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Risk Averse Optimal Operation of Coastal Energy Hub Considering Seawater Desalination and Energy Storage Systems

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Abstract- *An optimal day-ahead operation of a microgrid based on coastal energy hub is presented in this paper. The proposed CEH included wind turbine, photovoltaic unit, combined cooling, heat and power, and seawater desalination. The purpose of the optimization is minimization of the operational and environmental costs considering several technical limitations. The CEH includes an ice storage conditioner together with an energy storage system, i.e. thermal energy storage system. Particularly, the impacts of an innovative rechargeable and emerging ESS that is solar-powered compressed air energy storage is scrutinized, on the efficiency and operational and pollution costs of the CEH. It is clear that there is an intrinsic deviation between predicted and actual uncertainty variables in MG. This paper presents a bi-level stochastic optimal operation model based on risk averse strategy of information gap decision theory to overcome this information gap and to help Microgrid operator. To reduce the complexity of the proposed model, Karush-Kuhn-Tucker method is used for converting the bi-level problem into a single level. The Augmented Epsilon Constraint method is used to deals with multi objective optimization problem to harvest the maximum horizon of the uncertainties of the parameters. The proposed model implemented the Time of Use program as a price-based demand response program. Finally, the efficacy of the SPCAES for minimizing the operational cost and pollutions in the day-ahead operation is depicted by implementation of the presented model on the typical CEH.*

Keyword: Augmented Epsilon Constraint method; Compressed Air Energy Storage; Combined Cooling, Heat and Power; Coastal Energy Hub; Ice Storage Conditioner; Information Gap Decision Theory; Microgrid.

NOMENCLATURE

Sets

T	Set of hours.
M	Set of objective functions.
L	Set of Pareto solutions.
Λ_{ws}	Robustness zone set defined for electricity price.
Λ_{LD}	Robustness zone set defined for energy demand.
Λ_{REN}	Robustness zone set defined for renewable generation.
$DV1$	First level decision variables.
$DV2$	Second level decision variables.

Variables

$C_{pe}(t)$	Cost of net electricity buying at hour t ($).
$C_{pg}(t)$	Natural gas purchasing cost at hour t ($).
$C_{oe}(t)$	Carbon emission at hour t ($).
$P^{GRD}(t)$	Amount of the active electrical power traded with the main grid, positive for buying and negative for exporting at hour t (kW).
$P_{gas}^{PGU}(t)$	Amount of the natural gas bought from gas network used via PGU at hour t (kW).
$P_{gas}^{AB}(t)$	Amount of the natural gas bought from gas network used via AB at hour t (kW).
$P_{gas}^{CAES}(t)$	Amount of the natural gas bought from gas network used via CAES at hour t (kW).
$P_{e}^{PGU}(t)$	Amount of the active electrical power produced via PGU at hour t (kW).
$H^{HRU}(t)$	Amount of the thermal power produced via HRU at hour t (kW).
$H^{AB}(t)$	Amount of the thermal power produced via AB at hour t (kW).
$P_{CAES}^{dis}(t)$	Amount of the active electrical power produced via CAES at hour t (kW).
$P_{CAES}^{ch}(t)$	Amount of the active electrical power received via CAES at hour t (kW).
$P^{ELE}(t)$	Amount of active electrical power received from the main grid after transformer at hour t (kW).
$P^{WT}(t)$	Amount of the active electrical power produced via WT at hour t (kW).
$P^{PV}(t)$	Amount of the active electrical power produced via PV at hour t (kW).

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$P^L(t)$	Amount of the electrical demand at hour t (kW).
$H^L(t)$	Amount of the thermal demand at hour t (kW).
$C^L(t)$	Amount of the cooling demand at hour t (kW).
$P^{ISC}(t)$	Amount of the active electrical power received through ISC unit at hour t (kW).
$P^{des}(t)$	Amount of the active electrical power received through SWD unit at hour t (kW).
$U_{ESS}^{ch}(t)$	Status of ESS in charging mode at hour t (1 for importing mode; if not 0).
$U_{ESS}^{dis}(t)$	Status of ESS in discharging mode at hour t (1 for exporting mode; if not 0).
$P_{TESS}^{ch}(t)$	Amount of the thermal power received via TESS at hour t (kW).
$P_{TESS}^{dis}(t)$	Amount of the thermal power produced through TESS at hour t (kW).
$C^{AC}(t)$	Amount of the cooling power produced via AC at hour t (kW).
$C_{ISC}^{dis}(t)$	Amount of the cooling power produced through ISC at hour t (kW).
$P_{ESS}^{ch}(t)$	Amount of the active electrical power received through ESS at hour t (kW).
$P_{ESS}^{dis}(t)$	Amount of the active electrical power produced via ESS at hour t (kW).
$E_{ESS}(t)$	ESS stored energy at hour t (kWh).
$f_i(x)$	i^{th} objective function.
γ	Electricity price uncertainty horizon.
$\pounds$	Energy demand uncertainty horizon.
ω	Renewable generation uncertainty horizon.
$\theta^{LD}(t)$	Energy demand at hour t (kW).
$\theta^{WS}(t)$	Electricity price at hour t ($/kWh).
$\theta^{REN}(t)$	Renewable generation at hour t (kW).
δ_t^1, δ_t^1	Coefficients of Lagrangian.
$\widehat{\Lambda}$	Robustness functions of IGDT method.

Parameters

Δt	Time interval of scheduling equal to one hour.
$\rho_e(t)$	Price of electricity for selling and purchasing at hour t ($/$kWh$).
$\rho_g(t)$	Price of gas at hour t ($/$kWh$).
φ_{in}	Emission coefficient for electrical power generation (*kg/kWh*).
φ_g	Emission coefficient of natural gas (*kg/kWh*).
θ	Carbon dioxide processing cost (*$/kg*).
η_e^{PGU}	Efficiency of the electricity generation by PGU.
η_h^{AB}	Heat generation efficiency of AB.
η_h^{PGU}	Heat generation efficiency of PGU.
η^{HRU}	Heat generation efficiency of HRU.
η^{TRA}	Transformer efficiency.
K^{ISC}	Performance factor of ISC.
K^{AC}	Performance factor of AC.
K^{des}	Performance coefficient of SWD (m^3/kW).
W^d	Water demand (m^3).
P_{PGU}^{min}	Minimum admissible real electrical power produced via PGU (kW).
P_{PGU}^{max}	Maximum admissible real electrical power produced via PGU (kW).
H_{HRU}^{min}	Minimum admissible thermal power produced via HRU (kW).
H_{HRU}^{max}	Maximum admissible thermal power produced via HRU (kW).
H_{AB}^{min}	Minimum permissible thermal power produced via AB (kW).
H_{AB}^{max}	Maximum permissible thermal power produced via AB (kW).
H_{AC}^{min}	Minimum permissible cooling power produced via AC (kW).
H_{AC}^{max}	Maximum permissible cooling power produced via AC (kW).
P_{des}^{min}	Minimum allowable electrical power consumed by SWD (kW).
P_{des}^{max}	Maximum allowable electrical power consumed by SWD (kW).
P_{min}^{ELE}	Minimum active electrical power received from the main grid at hour t (kW).
P_{max}^{ELE}	Maximum active electrical power received from the main grid at hour t (kW).
P_{ESS}^{ch-max}	Maximum real power imported by ESS (kW).
$P_{ESS}^{dis-max}$	Maximum real power exported by ESS (kW).
η_{ESS}^{ch}	Charging efficiency of ESS.
η_{ESS}^{dis}	Discharging efficiency of ESS.
E_{ESS}^{min}	Minimum stored energy in ESS (kWh).
E_{ESS}^{max}	Maximum stored energy in ESS (kWh).
π	Cost deviation factor of IGDT method.
$Cost^{Exp}$	Expected cost calculated regarding forecasted amounts ($).

Abbreviations

AB	Auxiliary Boiler.
AUGMECON	Augmented ε-constraint.
BESS	Battery Energy Storage System.
CAES	Compressed Air Energy Storage.
CCHP	Combined Cooling, Heating and Power.
CEH	Coastal Energy Hub.
EH	Energy Hub.
DG	Distributed Generation.
ESS	Energy Storage System.
FC	Fuel Cell.
GAMS	General Algebraic Modelling System.
GT	Gas Turbine.
ISC	Ice Storage Conditioner.
KKT	Karush-Kuhn-Tucker.
MILP	Mix Integer linear Problem.
MG	Microgrid.
MGO	Microgrid Operator.
MOOP	Multi Objective Optimization Problem.
MOO	Multi Objective Optimization.
OS	Opportunities Seeker.
PV	Photovoltaic
RA	Risk Averse.
SPCAES	Solar-Powered Compressed Air Energy Storage.
SOOP	Single Objective Optimization Problem.
SWD	Seawater Desalination.
ToU	Time of Use.
TESS	Thermal Energy Storage System.
WT	Wind Turbine.

1. INTRODUCTION

1.1. Motivation and incitement

The need to improve procedures and processes in renewable energies generation and fulfil competitive environmental friendly technologies is an ongoing challenge for researchers around the world. If the growth in consumption of various energy carriers is not properly managed, it may lead to increase emissions and to waste natural resources [1]. Optimal dispatching of energy resources among various consumptions is in line with the bids to preserve energy resources for future. A solution is utilizing dispersed energy resources by saving available infrastructures. More precisely, one of the promising solutions is integration in energy exploitation. In fact, energy integrated system is taken into account in numerous area of expertise in scheduling field [2, 3]. For integrating, transferring, and saving energy and energy convertibility, a small system named EH is used that is dealt with different energy carriers.

One of the most important concerns in the coastal area is to obtain freshwater. Therefore, the EH is usually equipped with SWD apparatus which is named CEH [4]. Day-ahead operation can bring about many unforeseen problems for MGO due to the implementation of the different devices and technologies such as DGs and ESSs in the CEH. In this paper, a framework is presented to overwhelm various difficulties affecting the optimal operation of proposed CEH.

The generations, demands, and prices in the operation of MGs face with severe uncertainties. Moreover, it can be noted that probabilistic methods need precise information about the probability density function of uncertain input data. There are four basic methods for uncertainty modelling including: (a) scenario based stochastic decision making; (b) fuzzy decision making; (c) robust optimization and interval based decision making; and (d) information gap decision theory [5]. The nature of scenario based stochastic optimization is multi-stage stochastic optimization and the combinatorial growth of computation burden. The fuzzy optimization needs a membership function and solving the problem for multiple values of cuts and is computationally expensive. The interval optimization or robust optimization method requires exact uncertainty set to which uncertain inputs belong. In addition, the interval optimization usually needs two optimizations for each objective function. The robust optimization methods usually require solving bi-level optimization, which is usually difficult to solve. IGDT method needs an uncertainty set but in contrast to other techniques, this uncertainty set is not needed to be exactly known [5]. The IGDT method receives the indeterminate uncertainty set and tries to make the objective function resilient against the uncertainty of input parameters. Therefore, this paper uses IGDT method to model uncertainties.

1.2. Literature review

Studying the power flow of the energy systems with single/multi energy carrier shows that several researches have been done for the optimal operation of EH [6] as well as power flow of the systems with several energy carrier. In order to investigate the optimum operation of the systems with multi energy carrier, a non-linear technique was introduced in Ref. [7]. The day-ahead optimal utilization of EH was studied in Ref. [8] taking into account the economic dispatch of both renewable and non-renewable generations but it do not consider the uncertain behaviour related to renewable generations. In Ref. [9], a coordinated control based on multi-step method is suggested for MG day-ahead operation in which environmental and economic aspects are considered. The new method presented in Ref. [10] models the EH for MG in static mode and claims that it avoids a number of limitations inherent in the original EH model. Furthermore, an inclusive linearized model was proposed in Ref. [11] with the goal of optimal design and operation of EHs hubs taking into account the reliability constraints. During the optimization procedure, maximum-permissible loss of load probability as well as adequacy indices are examined for a single contingency while various factors limiting reliability are introduced to achieve the satisfactory reliability level required for various load categories. The study reported in Ref. [12] proposed a general optimization framework based on the EH approach along with a hierarchical control architecture for systems that involve several carriers of the energy such as electricity, heat, natural gas, etc. In another development, a mathematical formulation was presented [13] to optimally plan an EH under a number of operation constraints. Parameters for deterministic conditions including electricity cost, wind power, and the demand of electrical hub were considered by means of two objective functions. In fact, the objective functions involved the issues and costs pertaining to the reliability, investment, operation, and pollution. The coordinated operation and optimal dispatch strategies were also among the issues investigated in a multiple energy system at the MG level [14]. The novel sub-EH structure including power hubs as well as heating and cooling hubs have also been propounded in an attempt to enhance the operational flexibility of EH. In Ref. [15], an optimized model for expansion planning was also presented for a multiple-energy-system EH in which the EH served for joining different energy infrastructures to provide demands that are electricity, heating, and natural gas. Furthermore, a suburban EH was designed in Ref. [16] which took electric energy, natural gas, and solar energy as input and was able to provide electrical as well as heating and cooling needs as its output. An inclusive demand response (DR) program was employed involving load shifting and restricting as well as modelling of flexible thermal load for operational flexibility enhancing the of the hub. In

Ref. [17], a suburban EH employed was suggested for a smart home which employing a cogeneration technology, it could combine power and heat, and featured hybrid plug-in electric vehicles. The objective function for optimized operation of the hub is minimizing the cost of customer payment. The study reported in Ref. [18] presented a strong optimization problem for the EH operation. The solution to EH operation problem involves determining the energy carriers to be procured and put away so as to satisfy energy requests while keeping the cost function as low as possible. In Ref. [19], an optimal planning method was developed on the EH model for a small system with multi carriers energy aiming to minimize the operational and investment costs taking into account the variables involved in choosing energy converters, energy storage, and the possible interrelations between them.

On the other hand, numerous studies have addressed that energy generations and energy demands in the EH-based MGs have a stochastic behaviour. An real time economic dispatch of EH was proposed in Ref. [20] as a model elucidated by a robust method based on genetic algorithm. The EH planning for a day-ahead duration in Ref. [21] included demand response program, different energy storage types, e.g. ISC and renewable generations. A hybrid interval-stochastic model was dealt with for robust programming of EH in Ref. [22] where based on parameters such as thermal energy market, thermal demand response program, and electrical demand response program, a flexible energy management scheme was implemented with the aim of moderating the cost of operation. In Ref. [23], the flexible energy management scheme in an MG is treated where a two-stage stochastic formwork is introduced for planning coordinated distributed battery ESSs based on EH and in the presence of non-dispatchable renewable energy resources and electric vehicles. A stochastic model of EH is proposed in Ref. [24] to represent a model of the varied energy generation power system where the proposed power flow joined matrix model for the EH of the system and involved features of energy converters and interrelationships among them. Ref. [25] presents a new island-mode operation method for EHs where in case of the happening of a fault or critical event, EH is disconnected from the upstream grid. Ref. [26] proposes a tri-objective optimal performance of a smart EH in the presence of customer's participation to optimally redesign the demand profile in the day-ahead energy market. Minimizing the operation costs and the emission pollution as well as maximizing the customer satisfaction level are considered as the objectives of this problem. In Ref. [27], the optimal scheduling problem of an EH is modelled as a tri-objective optimization problem in which the operation cost, the emission pollution, and the deviation of the electrical load profile from its desired value is minimized. In Ref. [28], a renewable based grid-photovoltaic-boiler-battery-fuel cell hybrid energy system has been scheduled according to the uncertainty modelling of upstream net price and employment of demand response program. One of the effective ways to repeal the generations uncertainty is to utilize ESSs e.g. BESS. A technique is presented in Ref. [29] for stochastic operation and configuration of a multiple EH that features multi-type energy storage devices including BESS as well as various sources of energy and generation. Furthermore, a two-stage robust planning-operation co-optimization method was introduced in Ref. [30] for EH which took into account a range of uncertainties involved in the use of renewable energy resources and also those related to multi-load demands, the problem of sizing, and an accurate economic model of BESS with its lifetime loss cost. Despite the studies on BESS as reviewed above, its large scale application is restricted by constraints such as the initial investment cost and also environmental concerns and relevant recycling cost [31].

Another ESS technology that has the potential to be employed in areas with rich water resources is pumped-hydro energy storage even though this technology is also limited by problems associated with finding suitable storage sites as well as environmental concerns [31]. Regarding the need for efficient performance with fewer construction constraints and less harmful ecological effects, CAES is among the most viable ESSs to solve the problems resulting from the introduction and ever-increasing penetration of renewable energy technologies in the power system [31]. CAES is introduced as an efficient and fast response storage with an essential role in managing the energy, shaving peaks, enhancing power quality, etc. [32]. In Ref. [33], an MG was studied involving CAES, thermal units, and WT in trading electricity reserve with a risk index. Furthermore, a novel precise model is introduced in Ref. [34] as a stochastic strong technique to yield the most expected revenue of the CAES and to model the uncertainty of electricity trading with a set of scenarios in the stochastic technique. The MG economic and technical investigation, such as FC, CAES, PV, GT, and BESS was carried out in Ref. [35]. Solar thermal can be integrated with CAES is a novel method denoted as SPCAES, which can improve the effectiveness of the conventional CAES [36].

Providing reliable clean fresh water sources for various uses of human societies has always been a major world problem particularly in the area suffering from water shortage [37]. A model for optimization of an MG operation was presented in Ref. [38] for desalinating seawater where the impacts of the electric cooling and heating ratios were investigated with the objective of reducing the life cycle costs of the device. In Ref. [4] a coastal MG for SWD was proposed through optimal use of the coastal renewable energy sources available in an attempt to supply the local community with fresh water.
Studies performed for energy management of the EH can be classified from different perspectives, including the model type, objective functions, solution method, DG types, and the ESS types. Table 1 reviews some recent studies regarding the above-mentioned perspectives. This table also presents the novelties of the current work compared to other works.

1.3. Contributions and organization

Optimal operation of the CCHP based CEH and possible effects of SPCAES and ISC on its performance is a gap in the current research avenue which is addressed in this study. The study probes into the SPCASE, ISC, and SWD with considering uncertainty of parameters with the overall aim of achieving an optimal mode of operation for an CEH that includes generations such as WT, PV, CCHP, and AB and a storage that is TESS. A two level RA-IGDT [39] algorithm with risk averse strategy is proposed and KKT converts it into a single level to reduce complexity. Finally, AUGMECON technique is utilized to harvest Pareto optimal solutions pertaining to uncertainty zones. The objectives of the study are as follows:

- Modeling of optimal operation in an CCHP based CEH that includes a SPCASE and ISC,
- Using SWD to supply freshwater demanded by an MG,
- Applying RA-IGDT method with risk averse strategy to involve uncertainties and using AUGMECON method to obtain Pareto solutions, and
- Minimization of operational and environmental costs of the total system.

Rest of the paper is organized as follows: An MOOP is formulated in Section 2. Section 3 addresses the uncertainties involved in demand and generation profiles. The proposed solution algorithm is introduced in Section 4. Simulation results are presented and discussed in Section 5 and finally, Section 6 concludes of this research report.

2. ARCHITECTURE AND FORMULATION OF THE PROBLEM

2.1. CEH architecture

The investigated system was a CEH-based typical MG involving CCHP, AB, SPCAES, PV, WT, ISC, and TESS. Fig. 1 depicts the architecture of the proposed CEH. The CCHP was made up of a number of components including a power generation unit (PGU), a heat recovery unit (HRU), and an absorption chiller (AC). ISC which is extensively employed to meet cooling demands [14], can shift electricity consumption at peak times when there is a tension in the power supply to the hours of off-peak and thereby, mitigate the supply tension [14]. The ISC used in the study consists of a single-duty chiller, which can operate in the mode of making ice, along with the relevant ice storage tank

Table 1. Recent studies on energy management of EH

Ref.	Type of the model		Objective function	Solution method		DGs		Type of ESS
	Dete	Sto		Math.	Heu.	Disp.	Non-Dis	
[6]	-	✓	Operation cost and emission	Simplex	GA	CHP, AB	PV	BESS, TESS
[7]	-	✓	Operation cost and emission	Simplex	-	CHP, AB	PV	BESS, TESS, EV
[8]	✓	-	Operation cost	Simplex	-	MT, FC, DE	WT, PV	BESS
[9]	✓	-	Operation cost and emission	Simplex	-	DE	WT, PV	BESS
[10]	✓	-	Operation cost	Simplex	-	CHP	-	BESS, TESS
[11]	✓	-	Operation cost	Simplex	-	General form	-	General form
[12]	✓	-	Operation cost	Simplex	-	General form	-	General form
[13]	✓	-	Operation cost	Simplex	-	CHP, AB	WT	BESS, TESS
[14]	✓	-	Operation cost and emission	Simplex	-	CCHP, AB	WT, PV	BESS, TESS, ISC
[15]	✓	-	Operation cost, reliability, emission	Simplex	-	CHP, AB	-	-
[16]	✓	-	Operation cost	Simplex	-	CHP, AB	PV	EV
[17]	✓	-	Operation cost	Simplex	-	CHP	-	EV
[18]	-	✓	Operation cost	Simplex	-	CHP, AB, FC	-	BESS, TESS
[19]	✓	-	Operation cost	Simplex	-	CCHP, AB	-	BESS, TESS
[20]	-	✓	Operation cost	-	GA	CHP, AB	WT	-
[22]	-	✓	Operation cost	Simplex	-	CHP, AB	WT	BESS, TESS
[23]	-	✓	Operation cost	Simplex	-	General form	✓	BESS, EV
[24]	✓	-	Operation cost	Simplex	-	GT	WT, PV	BESS
[29]	-	✓	Operation cost	Simplex	-	CHP, AB	WT, PV	BESS, TESS
[30]	-	✓	Operation cost	Simplex	-	CHP, AB	WT, PV	BESS, TESS
[35]	✓	-	Operation cost and emission	Simplex	-	GT, FC	PV	CAES, BESS, TESS
Current paper	-	✓	Operation cost and emission	Simplex	-	CCHP, AB	WT, PV	SPCAES, ISC, TESS

in way that ice is stored to be melt through peak hours. The ISC is designed in a way that it cannot operate at ice-creating and ice-melting conditions simultaneously. The CCHP acts in a following hybrid demand operation mode [40]. The studied system consists of three kinds of demands of energy including thermal, electrical, and cooling demands, as well as water demand. A SWD system was considered in the proposed CEH to supply freshwater demanded by consumers. The operator of MG was assumed to receive all required information. The energy planning was performed for day-ahead within one hour. SPCAES structure is depicted in Fig. 2.

The operation procedure of a traditional CAES plant is much similar to that of the power plants with a gas turbine barring the cycles of the compression and expansion that are functionally separated by the CAES procedure into two distinct processes that do not coincide. Compression and combustion cycles decoupling improves the performance of the CAES plant, making it possible to generate three times more energy in comparison with a natural gas power plant with simple-cycle that consumes the same volume of fuel [36]. The off-peak power is used to compress air in the CAES and thereby, to economize on the energy cost. Before being stored in an underground cavern, the compressed air is then cooled down to the nearby ambient temperature via intercoolers. During the generation phase (peak periods), the pre-compressed air derived from the storage cavern is preheated using a recuperator before it is mixed with the fuel, e.g. natural gas or oil, and is burned in a combustion chamber and then, it is supplied into a multi-stage coupled turbine–generator [36]. likewise, a conventional CAES, SPCAES stores the compacted air, too. However, it integrates the heat recuperator output together with a solar collector within the discharge process and hence improves the efficiency of the plant. As illustrated in Fig. 1, the natural gas is fed into the system at three stages. The first portion flows into the PGU for heat and electricity generation. The second portion of the natural gas is burnt by AB for heat generation, and the last portion is used to supply the SPCAES. Therefore, the natural gas dispatch can be defined as follows:

$$P_{gas} = P_{gas}^{PGU} + P_{gas}^{AB} + P_{gas}^{CAES} \tag{1}$$

The natural gas P_{gas}^{PGU} is used by gas turbine in order to produce electrical power P_e^{PGU} and heat H^{HRU} as follows:

$$\eta_e^{PGU} \times P_{gas}^{PGU} = P_e^{PGU} \tag{2}$$

$$\eta_h^{PGU} \times P_{gas}^{PGU} = H^{HRU} \tag{3}$$

Therefore, from Eq. (2) and Eq. (3), it can be written:

$$H^{HRU} = \frac{P_e^{PGU}}{\eta_{eh}^{PGU}} \tag{4}$$

Where, $\eta_{eh}^{PGU} = \eta_e^{PGU} \times \eta_h^{PGU}$. The natural gas P_{gas}^{AB} is consumed by AB in order to produce heat H^{AB} as follows:

$$\eta_h^{AB} \times P_{gas}^{AB} = H^{AB} \tag{5}$$

Upstream grid trades electrical power with CEH via a transformer. When CEH cannot supply the electrical power it needs, it provides needed electrical power from the upstream grid. Alternatively, in cases of electricity excess, the hub trades the redundant electricity with the upstream grid.

$$\eta^{TRA} \times P^{GRD} = P^{ELE} \tag{6}$$

The capacity of the chiller to make ice is described as follows:

$$P^{ISC} \times K^{ISC} = P_{ISC}^{dis} \tag{7}$$

The heat H^{HRU} from PGU is entered into the HRU as the heating hub gathers the output heat of HRU $\eta^{HRU} \times H^{HRU}$ and the heat produced by AB. The collected heat is then transferred to the AC to serve as the cooling energy.

$$H^{AC} \times K^{AC} = C^{AC} \tag{8}$$

SWD process consumes electricity and produces fresh water. The energy is mainly drawn by the water pump and the high pressure pump. The relationship between water production W^d and electricity consumption can be calculated as:

$$P^{des} \times K^{des} = W^d \tag{9}$$

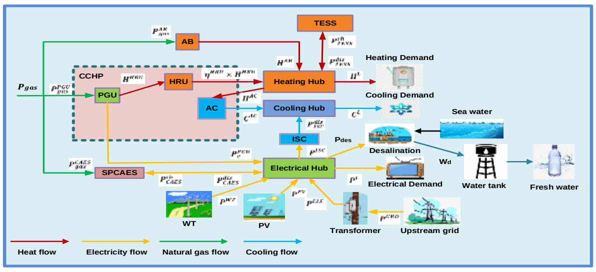


Fig. 1. The structure of CEH

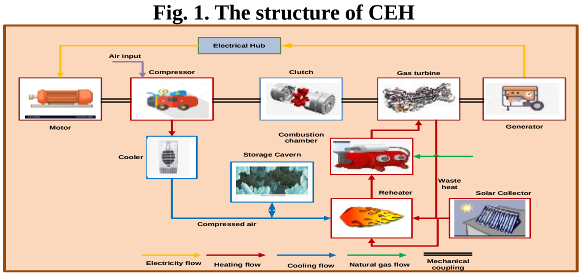


Fig. 2. The SPCASE structure

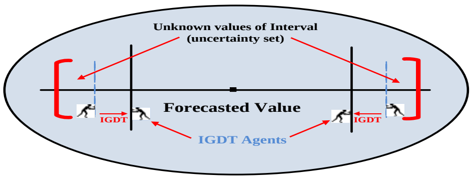


Fig. 3. Illustration of information gap uncertainty

2.2. Mathematical Formulation

The objective function along with the grid and generation unit constraints are presented as follows:

A. Objective Functions

The suggested objective functions, i.e. the MG operation cost and emissions in the day-ahead, are given by the following equations, the first objective function included two components, namely the net costs of the electricity and gas to be purchased. The second objective function consisted of carbon emission.

$$Min\{Cost\} = Min\left\{\sum_{t\in T}\left[C_{pe}(t)+C_{pg}(t)+C_{oe}(t)\right]\right\} \tag{10}$$

$$C_{pe}(t)=\rho_e(t)\times P^{GRD}(t)\times\Delta t \qquad \forall t\in T \tag{11}$$

$$C_{pg}(t)=\rho_g(t)\times\left[P_{gas}^{PGU}(t)+P_{gas}^{AB}(t)+P_{gas}^{CAES}(t)\right]\times\Delta t =$$

$$\rho_g(t)\times\left[\frac{P_e^{PGU}(t)}{\eta_e^{PGU}}+\frac{H^{HRU}(t)}{\eta_h^{PGU}}+\frac{H^{AB}(t)}{\eta_h^{AB}}+\frac{P_{CAES}^{dis}(t)}{\eta_{CAES}^{dis}}\right]\times\Delta t \qquad \forall t\in T \tag{12}$$

$$C_{oe}(t)=\theta\times\left[\begin{array}{c}\phi_{in}\times P^{GRD}(t)+\phi_g\times\\ \left(\frac{P_e^{PGU}(t)}{\eta_e^{PGU}}+\frac{H^{HRU}(t)}{\eta_h^{PGU}}+\frac{H^{AB}(t)}{\eta_h^{AB}}+\right.\\ \left.\frac{P_{CAES}^{dis}(t)}{\eta_{CAES}^{dis}}\right)\end{array}\right]\times\Delta t \qquad \forall t\in T \tag{13}$$

B. Constraints of ESS and generation units

The restrictions taken into account for the presented optimization problem are delineated as follows:

- **Energy balance at CEH**

The electrical power is balanced in electrical hub as:

$$P^{ELE}(t)+P^{PV}(t)+P^{WT}(t)+P_e^{PGU}(t)+P_{CAES}^{dis}(t) \tag{14}$$

$$=\mathrm{P^L}(t)+P^{ISC}(t)+P_{CAES}^{ch}(t)+\mathrm{P^{des}}(t) \qquad \forall t\in T$$

Additionally, the heat balance is given by:

$$\eta^{HRU}\times H^{HRU}(t)+H^{AB}(t)+P_{TESS}^{dis}(t)= \tag{15}$$

$$\mathrm{H^L}(t)+H^{AC}(t)+\mathrm{P_{TESS}^{ch}} \qquad \forall t\in T$$

The cooling energy balance is given as:

$$C^{AC}(t)+C_{ISC}^{dis}(t)=C^L(t) \qquad \forall t\in T \tag{16}$$

- **Operational constraints of ESS**

The following constraints are taken into account for ESSs operation in CEH [40, 41] as the generic models. It is noteworthy that in the following model the ESS are referred to SPCAES, TESS, and ISC.

$$0\le P_{ESS}^{ch}(t)\le P_{ESS}^{ch\text{-}max}\times U_{ESS}^{ch}(t) \qquad \forall t\in T \tag{17}$$

$$0\le P_{ESS}^{dis}(t)\le P_{ESS}^{dis\text{-}max}\times U_{ESS}^{dis}(t) \qquad \forall t\in T \tag{18}$$

$$U_{ESS}^{dis}(t)+U_{ESS}^{ch}\le 1 \qquad \forall t\in T \tag{19}$$

$$E_{ESS}(t)=E_{ESS}(t-1)-\left(\frac{P_{ESS}^{dis}(t)}{\eta_{ESS}^{dis}}\right)+P_{ESS}^{ch}(t)\times\eta_{ESS}^{ch} \qquad \forall t\in T,\ t>1 \tag{20}$$

$$E_{ESS}^{min}\le E_{ESS}(t)\le E_{ESS}^{max} \qquad \forall t\in T \tag{21}$$

$$E_{ESS}(0)=E_{ESS}(24) \tag{22}$$

- **Generation constraints for PGU and HRU**

The thermal and electrical generated by CCHP in CEH must meet the some constraints as follows [40, 42]:

$$P_{PGU}^{min}\le P_e^{PGU}(t)\le P_{PGU}^{max} \qquad \forall t\in T \tag{23}$$

$$H_{HRU}^{min}\le H^{HRU}(t)\le H_{HRU}^{max} \qquad \forall t\in T \tag{24}$$

- **Operation constraints for the AB, AC, and SWD**

The generated thermal power of AB, AC, and SWD must satisfy the following minimum and maximum constraints [40]:

$$H_{AB}^{min}\le H^{AB}(t)\le H_{AB}^{max} \qquad \forall t\in T \tag{25}$$

$$H_{AC}^{min}\le H^{AC}(t)\le H_{AC}^{max} \qquad \forall t\in T \tag{26}$$

$$P_{des}^{min}\le P^{des}(t)\le P_{des}^{max} \qquad \forall t\in T \tag{27}$$

- **The transformer power constraints**

The transformers real power output is limited by the constraint as follows:

$$P_{min}^{ELE}\le P^{ELE}(t)\le P_{max}^{ELE} \qquad \forall t\in T \tag{28}$$

3. UNCERTAINTY MODELLING

Section 2 considers all of the parameters as deterministic. However, some variables pertaining to MG, including electrical/thermal/cooling (energy) and water demands, WT and PV generation, and electricity price suffer from uncertainty. It causes some difficulties for MGO to make optimal decisions. Therefore, the deterministic formulation introduced in the last subsection are rewritten in a stochastic space based IGDT method to better manage these uncertainties.

3.1. IGDT technique

IGDT improves the uncertainty horizon, offering a solution and affording certain expectation in terms of the objective [43]. IGDT method has two main strategies that are RA and OS. In RA-IGDT strategy, the decision maker (MGO) tries to increase the robustness of objective function (operation cost) against the uncertainty. The uncertainty is an undesired phenomenon in this case and it is associated with the values lower/higher (dependent on uncertain parameters) than the predicted ones [5]. In OS-IGDT strategy, the decision maker is optimistic about the uncertain parameters. In other words, the uncertainty deviates in such a way that total costs reduce compared to the base case (deterministic case). The OS-IGDT tries to increase this chance [5]. The uncertainty is a desired phenomenon in this strategy and it is associated with higher/lower (dependent on uncertain parameters) values than the predicted ones. This paper uses the RA-IGDT method for uncertainty modelling.

It can be noted that MGO should manage the uncertainties related to the electricity price and energy and water demand, and the other variables, until it is not faced with unplanned conditions in day-ahead optimal operation. Regarding to Fig. 3, it is seen that operation based on RA-IGDT method can meet the planned goals while the uncertain parameters fall within their maximum permitted boundaries. This paper uses RA-IGDT based on risk-averse strategy that MGO can make decisions with high degree of the robustness in the aspect of the uncertainty variables. Here, the robustness concept is to secure a target value for objective function despite variations in the amounts of uncertain variables. Normally, a larger uncertainty horizon results in higher level of robustness. Indeed, variance between the forecasted and actual values of uncertain variables makes the foundation of the RA-IGDT decisions. This method doesn't need assumed probability distributions for uncertainties, consequently, it is a suitable alternative for MGO in the highly uncertain situations or shortage in historical data. Ref. [43] has introduced various RA-IGDT uncertainty models. However, the commonly used envelope-bound uncertainty model is considered in the current work to model uncertainty related to the renewable generation, price of electricity, and the energy and water demand based on (28)- (30), respectively.

$$\Lambda_{WS}(\gamma,\hat{\theta}^{WS}(t)=\left\{\theta^{WS}(t)\left|-\gamma\le\frac{\theta^{WS}(t)-\hat{\theta}^{WS}(t)}{\hat{\theta}^{WS}(t)}\le\gamma\right.\right\}\gamma\ge 0,\forall t\in T \tag{28}$$

$$\Lambda_{LD}(\gamma,\hat{\theta}^{LD}(t)=\left\{\theta^{LD}(t)\left|-\Gamma\le\frac{\theta^{LD}(t)-\hat{\theta}^{LD}(t)}{\hat{\theta}^{LD}(t)}\le\Gamma\right.\right\}\Gamma\ge 0,\forall t\in T \tag{29}$$

$$\Lambda_{REN}(\gamma,\hat{\theta}^{REN}(t)=\left\{\theta^{REN}(t)\left|-\omega\le\frac{\theta^{REN}(t)-\hat{\theta}^{REN}(t)}{\hat{\theta}^{REN}(t)}\le\omega\right.\right\}\omega\ge 0,\forall t\in T \tag{30}$$

$$\theta^{LD}(t)=\left\{P^{L}(t)\ \ H^{L}(t)\ PC^{L}(t)\ \ P^{des}(t)\ \right\}\quad \forall t\in T \tag{31}$$

$$\theta^{REN}(t)=\left\{P^{PV}(t)\ \ P^{WT}(t)\ \right\}\quad \forall t\in T \tag{32}$$

The RA-IGDT technique want to make the most of the robustness of the operation, while it guarantee a target cost [43]. To put it more simply, the IDGT models the uncertainty and optimally solves the proposed simultaneously:

$$\hat{\Lambda}(DV1,DV2,\mathrm{Cos}\,t^{Exp})=Max_{DV1}\left\{(\gamma,\Gamma,\omega\left|\begin{matrix}Max_{DV2}\,\mathrm{Cos}\,t(\Lambda_{WS},\\ \Lambda_{LD},\Lambda_{REN},DV1)\le\\ \mathrm{Cos}\,t^{Exp}\times(1+\pi)\end{matrix}\right.\right\} \tag{33}$$

The RA-IGDT method considers with two categories of decision variables that are MGO's decision variable as given in Eq. (34) and those related to the uncertain parameters as given in Equation (34).

$$DV1=\left\{\begin{matrix}\gamma,\varepsilon,\omega,P_{e}^{PGU}(t),H^{AB}(t),P_{CAES}^{\frac{dis}{ch}}(t),\\ P_{TESS}^{dis/ch}(t),C_{ISC}^{dis}(t),P^{GRD}(t)\end{matrix}\right\}\quad\forall t\in T \tag{34}$$

$$DV2=\left\{\theta^{WS}(t),\theta^{LD}(t),\theta^{REN}(t)\right\}\quad\forall t\in T \tag{35}$$

Equations (33)-(35) are formulated as a bi-level problem as follows:

3.2. Two level RA-IGDT optimization problem

The RA-IGDT-based two level problem is written as Eq. (36):

$$Max_{DV1}(\gamma,\Gamma,\omega) \tag{36}$$

Subject to:

$$Cost^{Max}\le Cost^{Exp}\times(1+\pi) \tag{37}$$

$$Cost^{Max}=Max_{DV2}\left\{\sum\nolimits_{t\in T}\left[C_{pe}(t)+C_{pg}(t)+C_{oe}(t)\right]\right\} \tag{38}$$

$$-\gamma\le\frac{\theta^{WS}(t)-\hat{\theta}^{WS}(t)}{\hat{\theta}^{WS}(t)}\le\gamma\qquad\gamma\ge 0,\forall t\in T \tag{39}$$

$$-\Gamma\le\frac{\theta^{LD}(t)-\hat{\theta}^{LD}(t)}{\hat{\theta}^{LD}(t)}\le\Gamma\qquad\Gamma\ge 0,\forall t\in T \tag{40}$$

$$-\omega\le\frac{\theta^{REN}(t)-\hat{\theta}^{REN}(t)}{\hat{\theta}^{REN}(t)}\le\omega\qquad\omega\ge 0,\forall t\in T \tag{41}$$

Solving the first level including (36) and (37) determines day-ahead operation decisions while guarantees maximum uncertainty horizons and harvest cost targeted by MGO. In the other hands, (38) – (41) representing the second level formulation model the worst situation in terms of the uncertain parameters bounded by the models of envelope-bound as expressed in Eqns. (39)-(41), respectively.

3.3. Single level problem

Commercial software has difficulties with manipulating and solving bi-level problems. Consequently, the paper converts two level problem to a single level problem by KKT. The paper assumes that the decision variables of the first level (DV1) are constant in the second level. Consequently, linear Equations (38) – (41) are optimally solved and the supreme value of the objective function are harvested in either the superior limits (39) and (40) or inferior limits of the robust intervals (41). That's to say, for the Equations (39)-(41), if $P^{GRD}(t)\ge 0$, the maximum cost is happened during purchasing maximum electrical power with the topmost price at the electrical power market at each hour t. Conversely, Equations (39)-(41) express that under the condition of $P^{GRD}(t)\le 0$, minimum profit is when MGO sells its electrical power to the electricity market with the minimum price. Indeed, the worst case is when lowest/highest electrical power is exported to/ purchased from the electrical power market, i.e. when the MO is faced with a peak electrical demand and while the renewable generations are minimum. Obviously, purchasing at highest price and sold at lowest price in the electrical power market make the highest cost for MGO. These impressions are mathematically written as follows:

$$\theta^{WS}(t)=\begin{cases}(1+\gamma)\times\hat{\theta}^{WS}(t) & P^{GRD}(t)\geq 0\\(1-\gamma)\times\hat{\theta}^{WS}(t) & P^{GRD}(t)\leq 0\end{cases} \tag{42}$$

$$\theta^{LD}(t)=(1+\Gamma)\times\hat{\theta}^{LD}(t) \qquad \forall t\in T \tag{43}$$

$$\theta^{REN}(t)=(1+\omega)\times\hat{\theta}^{REN}(t) \qquad \forall t\in T \tag{44}$$

The second level formulation can be replaced with its KKT optimality circumstances due to its problem is linear, continuous, and convex [44], these conditions are formulated in the following equations:

$$P^{GRD}(t)-\delta_t^1+\delta_t^2=0 \qquad \forall t\in T \tag{45}$$

$$\delta_t^1\times(\theta^{WS}(t)-(1-\gamma)\times\hat{\theta}^{WS}(t))=0 \qquad \forall t\in T \tag{46}$$

$$\delta_t^2\times(\theta^{WS}(t)-(1+\gamma)\times\hat{\theta}^{WS}(t))=0 \qquad \forall t\in T \tag{47}$$

$$\delta_t^1,\delta_t^2\geq 0 \qquad \forall t\in T \tag{48}$$

$$\theta^{LD}(t)=(1+\Gamma)\times\hat{\theta}^{LD}(t) \qquad \forall t\in T \tag{49}$$

$$\theta^{REN}(t)=(1+\omega)\times\hat{\theta}^{REN}(t) \qquad \forall t\in T \tag{50}$$

If $P^{GRD}(t)\geq 0$, given (42), $\theta^{WS}(t)$ equals $(1+\gamma)\times\hat{\theta}^{WS}(t)$ Thus, the second term in Eq. (46) is not equal to zero and consequently δ_t^1 is zero. With Eq. (45), the value of δ_t^2 is obtained as follows:

$$\delta_t^2=-P^{GRD}(t) \qquad \forall t\in T \tag{51}$$

With substituting Eq. (51) in Eq. (50), the first term of (42) can rewrite as:

$$P^{GRD}(t)\times(\theta^{WS}(t)-(1+\gamma)\times\hat{\theta}^{WS}(t))=0 \qquad \forall t\in T \tag{52}$$

Also, the second term of Eq. (50) is reformulated as:

$$P^{GRD}(t)\times(\theta^{WS}(t)-(1-\gamma)\times\hat{\theta}^{WS}(t))=0 \qquad \forall t\in T \tag{53}$$

Finally, using the equivalent of Eq. (42) as acquired via Eq. (52) and Eq. (53) reorganizes the proposed bi-level optimization problem as Eq. (54):

$$Max_{DV1,DV2}(\gamma,\Gamma,\omega) \tag{54}$$

Subject to:

$$Cost^{Max}\leq Cost^{Exp}\times(1+\pi) \tag{55}$$

$$Cost^{Max}=Max_{DV2}\left\{\sum_{t\in T}\left[C_{pe}(t)+C_{pg}(t)+C_{oe}(t)\right]\right\} \tag{56}$$

$$-\gamma\leq\frac{\theta^{WS}(t)-\hat{\theta}^{WS}(t)}{\hat{\theta}^{WS}(t)}\leq\gamma \qquad \gamma\geq 0,\forall t\in T \tag{57}$$

$$-\Gamma\leq\frac{\theta^{LD}(t)-\hat{\theta}^{LD}(t)}{\hat{\theta}^{LD}(t)}\leq\Gamma \qquad \Gamma\geq 0,\forall t\in T \tag{58}$$

$$-\omega\leq\frac{\theta^{REN}(t)-\hat{\theta}^{REN}(t)}{\hat{\theta}^{REN}(t)}\leq\omega \qquad \omega\geq 0,\forall t\in T \tag{59}$$

$$P^{GRD}(t)\times(\theta^{WS}(t)-(1-\gamma)\times\hat{\theta}^{WS}(t))\geq 0, \qquad \forall t\in T \tag{60}$$

$$P^{GRD}(t)\times(\theta^{WS}(t)-(1+\gamma)\times\hat{\theta}^{WS}(t))\geq 0, \qquad \forall t\in T \tag{61}$$

$$\theta^{LD}(t)=(1+\Gamma)\times\hat{\theta}^{LD}(t) \qquad \forall t\in T \tag{62}$$

$$\theta^{REN}(t)=(1+\omega)\times\hat{\theta}^{REN}(t) \qquad \forall t\in T \tag{63}$$

(13) - (26) (64)

Indeed, MGO based on its policy for operation determines the cost deviation factor (π) and consequently controls the amount of robustness in the problem. It can be noted that, non-equality constraints are usually preferred over the equality constraints in commercial solvers, therefore the equality constraints (52) and (53) were substituted with the non-equality limitations (60) and (61), respectively. To conclude, the technique proposed by [45] liners (60) and (61).

4. PROPOSED MODEL AND SOLUTION ALGORITHM

The suggested model for the optimum operation is MILP, which is a mathematical optimization with mix variables that are integer (binary) and continues. It also has linear objective function and constraints other than the integer constraints [46]. The binary variables are considered to avoid the simultaneously running of importing/ exporting mechanism of ESSs. The continues variables include the electrical power output of CCHP, the heating power output of ABs, the electrical power exchanged with the upstream grid and SPCASE, the thermal power traded with TESS, and the cooling power fed by ISC at each hour. Variables multiplication, exponential or logarithm form, inverse form, etc. are the nonlinear terms of the problem [46]. However, the proposed model does not involve any nonlinear relations in the objective function together with the constraints. It can be noted that MOOP cannot harvest a single optimal solution when it simultaneously considers all objective functions. Consequently, MOOPs use the concept of Pareto fronts to derive optimal solutions. Indeed, the optimization based on Pareto fronts optimizes an objective function while reduces the performance of at least one of the other objective functions [47, 48]. In this type of optimization, a decision maker should be used until the best compromised solution is derived among the Pareto solutions. The following subsection of paper introduces AUGMECON technique to optimize the proposed problem founded on RA-IGDT method.

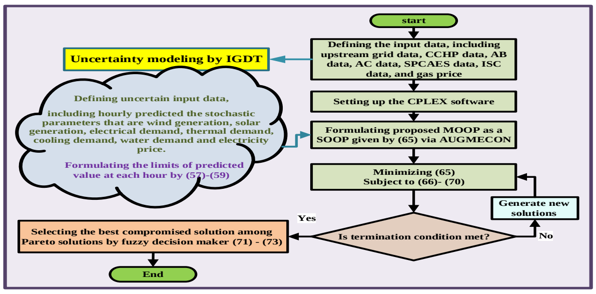


Fig.4. Flowchart of employing the proposed model

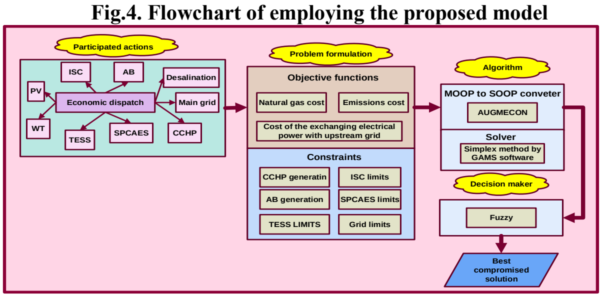


Fig. 5. Structure of the suggested model

4.1. AUGMECON technique

AUGMECON is a practiced optimization technique which only wants to maximize the uncertainty limit of the electrical energy price, i.e. γ which acts as the foremost objective function. Therefore, in the electrical power and water demand (Γ), and the renewable generation (ω), the uncertain limits are divided into *Int*-equal intervals by means of $(Int+1)\times(Int+1)$ grid points. Accordingly, for obtaining Pareto optimal solutions, $(Int+1)\times(Int+1)$ problems must be optimally solved. More information are obtainable in Ref. [49]. The MOOP format of Eqns. (54) – (64) based on the AUGMECON is:

$$Max(\gamma+\varepsilon\times(\frac{S_{\omega}}{\omega^{max}-\omega^{min}})+\varepsilon\times(\frac{S^{\Gamma}}{\Gamma^{max}-\Gamma^{min}})) \tag{65}$$

Subject to

$$\Gamma - S_{\Gamma} = L_{\Gamma} \qquad S_{\Gamma} \geq 0 \tag{66}$$

$$L_{\Gamma} = \Gamma^{max} - \left(\frac{\Gamma^{max}-\Gamma^{min}}{Int}\right)\times b \qquad b = 0,1,\ldots,Int \tag{67}$$

$$\omega - S_{\omega} = L_{\omega} \qquad S_{\omega} \geq 0 \tag{68}$$

$$L_{\omega} = \omega^{max} - \left(\frac{\omega^{max}-\omega^{min}}{Int}\right)\times b \qquad b = 0,1,\ldots,Int \tag{69}$$

(54)- (64) (70)

Where, ε is assumed as minor quantity commonly stuck between 10^{-4} and 10^{-7}, S_{Γ} and S_{ω} represent relaxed variables, and Γ^{max} and Γ^{min} signify the highest and lowest limits of the uncertainty in the electrical energy and water demand, respectively. Also, ω^{max} and ω^{min} signify the highest and lowest limits of the uncertainty in the stochastic renewable generation, respectively. Lexicographic method [50], is utilized in this paper to acquire the range of Γ and ω . To obtain the Pareto optimal solutions, the amount of b is varied and the resulted single objective optimization problems (65) – (70) are solved. To reach a denser Pareto set, the amount of intervals (Int) are augmented while this rises the burden time. Therefore, considering a trade-off between Pareto set compactness and the time essential for calculations, 4 intervals are taken into account in the presented work, i.e. 25 grid points. $Cost^{Exp}$ is computed by solving (10) subject to Eqns. (11)-(28) barring uncertainties such that $\alpha=\Gamma=\omega=0$. Fig. 4 illustrates the flowchart for MOOP based on AUGMECON-IGDT (54) – (64). In order to solve the proposed model, the CPLEX solver—a tool in the GAMS software which has been founded on the Simplex mathematical technique as a deterministic technique is utilized since it has a good potential in solving MILP problems [51]. The simulation is executed on a PC with Intel Core i7, 2.5GHz CPU with 12 GB of RAM. The application flowchart of the suggested model is illustrated in Fig. 4.

4.2. Best compromised solution

In the end, a set of Pareto optimal solutions is offered to MGO who should select a final decision. There are several approaches such as Fuzzy Membership Function [40], AHP [52], TOPSIS [53], etc. which can help MGO to obtain the best decision. Yet, the preference of the MGO is the important criteria to choose the final optimal solution. The best compromised solution in the current paper was found by using a fuzzy-based technique as follows [54]:

$$\mu_j^l = \frac{f_j^{max} - f_j^l}{f_j^{max} - f_j^{min}} \qquad \forall l \in L \quad \forall j \in M \tag{71}$$

$$\mu^l = \frac{\sum_{j=1}^{n} \mu_j^l}{\sum_{l\in L}\sum_{j\in M} \mu_j^l} \qquad \forall l \in L \tag{72}$$

$$opt = \left\{ o \middle| \mu^o = MAX(\mu^l) \right\} \tag{73}$$

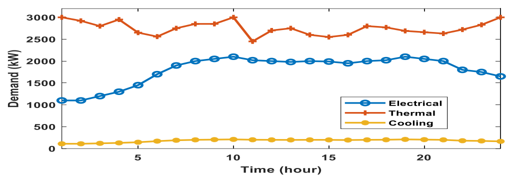
Fig. 5 illustrates the arrangement of the problem formulation together with the solving procedure of the proposed model.

5. SIMULATION RESULTS

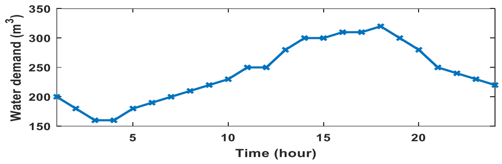
As depicted in Fig. 1, The presented algorithm for solving the optimization problem formulated in the study is applied to MG based on CEH.

5.1. Data of MG

The forecasted demand profile of the MG that are electrical, cooling, thermal, and water demands are shown by Fig. 6. Also, the predicted the day-ahead price of electrical energy as ToU and price of natural gas are illustrated in Fig. 7. Fig. 8. depicts the predicted WT, PV, and solar generations during day-ahead.



(a) electrical, thermal, and cooling demands [55]



(b) water demand

Fig. 6. The forecasted hourly demands of CEH

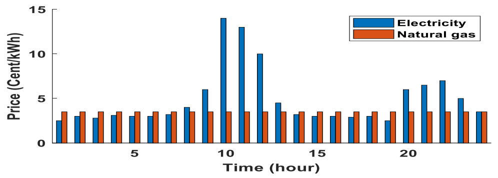


Fig. 7. Predicted day-ahead prices of electricity and natural gas

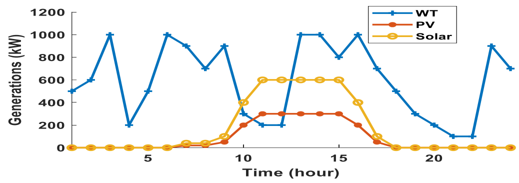


Fig. 8. Predicted renewable generations (WT, PV, solar collector)

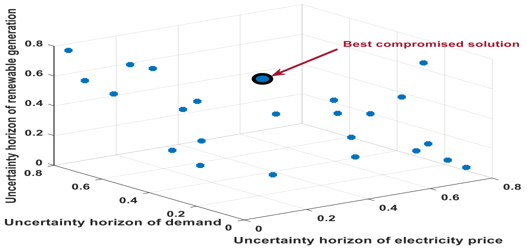


Fig. 9. Pareto front obtained by the AUGMECON method

Table 2. Parameters of the CEH

CCHP, AB, AC , and SWD					
Parameter	Val.	Parameter	Val.	Parameter	Val.
η_e^{PGU}	0.42	$P_{PGU}^{min}(kW)$	140	$H_{HRU}^{max}(kW)$	2200
η_h^{PGU}	0.48	$P_{PGU}^{max}(kW)$	1600	$H_{AB}^{min}(kW)$	0
η^{HRU}	0.82	$H_{HRU}^{min}(kW)$	155	$H_{AB}^{max}(kW)$	3000
$H_{AC}^{min}(kW)$	0	$H_{AC}^{max}(kW)$	300	K^{AC}	0.9
K^{des}	2.66				
ESS (CAES, SPCAES, TESS, and ISC)					
Parameter	Val.	Parameter	Val.	Parameter	Val.
$P_{ESS}^{ch-max}(kW)$	700	η_{ESS}^{ch}	0.90	$E_{ESS}^{min}(kWh)$	0
$P_{ESS}^{dis-max}(kW)$	700	η_{ESS}^{dis}	0.95	$E_{ESS}^{max}(kWh)$	2500
K^{ISC}	0.9				
Grid [59]					
Parameter	Val.	Parameter	Value	Parameter	Value
η^{TRA}	0.99	$P_{max}^{ELE}(kW)$	2000	$P_{min}^{ELE}(kW)$	0
Other parameters					
Parameter	Val.	Parameter	Val.	Parameter	Val.
$\theta(\$/kg)$	0.013	$\varphi_g(kg/kWh)$	0.26	$\varphi_{in}(kg/kWh)$	0.28

Table 3. Bounds of objective functions in AUGMECON technique

Uncertainty limit	γ	Γ	ω
Lowest	0	0	0
Highest	0.82	0.78	0.85

CEH and grid parameters are shown in Table 2. It can be noted that to set the EH equipment parameters reported in Table. 2, the commercial specifications of the equipment were evaluated and the acceptable rating for equipment used by the proposed case study was customized according to these specifications [56-58].

5.2. Outcomes

- **Optimal calculation of the uncertainty limit in the energy demand, renewable generations, water demand, and price of electricity**

This simulation wants to optimally determine uncertainty limit of the energy demand, renewable generations, water demand and price of electricity by RA-IGDT technique to find the lowest cost for utilization of MGO. These uncertainty limits (horizons) are simultaneously maximized as an MOOP. In this simulation, MGO tracked the policy of selecting the suitable robust operational decisions pertaining to energy and water demand, electricity price, renewable generations uncertainties considering a target cost. The Pareto optimal solutions of γ,Γ, and ω for target cost of 6989.27$ and $Cost^{Exp}$ of 5934.67$ are shown in Fig. 9.

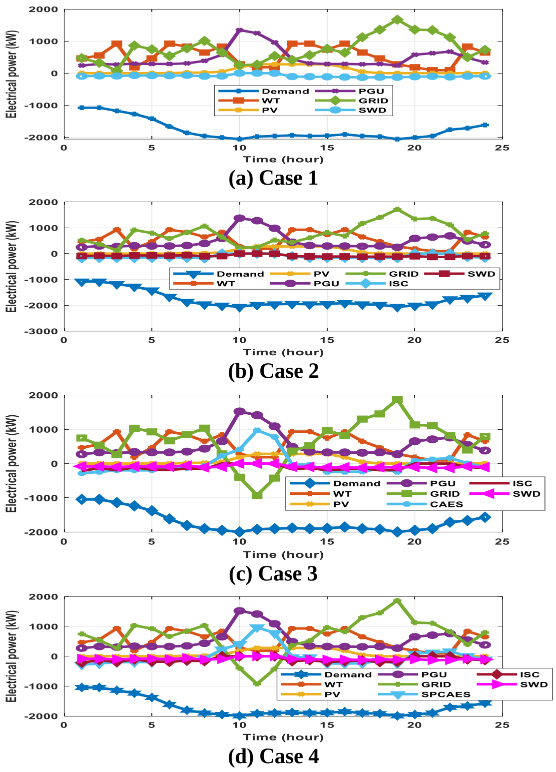
Table 3 presents limitations of objective functions achieved by Lexicographic optimization method that engaged by the AUGMECON technique to accomplish the optimization procedure. Regarding Fig. 9, the best compromised solution which is achieved by the fuzzy-based method is ($\gamma = 0.57, \Gamma = 0.59, and \omega = 0.79$) . The next simulations were done based on the best compromised solution stated in Fig. 9.

- **Optimal operation of MG in various scenarios**

In order to assess the effects of SPCAES and ISC on the operation of CEH, four cases were taken into account:

- **Case 1:** MG operation barring ISC and any kinds of CAES;
- **Case 2**: MG operation with ISC and barring any kinds of CAES;
- **Case 3**: MG operation with conventional CAES and ISC; and
- **Case 4**: MG operation with SPCAES and ISC.

Sub-EHs play a crucial role in multi energy collection and allocation and thus, there should always be a balanced flow of energy at each sub-energy hub. The best dispatch outcomes of energy flow under the four cases of the study at power, heating, and cooling hubs are shown in Figs. 10-12, respectively. In these figures the upper and lower parts of the vertical axis show the energy fed into and flowed out from the sub-energy hubs, respectively. Also, in the Figs. 10-12, the positive and negative signs show discharging and charging modes of ESSs, respectively. Fig. 10 (a) exemplifies the optimum management of the power flow at electrical hub in Case 1. The electrical demand is supplied by the upstream grid and WT at most of the time. Although during hours 10 to 12 when the generation of WT is low and the price of electricity is high, the majority of the electrical demand was fed by PGU and a smaller amount of the electrical power was purchased from the upstream grid. Furthermore, during the hours 10 to 16, the generation of PV has an efficient role for providing electrical demand. Due to the reduced generation by WT during hours 20 to 22, the upstream grid and PGU take care of the most portion the of electrical demand. The power flow results in Case 2 are presented in Fig. 10 (b) showing a similar trend to that of Case 1. However, the ISC is charged during the low electricity price hours and increase the electrical demand in these hours while it discharges at hours 10 to 12 when price of the electricity is high to feed the cooling demand. The outcomes of Case 3 are depicted in Fig. 10 (c) presenting that the total cost of CEH is decreased at the presence of CAES.



(a) Case 1

(b) Case 2

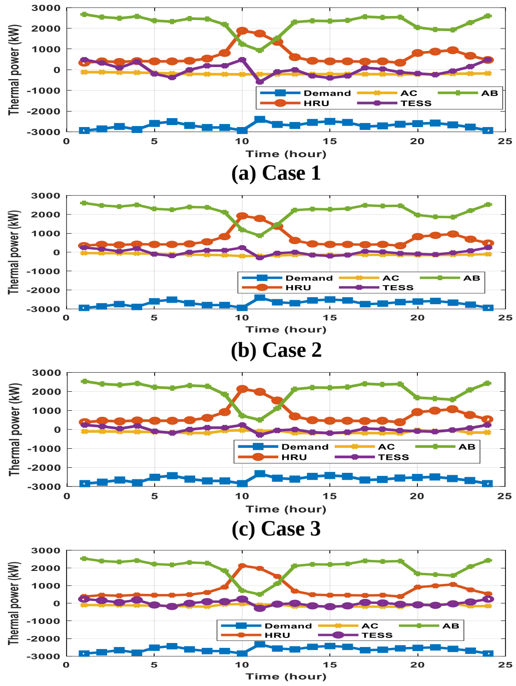
(c) Case 3

(d) Case 4

Fig. 10. Optimal dispatch outcomes of the power flow at electrical hubs under the four cases considered in the study

Table 4. Results comparison in four case studies

Case study	Total Cost ($)	Components of the objective function		
		Electricity purchase Cost ($)	Natural gas purchase cost ($)	Emission Cost ($)
Case 1	6989.547	5550.487	1064.786	368.3537
Case 2	6905.423	5384.635	1137.694	294.2027
Case 3	6882.587	5491.463	843.8265	578.2458
Case 4	6735.362	5586.886	611.7078	648.8911



(a) Case 1

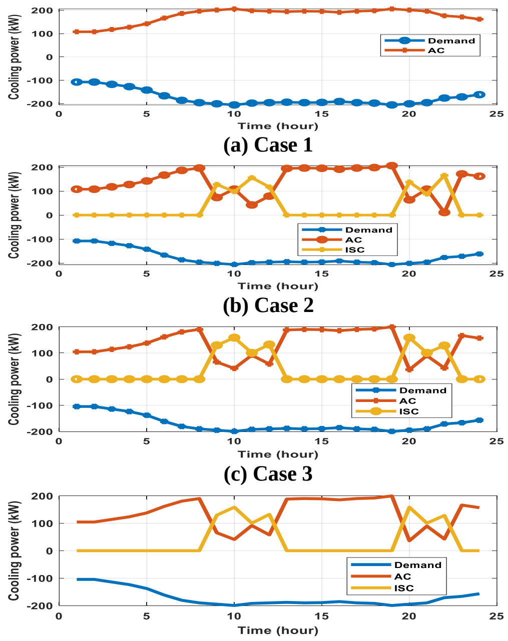
(b) Case 2

(c) Case 3

(d) Case 4

Fig. 11. Optimal dispatch outcomes of thermal flow at thermal hub under the four cases considered in the study

During low electricity price hours, CAES is charged and it is discharged within hours 10 to 12 and 20 to 22 when the electricity is expensive. Without a doubt, the electricity is sold by CEH to the upstream grid during hours 10 to 12 and 20 to 22 as a result of the attendance of CAES. Fig. 10 (d) (Case 4) illustrates that during the sunny hours the more electrical power is discharged by SPCAES compared to traditional CAES and hence, CEH is able to trade more electrical power to the upstream grid, thereby reducing the total cost of CEH.



(a) Case 1

(b) Case 2

(c) Case 3

(d) Case 4

Fig. 12. Optimal dispatch outcomes of cooling flow at cooling hub under the four cases considered in the study

The optimum management of the thermal flow at the thermal hub in Case 1 is exemplified in Fig. 11 (a) revealing that in the majority of hours the thermal demand is provided by the AB. Nevertheless, when price of electricity is high and the PGU runs to supply the electrical demand, HRU has to provide the thermal demand and the participation of AB is decreased. Moreover, the total cost in the thermal hub is reduced by the charging/discharging TESS in appropriate hours.

Fig. 11 (b) (Case 2) reveals that the ISC discharging during hours 10 to 12 and 20 to 22 reduces the role of the AC to supply the cooling demand. Regarding Fig. 11 (b) to Fig. 11(d), it can be noted that when ISC, CAES, and SPCAES are used in Case 2, 3, and 3, respectively, electrical power balance changes in electrical hub, therefore, the PGU generation and consequently HRU generations change. Then the thermal power exchanged by TESS and generated by AB also change. Fig. 12 (a) illustrates the optimum dispatch of the cooling flow at the cooling hub in Case 1. It can be noted that at all hours, the cooling demand is supplied with AC. Employing the ISC in Cases 2-4 (Figs. 12 (b), (c), and (d)) led to the ISC discharging within hours 10 to 12 and 20 to 22 resulting in the reduction of the total cost.

5.3. Comparative study

Based on the Case 3 and Case 4 in Figs. 10-12, it can be deduced that SPCAES and CAES are charged when there is excess electricity or the price of electricity is high and if not, they are discharged. Likewise, when the heat supply is excess, the TESS stores the heat and releases it when there is not enough heat supply to meet demands. During the off-peak time, the ISC starts making and storing ice. On the other hand, during high electricity or when there is a shortage of the cold supply, the ice melts to meet the cooling demand. This process

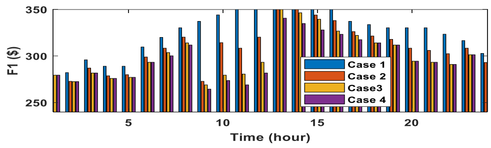


Fig. 13. The electricity and gas cost at each hour for the four case studies

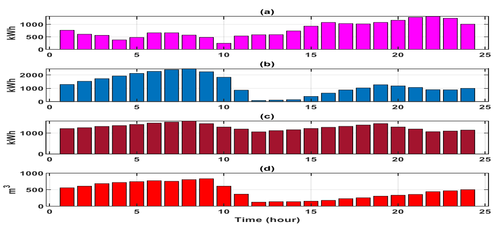


Fig. 14. SoC of storages at each hour in Case study 4 (a) TESS , (b) CAES , (c) ISC , (d) water tank

explains why the electricity/heat/cold energy storage devices have a pivotal role in load balance and shifting. Fig. 13 shows the objective function at every hours of various case studies. Based on Fig. 13, it is observed that employing ISC at low electricity price hours has increased the operational (purchasing electricity and natural gas) cost; Nevertheless, ISC has effectively reduced the operational cost within high electricity price hours for Case 2 compared to that in Case 1. Utilizing the other storage that is CAES in Case 3, created a like tendency in the off-peak and peak hours. Fig. 13 shows that employing SPCAES in Case 4 did not vary the operational cost at night time and within the cloudy hours. Nonetheless, concerning the increasing generation of electrical power in sunny hours by SPCAES and thus, exporting electrical power to the upstream grid, the Case 4 had the minimum operational cost during high electricity price hours. Table 4 shows the results of total cost in the four cases. Considering CAES in Case 3 causes purchasing more electrical power from upstream grid and purchasing less natural gas compared to Case 2. With adding CAES, MGO buys more electrical power from upstream grid and power generation with PGU reduces. Therefore, PGU consumes less natural gas for its generation compared to Case 2. On the other hands, with purchasing more electrical power from upstream grid, emission tax paid by MGO is increased in Case 3 compared to Case 2. The comparison of total costs in Case studies show the potential of ESSs such as SPCAES, CAES, and ISC to reduce total costs considerably.

The optimal dispatch results clearly show a number of advantages for the MG. Firstly, the MG is able to accomplish the harmonized operation of multi energy carriers where the cascading use of energy reduces the costs and at the same time, improves the energy efficiency. The MG has the potential to promote the widespread use of renewable energy resources that decrease the greenhouse gas emissions. Furthermore, through employing various energy storage devices, the MG can control the fluctuations of renewable energy resources and maintain the balance in the load demand. Finally, integration of renewable energy sources makes it possible to lessen the tension between demand and energy supply particularly during peak hours. The various states of ESSs, i.e. charging/discharging processes, in Case 4 are detailed in Fig. 14.

6. CONCLUSIONS

The EH architecture proposed in this study introduces a generic method for minimizing the costs of transferring, conversion, and saving energies as well as the optimal dispatch in an MG with multiple energy carrier infrastructures for the day-ahead. The under study EH has been equipped by CCHP, WT, PV, ISC as well as a TESS. This paper tries to evaluate the effects of CAES and SPCAES on the efficiency of the EH operation and environmental costs. A bi-level RA-IGDT was taken into account to protect the MGO from natural risks in the information gap present between the predicted and actual uncertainty variables. As uncertainty variables compete to expand their enveloped-bounds, AUGMECON method was used to address the complicated RA-IGDT. Compared to the Case 1, the total costs of operation reduced by 1.3%, 1.67%, and 2.33% in Cases 2, 3, and 4, respectively. While this generic energy flow modelling technique and analysing method can be generalized to deal with more complex energy systems, the suggested CEH architecture is presently only applicable to analyse the steady-state energy flow of the MG. The random nature of renewable energy sources and the dynamic nature of the equipment used to trap the energy are the issues that need further investigation. A particularly important research issue is expanding the energy flow modelling technique and the analysis method to analyse the dynamic energy flow of the MG.

REFERENCES

[1] M. Mohammadi et al., “Energy hub: from a model to a concept–a review”, *Renew. Sustain. Energy Rev.*, vol. 80, pp. 1512-27, 2017.

[2] W. Ho et al., “Optimal scheduling of energy storage for renewable energy distributed energy generation system”, *Renew. Sustain. Energy Rev.*, vol. 58, pp. 1100-7, 2016.

[3] H. Shayeghi and Y. Hashemi, “Potentiometric of the renewable hybrid system for electrification of gorgor station”, *J. Oper. Autom. Power Eng.*, vol. 8, pp. 1-14, 2020.

[4] B. Zhou et al., “Multi-objective optimal operation of coastal hydro-electrical energy system with seawater reverse osmosis desalination based on constrained NSGA-III”, *Energy Conv. Manage.*, vol. 207, p. 112533, 2020.

[5] A. Soroudi, A. Rabiee, and A. Keane, “Information gap decision theory approach to deal with wind power uncertainty in unit commitment”, *Electr. Power Syst. Res.*, vol. 145, pp. 137-48, 2017.

[6] V. Amir and M. Azimian, “Dynamic multi-carrier microgrid deployment under uncertainty”, *Appl. Energy*, vol. 260, p. 114293, 2020.

[7] M. Sedighizadeh, M. Esmaili, and N. Mohammadkhani, “Stochastic multi-objective energy management in residential microgrids with combined cooling, heating, and power units considering battery energy storage systems and plug-in hybrid electric vehicles”, *J. Cleaner Prod.*, vol. 195, pp. 301-17, 2018.

[8] Z. Zhang et al., “A two-layer model for microgrid real-time dispatch based on energy storage system charging/discharging hidden costs”, *IEEE Trans. Sustain. Energy*, vol. 8, pp. 33-42, 2016.

[9] D. Zhu, R. Yang, and G. Hug-Glanzmann, “Managing microgrids with intermittent resources: A two-layer multi-step optimal control approach”, *North American Power Symp.,* 2010.

[10] J. Wasilewski, “Integrated modeling of microgrid for steady-state analysis using modified concept of multi-carrier energy hub”, *Int. J. Electr. Power Energy Syst.*, vol. 73, pp. 891-8, 2015.

[11] A. Shahmohammadi et al., “Optimal design of multicarrier energy systems considering reliability constraints”, *IEEE Trans. Power Del.*, vol. 30, pp. 878-86, 2014.

[12] L. Ramírez-Elizondo and G. Paap, “Scheduling and control framework for distribution-level systems containing multiple energy carrier systems: Theoretical approach and illustrative example”, *Int. J. Electr. Power Energy Syst.*, vol. 66, pp. 194-215, 2015.

[13] S. Pazouki and M. Haghifam, “Optimal planning and scheduling of energy hub in presence of wind, storage and demand response under uncertainty”, *Int. J. Electr. Power Energy Syst.*, vol. 80, pp. 219-39, 2016.

[14] T. Ma, J. Wu, and L. Hao, “Energy flow modeling and optimal operation analysis of the micro energy grid based on energy hub”, *Energy Conv. Manage.*, vol. 133, pp. 292-306, 2017.

[15] X. Zhang et al., “Optimal expansion planning of energy hub with multiple energy infrastructures”, *IEEE Trans. Smart Grid*, vol. 6, pp. 2302-11, 2015.

[16] F. Brahman, M. Honarmand, and S. Jadid, “Optimal electrical and thermal energy management of a residential energy hub, integrating demand response and energy storage system”, *Energy Build.*, vol. 90, pp. 65-75, 2015.

[17] M. Rastegar, M. Fotuhi-Firuzabad, and M. Lehtonen, “Home load management in a residential energy hub”, *Electr. Power Syst. Res.*, vol. 119, pp. 322-8, 2015.

[18] A. Parisio, C. Del Vecchio, and A. Vaccaro, “A robust optimization approach to energy hub management”, *Int. J. Electr. Power Energy Syst.*, vol. 42, pp. 98-104, 2012.

[19] Y. Wang et al., “Mixed-integer linear programming-based optimal configuration planning for energy hub: Starting from scratch”, *Appl. Energy*, vol. 210, pp. 1141-50, 2018.

[20] M. Moeini-Aghtaie et al., “Multiagent genetic algorithm: an online probabilistic view on economic dispatch of energy hubs constrained by wind availability”, *IEEE Trans. Sustain. Energy*, vol. 5, pp. 699-708, 2013.

[21] A. Heidari, S. Mortazavi, and R. Bansal, “Stochastic effects of ice storage on improvement of an energy hub optimal operation including demand response and renewable energies”, *Appl. Energy*, vol. 261, p. 114393, 2020.

[22] F. Jamalzadeh et al., “Optimal operation of energy hub system using hybrid stochastic-interval optimization approach”, *Sustain. Cities Soc.*, vol. 54, p. 101998, 2020.

[23] S. Bozorgavari et al., “Two-stage hybrid stochastic/robust optimal coordination of distributed battery storage planning and flexible energy management in smart distribution network”, *J. Energy Storage*, vol. 26, p. 100970, 2019.

[24] Y. Yao et al., “Coupled model and optimal operation analysis of power hub for multi-heterogeneous energy generation power system”, *J. Cleaner Prod.*, vol. 249, p. 119432, 2020.

[25] M. Rahmatian, A. Shamim, and S. Bahramara, “Optimal operation of the energy hubs in the islanded multi-carrier energy system using Cournot model”, *Appl. Thermal Eng.*, vol. 191, p. 116837, 2021.

[26] H. Chamandoust, G. Derakhshan, and S. Bahramara,

"Multi-objective performance of smart hybrid energy system with multi-optimal participation of customers in day-ahead energy market", *Energy Build.*, vol. 216, p. 109964, 2020.

[27] H. Chamandoust et al., Tri-objective optimal scheduling of smart energy hub system with schedulable loads", *J. Cleaner Prod.*, vol. 236, p. 117584, 2019.

[28] M. Taghizadeh et al., "Optimal operation of storage-based hybrid energy system considering market price uncertainty and peak demand management", *J. Energy Storage*, vol. 30, p. 101519, 2020.

[29] A. Eladl et al., "Optimal operation of energy hubs integrated with renewable energy sources and storage devices considering CO2 emissions", *Int. J. Electr. Power Energy Syst.*, vol. 117, p. 105719, 2020.

[30] C. Chen et al., "Two-stage robust planning-operation co-optimization of energy hub considering precise energy storage economic model", *Appl. Energy*, vol. 252, p. 113372, 2019.

[31] C. Laijun et al., "Review and prospect of compressed air energy storage system", *J. Modern Power Syst. Clean Energy*, vol. 4, pp. 529-41, 2016.

[32] X. Luo and J. Wang, "Overview of current development on compressed air energy storage", *School of Engineering, University of Warwick*, Coventry, UK, 2013.

[33] E. Akbari et al., "Stochastic programming-based optimal bidding of compressed air energy storage with wind and thermal generation units in energy and reserve markets", *Energy*, vol. 171, pp. 535-46, 2019.

[34] W. Cai et al., "Optimal bidding and offering strategies of compressed air energy storage: A hybrid robust-stochastic approach", *Renew. Energy*, vol. 143, pp. 1-8, 2019.

[35] S. Sadeghi and I. Askari, "Prefeasibility techno-economic assessment of a hybrid power plant with photovoltaic, fuel cell and Compressed Air Energy Storage (CAES)", *Energy*, vol. 168, pp. 409-24, 2019.

[36] M. Simpson et al., "Integrating solar thermal capture with compressed Air energy storage", London, UK, 2016.

[37] F. Jabari et al., "Day-ahead economic dispatch of coupled desalinated water and power grids with participation of compressed air energy storages", *J. Oper. Autom. Power Eng.*, vol. 7, pp. 40-8, 2019.

[38] J. Yu et al., "Planning and design of a micro energy network for seawater desalination and regional energy interconnection", *Glob. Energy Interconnection*, vol. 2, pp. 224-34, 2019.

[39] Y. Babaei, J. Salehi, and N. Taghizadegan, "Bi-level unit commitment considering virtual power plants and demand response programs using information gap decision theory", *J. Oper. Autom. Power Eng.*, vol. 9, pp. 88-102, 2021.

[40] M. Sedighizadeh, M. Esmaili, and N. Mohammadkhani, "Stochastic multi-objective energy management in residential microgrids with combined cooling, heating, and power units considering battery energy storage systems and plug-in hybrid electric vehicles", *J. Cleaner Prod.,* vol. 195, pp. 301-17, 2018.

[41] N. Mohammadkhani, M. Sedighizadeh, and M. Esmaili, "Energy and emission management of CCHPs with electric and thermal energy storage and electric vehicle", *Thermal Sci. Eng. Prog.*, vol. 8, pp. 494-508, 2018.

[42] M. Esmaeili, M. Sedighizadeh, and M. Esmaili, "Multi-objective optimal reconfiguration and DG (distributed generation) power allocation in distribution networks using big bang-big crunch algorithm considering load uncertainty", *Energy*, vol. 103, pp. 86-99, 2016.

[43] Y. Ben-Haim, "Info-gap decision theory: decisions under severe uncertainty", Elsevier, 2006.

[44] A. Conejo et al., "Decomposition techniques in mathematical programming: engineering and science applications", Springer Science & Business Media, 2006.

[45] M. Mazidi, H. Monsef, and P. Siano, "Design of a risk-averse decision making tool for smart distribution network operators under severe uncertainties: An IGDT-inspired augment ε-constraint based multi-objective approach", *Energy*, vol. 116, pp. 214-35, 2016.

[46] Z. Li and M. Ierapetritou, "A new methodology for the general multiparametric mixed-integer linear programming (MILP) problems", *Ind. Eng. Chem. Res.*, vol. 46, pp. 5141-51, 2007.

[47] Y. Collette and P. Siarry, "Multiobjective optimization: principles and case studies", Springer Science & Business Media, 2013.

[48] M. Karimi, M. Kheradmandi, and A. Pirayesh, "Risk-constrained transmission investing of generation companies", *IEEE Trans. Power Syst.*, vol. 34, pp. 1043-53, 2018.

[49] G. Mavrotas, "Effective implementation of the ε-constraint method in multi-objective mathematical programming problems", *Appl. Math. Comput.*, vol. 213, pp. 455-65, 2009.

[50] M. Sedighizadeh, S. Alavi, and A. Mohammadpour, "Stochastic optimal scheduling of microgrids considering demand response and commercial parking lot by AUGMECON method", *Iran. J. Electr. Electron. Eng.*, vol. 16, pp. 393-411, 2020.

[51] A. Zerrahn and W. Schill, "Long-run power storage requirements for high shares of renewables: review and a new model", *Renew. Sustain. Energy Rev.*, vol. 79, pp. 1518-34, 2017.

[52] Y. Zheng et al., "Assessment for hierarchical medical policy proposals using hesitant fuzzy linguistic analytic network process", *Knowledge-Based Syst.*, vol. 161, pp. 254-67, 2018.

[53] D. Singh and P. Kaushik, "Intrusion response prioritization based on fuzzy ELECTRE multiple criteria decision making technique", *J. Inf. Security Appl.*, vol. 48, p. 102359, 2019.

[54] G. Yalcin and N. Erginel, "Determining weights in multi-objective linear programming under fuzziness", *Proc. World Cong. Eng.*, 2011.

[55] M. Sedighizadeh et al., "Optimal distribution feeder reconfiguration and generation scheduling for microgrid day-ahead operation in the presence of electric vehicles considering uncertainties", *J. Energy Storage*, vol. 21, pp. 58-71, 2019.

[56] H. Chen et al., "Compressed air energy storage", *Energy Storage Tech. Appl.*, vol. 4, pp. 101-12, 2013.

[57] I. Dincer and M. Rosen, "Thermal energy storage: systems and applications", John Wiley & Sons, 2002.

[58] Z. Kang et al., "Research status of ice-storage air-conditioning system", *Procedia Eng.*, vol. 205, pp. 1741-7, 2017.

[59] M. Sedighizadeh, M. Esmaili, and M. Esmaeili, "Application of the hybrid Big Bang-Big Crunch algorithm to optimal reconfiguration and distributed generation power allocation in distribution system", *Energy*, vol. 76, pp. 920-930, 2014.