-Capacity (kW)	Max-Capacity (kW)	Discrete Steps (kW)	Installation costs ($/kW)
Tr	50	500	50	450
CHP	100	500	50	990
Boiler	50	500	50	450
Electric Heater	50	300	50	400
EHP	50	300	50	500
EC	50	500	50	470
AC	50	500	50	470
EES	50	300	50	250
TES	50	300	50	250

Table 5
Specifications of different equipment in the EH structure.

CHP		Boiler	
$\eta_{ge}^{CHP}, \eta_{g-Th}^{CHP}$	50, 40 (%)	η_{g-Th}^{B}	88 (%)
EI_{em}^{CHP}	CO_2=1.59 NO_2=0.008 SO_2=0.44	EI_{em}^{B}	CO_2=1.745 NO_2=0.0214 SO_2=0.614
Electric Heater		Converters and transformers	
η_{e-Th}^{Heater}	90 (%)	$\eta_{ee}^{Tr,Con}$	90 (%)
AC		EHP	
η_{Th-c}^{AC}	90 (%)	η_{e-Th-c}^{EHP}	85 (%)
IDR-DR Algorithm		ESS/TES	
DPR^{Sh-up}	10 (%)	$\eta_{E/Th}^{ch}, \eta_{E/Th}^{dis}$	90 (%)
$DPR^{Sh-down}$	10 (%)	$\delta_{E/Th}^{\min}, \delta_{E/Th}^{\max}$	30 (%)
$\Lambda_z^{DR/IDR}$	0.02 ($/kWh)	$\delta_{E/Th}^{\min,ch}, \delta_{E/Th}^{\max,ch}$	0–25 (%)
Λ_{UEC}	0.02 ($/kWh)	$\delta_{E/Th}^{\min,dis}, \delta_{E/Th}^{\max,dis}$	10–90 (%)
–	–	$\Lambda_{e,Th}^{S}$	0.03 ($/kWh)

problem approaches in the continuous-discrete problem space are presented. The topology of the energy distribution network in a residential complex is based on Fig. 1 and references [24–29]. According to Table 3,

Table 6
Optimal results of EH planning and operation with two approaches to problem solving in continuous and discrete space.

Scenario	Optimal planning and operation continuous problem solving approach					Optimal planning and operation discrete problem solving approach				
	1	2	3	4	5	6	7	8	9	10
TC($)	648,068.321	721,439.18	727,628.07	730,585.53	734,160.46	649,247.6	723,433.35	731,095.29	738,061.12	747,663.37
ICOC($)	171,207.041	177,272.76	179,850.74	182,407.93	185,037.46	175,341.82	182,813.77	185,813.77	190,186.09	199,351.69
OMC($)	476,861.28	544,166.42	547,777.33	548,177.6	549,122.5	473,905.78	540,619.58	545,281.52	547,875.03	548,311.84
Optimal capacity of EH equipment with continuous and discrete problem solving approach (Optimal planning)										
CHP (kW)	452.81	453.48	454.84	469.85	473.83	500	500	500	500	500
Boiler (kW)	80.14	114.69	113.49	149.89	139.96	100	150	150	150	150
EHP (kW)	50	50	50	50	50	50	50	50	50	50
Electric Heater (kW)	99.78	62.68	50	53.04	50	100	100	50	100	50
Tr (kW)	291.17	320.37	330.15	340.7	349.72	300	350	350	350	350
AC&EC(kW)	324.28	324.28	324.28	324.28	346	350	350	350	350	350
EES (kW)	50	69.54	82.97	83.26	83.52	50	100	100	100	100
TES (kW)	50	50	50	65.62	65.71	50	50	50	100	100

the uncertainties of electrical, thermal and cooling demands are presented in 10 scenarios. The problem-solving space is programmed based on two approaches of continuous and discrete analysis. According to Table 3, the results of scenarios 1 and 6 are presented without considering the uncertainties, while in other scenarios different uncertainties are considered.

Fig. 6 shows the profile of electricity, thermal and cooling demands along with the profile of the power generation of RES in different seasons. In order to simplify, the average of different demands as well as the generation of RES in a 24 h period is presented. The average electrical, thermal and cooling demands are 850 kW, 650 kW and 350 kW, respectively. Also, the power generated by RES is considered between the range of 200 kW to 300 kW and the variable. Fig. 7 also shows the average prices of different energy carriers in the seasons. Table 4 shows the capacity and installation cost of the EH equipment. Table 5 shows the specifications of different equipment in the EH structure.

4.2. Results of optimal planning and operation of EH based on two problem solving approaches in continuous and discrete space

According to Table 6, the optimal results of EH planning and operation are presented with two problem-solving approaches in continuous and discrete space. This table consists of two parts. In the first part, the cost of planning (ICOC) and operation-maintenance (O&M) of the optimal EH based on two continuous and discrete approaches are presented. In this section, the total cost of planning and optimal operation of the EH (TC) is also presented. In the second part, the optimal capacity of different EH equipment based on two approaches of continuous and discrete problem solving is presented. The difference between the results of the problem-solving approach in the continuous and discrete search space is due to the fact that the results presented in Table 6 and the continuous search space are exactly the optimal values obtained from the proposed algorithm. However, in the discrete search space section, the obtained values can be presented as the upper limit of the optimal values. The values obtained from discrete space can be the upper or lower limit of the values of continuous space. Because the values of the lower bound of continuous space are unacceptable, the values of discrete space include the upper limit of the values of continuous space. These conditions will have a margin of safety for the capacity of the various units and equipment of the EH to supply and convert energy. The results of optimal planning and operation of EHs based on the consideration of uncertainties are presented in Tables 3 and 6.

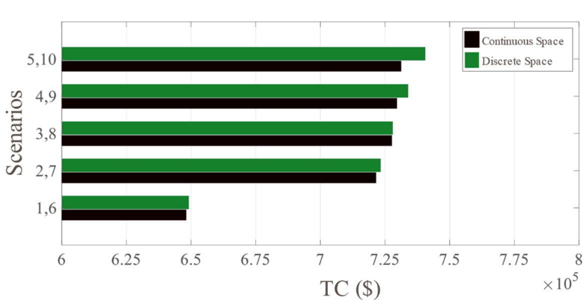

Fig. 8. Comparison of total optimal cost.

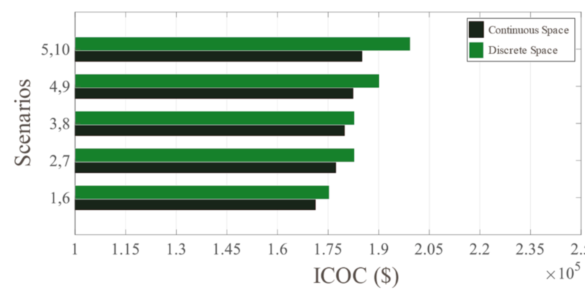

Fig. 9. Investment cost comparison.

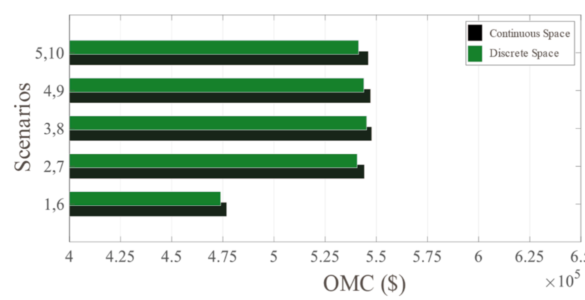

Fig. 10. Comparison of operating costs.

In this study, according to Table 3, the uncertainties of different demands and the uncertainties caused by the generation of power by RES have been considered. According to Table 6 and the problem-solving approach in continuous space, because uncertainty is not considered in the first scenario, the cost of planning and optimal operation of the EH shows the lowest value compared to Scenario 5. Scenario 5 contains the most uncertainty. These conditions also apply to the problem-solving approach in discrete space. However, taking into account uncertainties increases the indicators of reliability, flexibility and security of energy distribution systems, it also increases the costs of planning and operating an optimal energy distribution system. As can be seen from Table 6, scenarios 5 and 10, which have the most uncertainty, also include the highest planning and operation costs. According to Table 6, the cost of optimal EH programming based on the continuous space problem-solving approach is lower than the values obtained based on the discrete space problem-solving approach. This difference is due to the fact that the optimal capacity of the units and equipment of the EH is

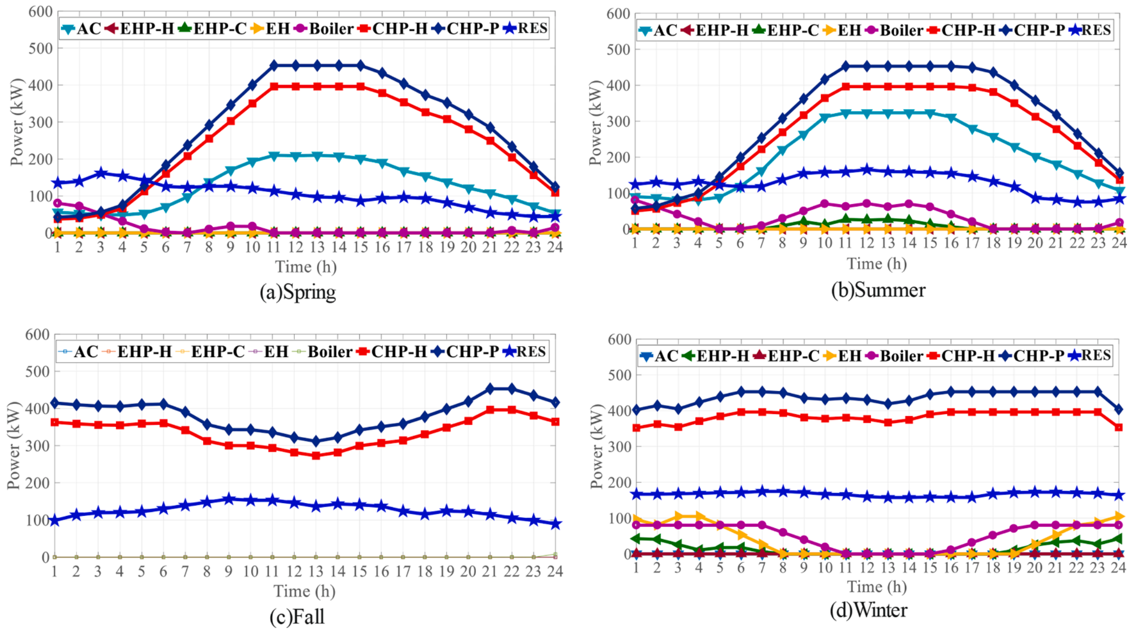

Fig. 11. Equipment operation points in the EH topology.

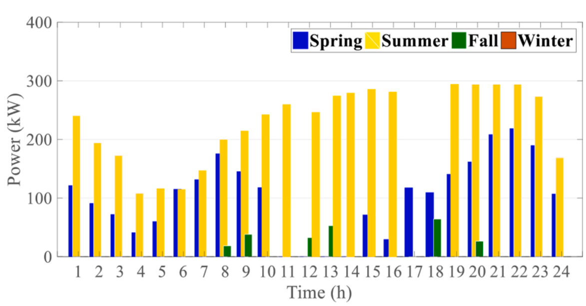

Fig. 12. Electric power purchased by the EH.

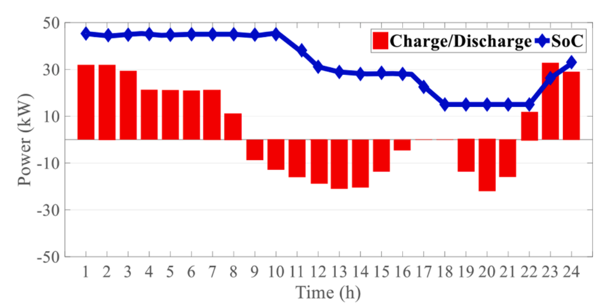

Fig. 14. Charging and discharging status of electric storage unit and EVs.

programmed in a discrete approach based on the upper limit of the values of the continuous approach. Therefore, the values of scenarios 6 to 10 are higher than scenarios 1 to 5.

The results of optimal operation based on the problem-solving approach in continuous space are more than the results obtained based on the discrete approach. This difference is due to the fact that the optimal capacity of the units and equipment of the EH is programmed in a discrete approach based on the upper limit of the values of the continuous approach. The capacity difference between these approaches causes that during operation and especially when electrical energy is required, more power is generated by different units such as the CHP unit, and this condition reduces the power purchase from the electrical network. Therefore, when the capacity of different units and equipment of the EH is considered more, although it brings more investment costs, it reduces the operating costs. Figs. 8-10 show the comparison of the total optimal costs of the EH, the EH optimal planning and the EH optimal operation based on two approaches to solving the problem of continuous and discrete space, respectively.

4.3. Results of optimal operation of energy hub equipment and environmental indicators based on continuous approach

In this section, the index of equipment operation in different season and based on the problem-solving approach in continuous space is presented. As stated in Section 4.1, one day from each seasons, which includes the average demands, is considered. According to Fig. 11a, in

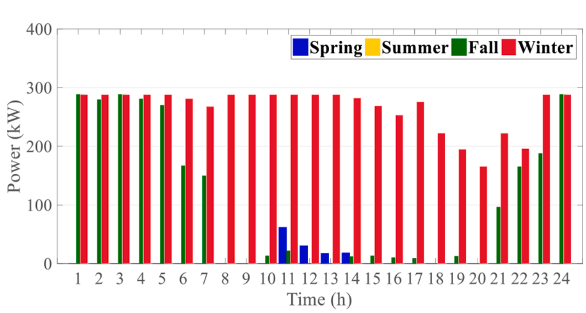

Fig. 13. Electric power sold by the EH.

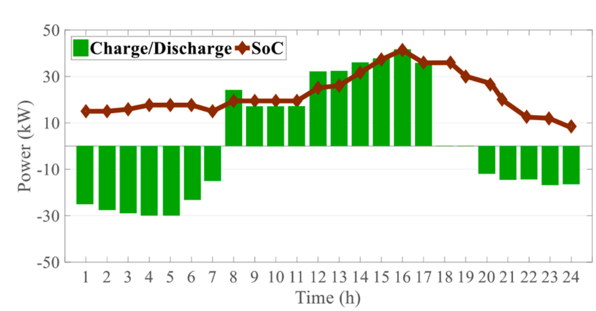

Fig. 15. Charging and discharging status of the thermal storage unit.

Table 7
Greenhouse gas emissions cost.

Equipment	Emissions Cost ($/day)			
	Spring	**Summer**	**Fall**	**Winter**
CHP	CO_2= 3.783	CO_2= 4.075	CO_2=5.132	CO_2=5.860
	NO_2= 312.906	NO_2=337.005	NO_2=424.419	NO_2=484.658
	SO_2= 1.341	SO_2=1.444	SO_2=1.819	SO_2=2.077
Boiler	CO_2= 0.090	CO_2=0.222	CO_2=0.002	CO_2=0.360
	NO_2=9.585	NO_2=23.514	NO_2=0.261	NO_2=38.117
	SO_2=0.040	SO_2=0.098	SO_2=0.001	SO_2=0.159
Total Cost	327.746	366.357	431.634	531.231

the spring, the CHP unit, RES, the AC unit, and the boiler are responsible for supplying electricity, thermal, and cooling demand. According to Fig. 11b, in the summer, when the most demand includes electrical and cooling power, CHP and AC units are responsible for supplying these demand. It should also be noted that the operation of the boiler unit in order to support the CHP unit in providing the required heat to the AC unit. The electrical distribution network also participates in the supply of electrical loads. However, the priority of power supply in the structure of the EH in order to reduce operating costs is the responsibility of the EH equipment. As shown in Fig. 11c and in the fall, the CHP unit and RES are responsible for customer demand. According to Fig. 11d, in the winter, the CHP units, the electric heater unit and the EHP, RES and boilers are responsible for supplying the subscribers. The structure of the EH is planned based on selling the excess power required to the energy market or purchasing the required power (in case the EH equipment is not able to supply the subscribers).

As shown in Fig. 12, the electrical power purchased from the electrical network to the EH is shown. Electricity is in greater demand in the middle of the day and at the beginning of the night. In the winter and autumn, the electrical demand is at its lowest. Fig. 13 shows the electrical power sold from the EH to the grid. As mentioned, the demand for electricity is lowest in the winter and autumn, and therefore the EH operator is able to sell the excess electricity generated by RES and the CHP unit to the grid. Also, in summer and spring, when the price of electricity carriers is high, part of the electrical demand is supplied from the electrical network. In addition to the electricity grid, CHP units and RES are also responsible for providing subscribers' demand. Fig. 14 also shows the charging and discharging status of electrical storage units, which mainly consist of separate batteries and EVs. Therefore, the participation of electrical energy storage units to supply the electrical demands of the EH is determined according to Fig. 14. The share of electric storage devices is higher in summer and spring, when the price of electricity carriers is high. Fig. 15 shows the performance of the charge and discharge status of the thermal energy storage unit. This unit also shows its greatest participation in the autumn and winter seasons when the price of natural gas increases.

Table 7 shows the emission of greenhouse gases and its cost according to the two equipments CHP and boiler. As shown in Table 7, the highest rates of greenhouse gas emissions occur in the winter and autumn. This is also due to the fact that CHP equipment and boilers are responsible for providing thermal demand in the winter and autumn. Therefore, these two equipments based on nominal values should be used. The CHP unit also produces more greenhouse gases because it has more nominal power.

4.4. *Optimal planning and operation of energy hub based on DR/IDR algorithms*

In this section, the effect of DR / IDR algorithms on the performance of the EH as well as the load curve and the change in the consumption pattern of the subscribers are investigated. The results of the performance analysis of the DR / IDR algorithm are presented in Table 8. This table shows the different classifications of the DR / IDR algorithm and the performance of the various equipment during the execution of these algorithms.Tables 9 and 10

Execution of DR algorithms is presented in the format of shiftable and price-based loads. The IDR algorithms are presented also based on the three formats of shiftable, transferable with fixed consumption time and interruptible loads. As shown in Table 8, with the implementation of DR / IDR algorithms, the cost of planning, operating costs and, consequently, the total cost of the optimal EH is significantly reduced compared to when the DR / IDR algorithm is not implemented. It should also be noted that the operators of the EH are able to select different DR / IDR algorithms according to the topology, demands, different seasonal conditions, operating conditions as well as the planning conditions of the energy distribution system. However, it should be noted that the DR algorithm based on interruptible loads or load transfer to other times with a fixed consumption time interval has a higher cost than the implementation of the DR algorithm based on shiftable and price-based loads.

Figs. 16-18 also show the implementation of DR / IDR algorithms for thermal, cooling and electrical loads. A noteworthy point in these figures is the change in the consumption pattern of subscribers compared to the implementation of different DR / IDR algorithms. As can be seen from the figures, the curve and load profile of the subscribers have been flattened by implementing DR / IDR algorithms. This is also because subscribers are changing their consumption patterns to maximize the benefits of implementing DR / IDR algorithms. The noteworthy point in Fig. 18 is that the candidates for participation in the implementation of the DR / IDR algorithm on electric loads are more in the spring and summer than in the autumn and winter. According to the electricity supplier's point of view, the implementation of DR / IDR programs will reduce the costs of operating, servicing and maintaining power plant equipment. Therefore, in addition to subscribers, power suppliers (especially electrical power) also benefit from the implementation of DR / IDR algorithms.

Table 8
Results of DR / IDR algorithm.

Scenario	DR Algorithm Types		IDR Algorithm Types		
	Price-Based	Shiftable	Shiftable	Transferable	Curtailable
TC ($)	639,443.46	644,971.79	629,645.66	646,930.97	646,923.64
ICOC ($)	172,895.45	173,098.35	166,035.82	171,133.76	168,560.38
OMC ($)	466,548.01	471,873.45	463,609.84	475,797.21	478,363.26
Equipment					
CHP (kW)	447.94	447.55	462.76	451.55	452.16
Boiler (kW)	94.35	97.13	60.69	91.30	85.56
EHP (kW)	50	50	50	50	50
Electric Heater (kW)	102.20	99.75	91.85	135.39	90
Tr (kW)	280.96	283.45	276.33	265.20	271.76
AC&EC (kW)	349.02	351.27	290.99	313.32	322.41
EES (kW)	50	50	50	50	50
TES (kW)	50	50	50	50	50

Table 9
Comparison of the proposed method and other meta-heuristic algorithms.

	Scenario	DR Algorithm Types		IDR Algorithm Types		
		Price-Based	Shiftable	Shiftable	Transferable	Curtailable
HRBC-GA	TC	**639,443.46**	**644,971.79**	**629,645.66**	**646,930.97**	**646,923.64**
	ICOC	172,895.45	173,098.35	166,035.82	171,133.76	168,560.38
	OMC	466,548.01	471,873.45	463,609.84	475,797.21	478,363.26
PSO	Scenario	**DR Algorithm Types**		**IDR Algorithm Types**		
		Price-Based	**Shiftable**	**Shiftable**	**Transferable**	**Curtailable**
	TC	**645,387.76**	**653,927.83**	**637,105.34**	**652,486.92**	**652,525.96**
	ICOC	175,642.22	178,691.42	169,561.23	174,612.78	172,546.58
	OMC	469,743.54	475,236.41	467,544.11	477,874.14	479,979.38
SFLA	Scenario	**DR Algorithm Types**		**IDR Algorithm Types**		
		Price-Based	**Shiftable**	**Shiftable**	**Transferable**	**Curtailable**
	TC	**645,914.66**	**654,818.43**	**637,888.29**	**653,110.68**	**654,511.01**
	ICOC	175,925.54	178,958.56	169,988.66	175,121.45	172,986.63
	OMC	469,989.12	475,859.87	467,899.63	477,989.23	481,524.38

Table 10
Comparison of characteristics of algorithms.

	Max FV	Min FV	Standard deviation	Total runs	TET
HRBC-GA	3.1145	2.6321	0.0284	250	3.24(s)
PSO	3.4546	3.7298	0.2626	250	4.35(s)
SFLA	3.4966	3.7302	0.2893	250	4.68(s)

*Fitness Values (FV).
*Total Execution Time (TET).

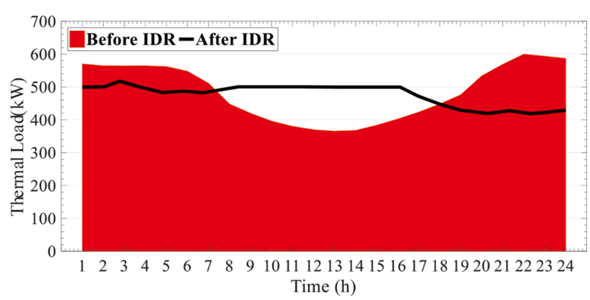

Fig. 16. Execution of DR / IDR programs on shiftable thermal loads.

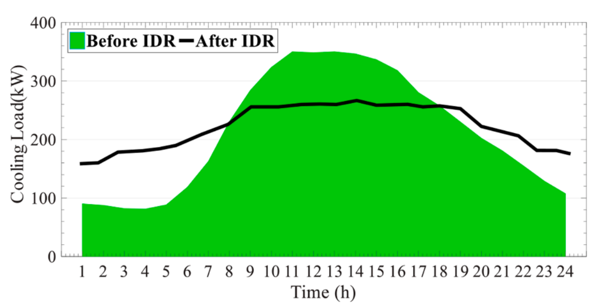

Fig. 17. Execution of DR / IDR programs on shiftable cooling loads.

4.5. Description and discussion

In this study, the optimal EH planning and operation model based on stochastic-probability indicators and considering demand response programs is presented. In recent years, due to the penetration of RES in providing power to consumers and also the upward trend of using EVs, the energy distribution systems have faced several challenges of the stochastic-probability behaviour of these equipment. Therefore, in this research, the stochastic-probability model of RES and EVs is presented with the aim of describing the precise behaviour of these equipment.

In this research, the optimal planning and operation model is presented at two the primary and secondary levels. Algorithms for optimal planning and determining the optimal capacity of EH equipment have been modelled at the primary level. Optimal operation based on the implementation of DR programs and also considering environmental indicators is also presented in the secondary level. The optimization problem is solved based on Mixed Integer Linear Programming (MILP) and Binary Real-Coded Hybrid Genetic Algorithm (HRBC-GA).

The process of implementing the optimization algorithms is as follows: first, the primary level, which includes the optimal planning model and determining the optimal capacity of the EH equipment, is implemented. In this section, after determining the optimal capacity of the equipment and optimal planning, the information obtained from this section is sent to the optimal operation section of EH. It should be mentioned that the primary level (optimal planning and determining the optimal capacity of the equipment) is generally invariant with time. In other words, the optimal planning indicators do not change until changes occur in the topology and EH equipment. But on the other hand, the optimal operation of the EH varies with time. Decision-making variables (variable with time) at the secondary level cause optimal EH operation algorithms to be continuously analysed and implemented. Therefore, by levelling the implementation of optimization algorithms, the calculation time will decrease significantly. The reduction of calculation time is due to the fact that if the proposed model was presented at one level, with every change in the operating conditions, the entire proposed model, which includes planning and operation, must be re-analysed and calculated. Therefore, by using the two-level model, repeating the calculations of the optimal planning part is avoided, and this condition reduces the calculation time of the proposed algorithm.

The proposed model is based on two approaches of discrete and continuous problem-solving space. In order to validate the proposed model, it has been analysed in 10 scenarios and in two parts of continuous and discrete problem-solving space. The proposed model is planned in the optimal operation section based on the implementation of DR/IDR programs. Implementation of DR/IDR programs is presented with two objectives. The first goal is to change the consumption pattern of subscribers, which is to increase the profit due to the implementation of DR/IDR algorithms. The second objective is to improve the profile and flatten the load curve caused by changing the consumption pattern of subscribers. The implementation of DR programs causes a reduction of 14.3% of the EH total cost, and the implementation of IDR programs also causes a reduction of 16.56% of the EH total cost. To validate the results obtained based on the proposed method, the results of Section 4.4 (Optimal Planning and Operation of EH based on DR / IDR Algorithms) have been compared with other meta-heuristic algorithms [25] and [26]:

Also, the following table shows the indicators of the implementation process of different algorithms.

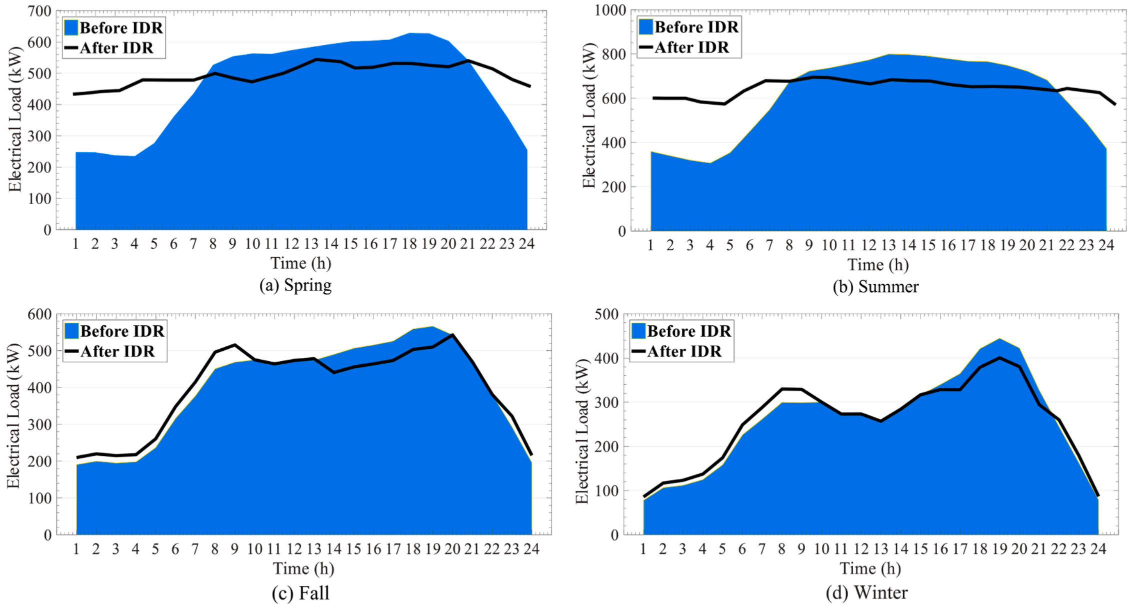

Fig. 18. Execution of DR / IDR programs on shiftable electrical loads in different seasons.

5. Conclusion

In this study, a two-level optimal planning and operation program based on uncertainty indices and stochastic-probability models is presented. Optimal planning and operation modelling is presented at both primary and secondary levels. The problem of optimal planning is designed in the primary and based on determining the optimal capacity of EH equipment and devices as well as optimizing the investment cost. The problem of optimal efficiency in the secondary is modelled and formulated based on optimizing the cost of operating the EH, examining the effect of implementing DR / IDR algorithms and changing the consumption pattern of subscribers, minimizing the cost of greenhouse gas emissions and increasing the penetration of RES. The optimization problem model is developed based on the Hybrid Real and Binary Coded Genetic Algorithm (HRBC-GA) method and problem solving approaches in discrete and continuous space.

In order to validate, the proposed model in the problem-solving approach in discrete and continuous space is analysed in 10 scenarios. The efficiency of the proposed method has been analysed by considering various uncertainties such as uncertainty of electrical demands, thermal and cooling demand, as well as uncertainties due to power generation by RES. In this study, in addition to the stated uncertainties, the EV probability model is also considered. EVs are considered in the structure of the EH and the problem of the optimal planning and operation in two ways. In the optimal planning and operation of the EH, the EVs unit are considered as an electric loads in some hours and in other hours as a backup unit to feed the electrical demands. Therefore, in this paper, EV unit probability modelling is used to investigate the exact behaviour of this equipment. In this study, the implementation of DR / IDR algorithms has two results. The first result is a change in the consumption pattern of subscribers in order to increase profits from the implementation of DR / IDR algorithms. The second result is the improvement of the profile and the flattening of the load curve due to the change in the consumption pattern of the subscribers. The results of this study show the efficiency of the proposed method in the optimal planning and operation of EHs based on various uncertainties and changing the consumption pattern of subscribers based on the implementation of various DR / IDR algorithms.

The most important challenge of this research can be considered big data analysis and data feature extraction. In recent years, intelligent algorithms have shown good performance in managing and extracting data and information. Therefore, the use of intelligent algorithms based on artificial intelligence and intelligent data algorithms can be expressed as a research perspective.

CRediT authorship contribution statement

Asghar Iranpour Mobarakeh: Conceptualization, Methodology, Software, Investigation, Validation, Writing – original draft, Formal analysis. **Ramtin Sadeghi:** Supervision, Project administration, Investigation, Conceptualization, Methodology. **Hadi Saghafi Esfahani:** Supervision, Project administration, Investigation. **Majid Delshad:** Conceptualization, Methodology, Software, Investigation, Validation, Writing – original draft, Formal analysis.

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

Data will be made available on request.

References

[1] Reza Govahian Jahromi, Ali Reza Seifi, The demand side management program considering AC/DC hybrid distribution system concept based on the energy hub, in: 2016 24th Iranian Conference on Electrical Engineering (ICEE), IEEE, 2016, pp. 384–388.

[2] Farnaz Safdarian, Amin Kargarian, Temporal decomposition-based stochastic economic dispatch for smart grid energy management, IEEE Trans. Smart Grid 11 (5) (2020) 4544–4554.

[3] Lorenzo Bartolucci, Stefano Cordiner, Vincenzo Mulone, Vittorio Rocco, Joao Luis Rossi, Renewable source penetration and microgrids: effects of MILP–Based control strategies, Energy 152 (2018) 416–426.

[4] Seyed Ehsan Ahmadi, Delnia Sadeghi, Mousa Marzband, Abdullah Abusorrah, Khaled Sedraoui, Decentralized bi-level stochastic optimization approach for multi-agent multi-energy networked micro-grids with multi-energy storage technologies, Energy 245 (2022), 123223.

[5] Reza Sepehrzad, Ali Reza Moridi, Mohammad Esmaeil Hassanzadeh, Ali Reza Seifi, Intelligent energy management and multi-objective power distribution control in hybrid micro-grids based on the advanced fuzzy-PSO method, ISA Trans. 112 (2021) 199–213.

[6] Reza Sepehrzad, Mostafa Khojasteh Rahimi, Ahmed Al-Durra, Mehdi Allahbakhshi, Alireza Moridi, Optimal energy management of distributed generation in micro-grid to control the voltage and frequency based on PSO-adaptive virtual impedance method, Electr. Power Syst. Res. 208 (2022), 107881.
[7] Reza Sepehrzad, Amirhossein Mahmoodi, Seyedeh Yosra Ghalebi, Ali Reza Moridi, Ali Reza Seifi, Intelligent hierarchical energy and power management to control the voltage and frequency of micro-grids based on power uncertainties and communication latency, Electr. Power Syst. Res. 202 (2022), 107567.
[8] Reza Sepehrzad, Mohammad Esmaeil Hassanzadeh, Ali Reza Seifi, Mahnaz Mazinani, An efficient multilevel interconnect control algorithm in AC/DC micro-grids using hybrid energy storage system, Electr. Power Syst. Res. 191 (2021), 106869.
[9] Reza Gholinejad Hamid, Jafar Adabi, Mousa Marzband, Hierarchical energy management system for home-energy-hubs considering plug-in electric vehicles, IEEE Trans. Ind. Appl. (2022).
[10] Reza Sepehrzad, Soheyl Nakhaeisharif, Ahmed Al-Durra, Mehdi Allahbakhshi, Alireza Moridi, Islanded micro-grid frequency control based on the optimal-intelligent lyapunov algorithm considering power dynamic and communication uncertainties, Electr. Power Syst. Res. 208 (2022), 107917.
[11] D. Fioriti, R. Giglioli, D. Poli, G. Lutzemberger, A. Micangeli, R. Del Citto, I. Perez-Arriaga, P. Duenas-Martinez, Stochastic sizing of isolated rural mini-grids, including effects of fuel procurement and operational strategies, Electr. Power Syst. Res. 160 (2018) 419–428.
[12] Hadi Niaei, Amin Masoumi, Amir Reza Jafari, Mousa Marzband, Seyed Hossein Hosseini, Amin Mahmoudi, Smart peer-to-peer and transactive energy sharing architecture considering incentive-based demand response programming under joint uncertainty and line outage contingency, J. Clean. Prod. (2022), 132403.
[13] Saeed Zeynali, Naghi Rostami, Ali Ahmadian, Ali Elkamel, Robust multi-objective thermal and electrical energy hub management integrating hybrid battery-compressed air energy storage systems and plug-in-electric-vehicle-based demand response, J. Energy Storage 35 (2021), 102265.
[14] Asghar Iranpour Mobarakeh, Ramtin Sadeghi, Majid Delshad, Techno-economic energy management of micro-grid in the presence of distributed generation sources based on demand response programs, Int. J. Electr. Power Energy Syst. 141 (2022), 108169.
[15] Iranpour Mobarakeh Saied, Ramtin Sadeghi, Hadi Saghafi, Majid Delshad, Robust management and optimization strategy of energy hub based on uncertainties probability modelling in the presence of demand response programs, IET Gener. Transm. Distribut. 16 (6) (2022) 1166–1188.
[16] Mostafa Mostafavi Sani, Hossein Mostafavi Sani, Michael Fowler, Ali Elkamel, Alireza Noorpoor, Amir Ghasemi, Optimal energy hub development to supply heating, cooling, electricity and freshwater for a coastal urban area taking into account economic and environmental factors, Energy 238 (2022), 121743.
[17] V.V. Thang, Thanhtung Ha, Qinhao Li, Yongjun Zhang, Stochastic optimization in multi-energy hub system operation considering solar energy resource and demand response, Int. J. Electr. Power Energy Syst. 141 (2022), 108132.
[18] Amir Mirzapour-Kamanaj, Majid Majidi, Kazem Zare, Rasool Kazemzadeh, Optimal strategic coordination of distribution networks and interconnected energy hubs: a linear multi-follower bi-level optimization model, Int. J. Electr. Power Energy Syst. 119 (2020), 105925.
[19] Mohsen Khorasany, Afshin Najafi-Ghalelou, Reza Razzaghi, Behnam Mohammadi-Ivatloo, Transactive energy framework for optimal energy management of multi-carrier energy hubs under local electrical, thermal, and cooling market constraints, Int. J. Electr. Power Energy Syst. 129 (2021), 106803.
[20] Mahdieh Monemi Bidgoli, Hamid Karimi, Shahram Jadid, Amjad Anvari-Moghaddam, Stochastic electrical and thermal energy management of energy hubs integrated with demand response programs and renewable energy: a prioritized multi-objective framework, Electr. Power Syst. Res. 196 (2021), 107183.
[21] a.Li Penghua, Wanxing Sheng, Qing Duan, Zhen Li, Cunhao Zhu, Xinyu Zhang, A Lyapunov optimization-based energy management strategy for energy hub with energy router, IEEE Trans. Smart Grid 11 (6) (2020) 4860–4870.
[22] Arsalan Najafi, Ahmad Tavakoli, Mahdi Pourakbari-Kasmaei, Matti Lehtonen, A risk-based optimal self-scheduling of smart energy hub in the day-ahead and regulation markets, J. Clean. Prod. 279 (2021), 123631.
[23] Xiao Xu, Weihao Hu, Wen Liu, Yuefang Du, Rui Huang, Qi Huang, Zhe Chen, Look-ahead risk-constrained scheduling for an energy hub integrated with renewable energy, Appl. Energy 297 (2021), 117109.
[24] Cong Chen, Hongbin Sun, Xinwei Shen, Ye Guo, Qinglai Guo, Tian Xia, Two-stage robust planning-operation co-optimization of energy hub considering precise energy storage economic model, Appl. Energy 252 (2019), 113372.
[25] S.A. Mansouri, A. Ahmarinejad, M. Ansarian, M.S. Javadi, J.P.S. Catalao, Stochastic planning and operation of energy hubs considering demand response programs using Benders decomposition approach, Int. J. Electr. Power Energy Syst. 120 (2020), 106030.
[26] Mohammad Sadegh Javadi, Matthew Gough, Seyed Amir Mansouri, Amir Ahmarinejad, Emad Nematbakhsh, Sergio F. Santos, João PS Catalão, A two-stage joint operation and planning model for sizing and siting of electrical energy storage devices considering demand response programs, Int. J. Electr. Power Energy Syst. 138 (2022), 107912.
[27] Seyed Amir Mansouri, Amir Ahmarinejad, Emad Nematbakhsh, Mohammad Sadegh Javadi, Ahmad Rezaee Jordehi, Joao PS Catalao, Energy management in microgrids including smart homes: a multi-objective approach, Sustain. Cities Soc. 69 (2021), 102852.
[28] Seyed Amir Mansouri, Amir Ahmarinejad, Mohammad Sadegh Javadi, Ali Esmaeel Nezhad, Miadreza Shafie-Khah, João PS Catalão, Demand response role for enhancing the flexibility of local energy systems, Distrib. Energy Resour. Local Integr. Energy Syst. (2021) 279–313.
[29] Beibei Wang, Xuechun Yang, Taylor Short, Shengchun Yang, Chance constrained unit commitment considering comprehensive modelling of demand response resources, IET Renew. Power Gener. 11 (4) (2017) 490–500.
[30] Zhi Qiu, Beibei Wang, Junhui Huang, Zhenjian Xie, Optimal configuration and sizing of regional energy service company's energy hub with integrated demand response, IEEJ Trans. Electr. Electron. Eng. 14 (3) (2019) 383–393.
[31] Tianhao Liu, Dongdong Zhang, Shuyao Wang, Thomas Wu, Standardized modelling and economic optimization of multi-carrier energy systems considering energy storage and demand response, Energy Convers. Manage. 182 (2019) 126–142.
[32] Ramin Bahmani, Hamid Karimi, Shahram Jadid, Cooperative energy management of multi-energy hub systems considering demand response programs and ice storage, Int. J. Electr. Power Energy Syst. 130 (2021), 106904.
[33] Davood Rakipour, Hassan Barati, Probabilistic optimization in operation of energy hub with participation of renewable energy resources and demand response, Energy 173 (2019) 384–399.
[34] Yuchun Li, Jinkuan Wang, Yinghua Han, Qiang Zhao, Generalized modeling and coordinated management of energy hub incorporating wind power and demand response, in: 2019 Chinese Control And Decision Conference (CCDC), IEEE, 2019, pp. 4214–4219.
[35] Kusum Deep, Krishna Pratap Singh, Mitthan Lal Kansal, C. Mohan, A real coded genetic algorithm for solving integer and mixed integer optimization problems, Appl. Math. Comput. 212 (2) (2009) 505–518.
[36] Ioannis G. Damousis, Anastasios G. Bakirtzis, Petros S. Dokopoulos, Network-constrained economic dispatch using real-coded genetic algorithm, IEEE Trans. Power Syst. 18 (1) (2003) 198–205.