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Optimal probabilistic operation of energy hub with various energy converters and electrical storage based on electricity, heat, natural gas, and biomass by proposing innovative uncertainty modeling methods

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A B S T R A C T

In recent years, attention to energy hubs (EHs) has increased significantly as active and intelligent elements in multi-energy systems (MESs). This article proposes a stochastic framework for the optimal operation of a new EH structure with various energy converters and electric storage based on electricity, heat, natural gas, and biomass. The proposed framework plays the role of a bidding strategy for a smart element in MESs. For modeling uncertainties in this framework, such as energy market prices, wind speed, and solar radiation, it is necessary to generate random scenarios based on recorded past behaviors or forecasting future trends. The Monte Carlo (MC) and the ARIMA methods have received significant attention in the literature to generate scenarios. Proposing uncertainty modeling methods in this paper, including the MC based on the Kolmogorov-Smirnov test, the ARIMA model based on Akaike Information Criterion, TBATS model, and the LSTM model of deep learning, as another innovation, has been such that efforts are made to make a significant improvement in the generated scenarios. Comparing various proposed uncertainty modeling methods is one of the most contributions. Based on the actual data in Finland, the simulation results demonstrate the effectiveness of the proposed operation strategy and the uncertainty modeling methods. Increasing the accuracy of uncertainty modeling has a significant impact on EH's profit and energy storage behavior and can also reduce the dependence of EHs on incoming energy carriers.

Keywords:
Energy hubs
Optimal operation
Energy converters
Energy storage
Uncertainty modeling
Biomass CHP unit

1. Introduction

According to the European Environment Agency (EEA), air pollution levels declined from 1990 to 2017 [1]. One of the most important reasons for this is the support of governments and organizations for clean energy and restrictions on pollution production. These conservations are concentrated in the fields of renewable energy sources (RESs) and multi-energy systems (MESs), both of which are co-generation units and fuel biomass [2]. The cases mentioned in the context of smart grids have been more developed and used. Accordingly, the growth and increase of the influence of these units in energy networks cannot be considered unsealed. On the other hand, the restructuring and formation of energy markets, one of the most important events in these industries, has changed the shape of transactions from traditional and tariff mode to competitiveness. One of the most important issues related to the operation and planning of market players in such an environment is the offer to market operators for buying and selling energy. The importance of optimal bidding/offering of competent actors on their profits is one of the common results among all investigations in the field of operation strategy problems [3].

In the last few decades, there have been actors in the energy markets who have two or more natures; for example, these actors, in addition to bidding to buy electricity carriers, offers to sell electricity or heat, etc. They also consider such actors to be called prosumers [4]. One of the actors showing such behavior is the energy hub (EH), an active element in smart grids. The EH can be considered a black box with several inputs and output energy and generally has three types of operations: conversion, transmission, and storage on various inlet energy such as electricity, heat, hydrogen, etc. The use of such units provides benefits such as increased productivity and flexibility in operation, as well as increased energy supply reliability [2,4,5]. Considering the mentioned cases about the elements of the EH, modeling, and how to operation them, it can be concluded that the behavior of the EH is a combination of

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Nomenclature

Indices

s Scenario index
t Time index (hour)

Acronyms

MES Multi-Energy System
EH Energy hub
DA Day-ahead
MC Monte Carlo
EES Electrical energy storage
CHP (by ICE) Combined heat and power by prime mover of the internal combustion engine
CHP (by ST) Combined heat and power by prime mover of steam turbine
EHP Electric heat pump
WF Wind farm
SF Solar farm
FOR Feasible operation region
WS Wind speed
SL Sunlight
PDF Probability distribution function
KS Kolmogorov-smirnov
AR Autoregressive
MA Moving average
ARIMA Autoregressive integrated moving average
AIC Akaike information criterion
LSTM Long short-term memory
RMSE Root mean square error

Variables

P_n, L_n, C_{nn} nth components of input, output, and energy coupling matrices
P_e^{out} Electric power sold to the day-ahead market
P_{th}^{out} Thermal power sold to the heat market
NG Total natural gas purchased from the natural gas market
P_e^{in} Total electricity purchased from the day-ahead market
C_{DA} Day-ahead market electricity price (€/MW)
NG_{ICE} Natural gas consumed by CHP (by ICE)
NG_{Boiler} Natural gas consumed by the boiler
P_e^{Bio}, P_{th}^{Bio} Electrical and thermally generated by CHP (by ST) and biomass fuel
P_e^{ICE}, P_{th}^{ICE} Electrical and thermally generated by CHP (by ICE)
P_{th}^{Boiler} Thermal generated by the boiler
P_{th}^{EHP} Thermal generated by the EHP
P_e^{EHP} Electric consumed by the EHP
P_e^{SOC} State of charge in the EES
P_e^{ch}, P_e^{dis} Charge and discharge power of EES
P_e^{loss} The power loss of electrical EES
I_e^{ch}, I_e^{dis} Binary for charge and discharge of EES
P_{WF} Electric power generated from the wind farm
v Wind speed (m/s)
k_t Clearness index
G Solar irradiance
T_c Solar cell temperature (°C)
T_a Ambient temperature (°C)
I Output current (A)
V Output voltage (V)
P_{SF} Electric power generated from the solar farm

Parameters

π_s Probability of scenarios occurring
C_{th} Thermal price (€/MWth)
C_{NG} Natural gas price (€/MW)
$P_{e,\min}^{in}$, $P_{e,\max}^{in}$ Minimum and the maximum allowable amount of electricity entering the EH
$NG_{\min}$, $NG_{\max}$ Minimum and the maximum allowable amount of natural gas entering the EH
η_e^{ICE} Natural gas to electricity efficiency of CHP (by ICE)
η_{th}^{ICE} Natural gas to heat efficiency of CHP (by ICE)
$P_{e,\min}^{ICE}$, $P_{e,\max}^{ICE}$ The minimum and maximum amount of electricity generation by CHP (by ICE)
$P_{th,\min}^{ICE}$, $P_{th,\max}^{ICE}$ The minimum and maximum amount of thermal generation by CHP (by ICE)
a, b, c, d, e, f CHP (by ST) cost function coefficients
$P_{ST,A}^{Bio}$, $P_{ST,B}^{Bio}$, $P_{ST,C}^{Bio}$, $P_{ST,D}^{Bio}$ Permissible amounts of electricity generation in FOR
$H_{ST,A}^{Bio}$, $H_{ST,B}^{Bio}$, $H_{ST,C}^{Bio}$, $H_{ST,D}^{Bio}$ Permissible amounts of thermal generation in FOR
η_{th}^{Boiler} Natural gas to heat efficiency of the boiler
COP Coefficient of EHP performance
$P_e^{SOC}(t_0)$ State of charge in t_0
η_e^{ch} EES charge efficiency
η_e^{dis} EES discharge efficiency
P_{Capa}^{ES} EES capacity
$\alpha_e^{\min}$, $\alpha_e^{\max}$ Minimum and maximum coefficients of EES
α_e^{loss} Loss coefficient of EES
$N_{turbine}$ Number of turbines in the wind farm
$P_{WT-rated}$ Rated wind power for wind turbine (kW)
v_{rated} Rated wind speed for wind turbine (m/s)
v_{cut-in} Cut-in speed of wind turbine (m/s)
$v_{cut-off}$ Cut-off speed of wind turbine (m/s)
G_0 Standard solar irradiance
N_{OT} Nominal operating temperature (°C)
I_{MPP} Maximum power point current (A)
K_I Current temperature coefficient (A/°C)
V_{MPP} Maximum power point voltage (V)
K_v Voltage temperature coefficient (V/°C)
N_{PV} Number of photovoltaic arrays
η_{Inv} Electricity efficiency of the inverter
η_e^{Tra} Electricity efficiency of the transformer

three elements of the producer, the aggregator, and the consumer.

These elements can contain a variety of energy converters of different sizes due to their defined application and connections to energy networks. In [6], by examining a relatively large number of past researches, it is tried to present general concepts about the EH. This study shows that most of the EHs had electricity and natural gas inputs, and simultaneously, generated energy converters are used as CHP. Electrical and thermal storage systems are the most used energy storage, while less attention is paid to hydrogen. In [7], the optimal operation framework of an EH consisting of CHP elements, boilers, and energy storage has been presented as a mathematical problem. In this framework, uncertainties related to wind speed, price, and electric load are considered. Authors in [8] have developed a two-stage stochastic mixed-integer linear programming (MILP) model for scheduling an MES the next day considering uncertain parameters. Researchers in [9] have proposed a dynamic stochastic programming framework to optimal dispatch of an EH in terms of uncertain parameters and minimize operating risk. The results of this paper have been appropriate in such a way that authors have suggested it for small distribution systems and home energy management systems. In [10], a new optimal operation model is

Table 1
Overview of the literature review on the optimal operation of EHs in energy markets considering uncertainty.

Ref.-Year	Uncertain parameters									Optimization problem approaches and uncertainty modeling methods					
	Weather		Price of energy carriers			Loads				Stochastic		Robust	Other		
	Wind	Solar	El	Th	NG	El	Th	Cool	NG	MC	TS		IGDT	2PEM	Hybrid
[14]-2011	×	×	✓	×	×	×	×	×	×	✓	×	×	×	×	×
[15]-2013	✓	×	×	×	×	×	×	×	×	×	×	✓	×	×	×
[16]-2014	✓	×	✓	×	×	✓	×	×	×	✓	×	×	×	×	×
[17]-2014	✓	×	✓	×	×	✓	×	×	×	✓	×	×	×	×	×
[18]-2015	×	×	×	×	×	✓	✓	×	✓	✓	×	×	×	×	×
[19]-2015	✓	×	×	×	×	✓	✓	×	×	×	×	×	✓	×	×
[20]-2016	✓	×	✓	×	×	×	×	×	×	×	✓	×	×	×	×
[21]-2016	×	✓	×	×	×	×	×	×	×	×	×	×	×	✓	×
[22]-2016	×	×	✓	×	×	✓	×	×	×	×	✓	×	×	×	×
[7]-2016	✓	×	✓	×	×	✓	×	×	×	✓	×	×	×	×	×
[23]-2017	✓	×	×	×	×	✓	✓	✓	×	✓	×	×	×	×	×
[24]-2017	✓	×	×	×	×	✓	✓	×	×	✓	×	×	×	×	×
[25]-2017	✓	×	✓	×	×	×	×	×	×	✓	×	×	×	×	×
[26]-2017	×	×	✓	×	×	✓	✓	✓	×	×	×	×	×	✓	×
[27]-2017	✓	✓	×	×	×	×	×	×	×	✓	×	×	×	×	×
[28]-2017	✓	✓	✓	×	×	×	×	×	×	×	✓	×	×	×	×
[8]-2018	×	✓	×	×	×	✓	✓	×	×	✓	×	×	×	×	×
[29]-2018	✓	×	✓	×	×	✓	✓	×	×	×	×	×	×	×	✓
[30]-2018	×	×	✓	✓	×	×	×	×	×	×	×	×	×	×	×
[9]-2018	×	×	✓	×	×	✓	✓	×	×	✓	×	×	×	×	×
[31]-2018	×	×	✓	×	✓	✓	×	×	×	✓	×	×	×	×	×
[32]-2018	✓	×	×	×	×	✓	✓	×	×	✓	×	×	×	×	×
[33]-2018	✓	×	✓	×	×	×	×	×	×	✓	×	×	×	×	×
[34]-2019	×	✓	×	×	×	✓	✓	×	×	×	×	✓	×	×	×
[35]-2019	×	✓	×	×	×	×	×	×	×	×	×	✓	×	×	×
[36]-2019	×	×	✓	×	×	×	×	×	×	×	×	✓	×	×	×
[37]-2019	✓	✓	×	×	×	✓	✓	×	✓	×	×	×	✓	×	×
[38]-2019	✓	✓	✓	×	✓	✓	✓	✓	×	✓	×	×	×	×	×
[39]-2019	✓	×	✓	✓	✓	✓	✓	×	×	✓	×	×	×	×	×
[40]-2019	×	✓	✓	×	×	✓	✓	✓	×	✓	×	×	×	×	×
[41]-2019	✓	✓	×	×	×	×	×	×	×	✓	×	×	×	×	×
[10]-2019	×	×	×	×	×	✓	×	×	×	×	×	×	✓	×	×
[42]-2020	×	✓	✓	×	✓	✓	✓	×	×	×	×	✓	×	×	×
[43]-2020	×	×	✓	×	×	×	×	×	×	×	×	✓	×	×	×
[44]-2020	✓	×	✓	×	×	✓	✓	×	×	×	×	×	×	×	✓
[45]-2020	✓	×	×	×	×	✓	✓	✓	×	✓	×	×	×	×	×
[46]-2020	✓	✓	×	×	✓	✓	✓	✓	×	✓	×	×	×	×	×
[47]-2020	×	×	✓	×	×	✓	×	×	×	✓	×	✓	×	×	×
[48]-2020	✓	✓	×	×	×	×	×	×	×	✓	×	×	×	×	×
[49]-2021	✓	✓	×	×	×	×	×	×	×	✓	×	×	×	×	×
[50]-2021	✓	×	✓	✓	✓	✓	✓	×	✓	✓	×	×	×	×	×
[11]-2021	✓	✓	×	×	×	✓	✓	✓	×	✓	×	×	×	×	×
[51]-2021	×	✓	✓	✓	✓	✓	✓	✓	×	✓	×	×	×	×	×
[52]-2021	✓	×	✓	×	×	✓	✓	✓	×	✓	×	×	×	×	×
[53]-2021	×	✓	✓	×	×	✓	✓	×	✓	✓	×	×	×	×	×
[12]-2021	×	✓	✓	×	×	×	×	×	×	✓	×	×	×	×	×

El: Electricity Th: Thermal NG: Natural gas TS: Time series.

presented for a sample EH that includes plug-in hybrid electric vehicles (PHEVs). In the model, a new method is also developed to estimate the uncertainty associated with energy consumption of PHEVs during mileage using information gap decision theory (IGDT). The results showed that the presented method maximizes the objective function under risk-neutral and risk-averse strategies and minimizes the risk-seeking strategy. Ref. [11] presents an optimal model for EH for optimal operation of multi-energy microgrid concerning environmental constraints and reduction of operating costs for the next day. As mentioned earlier, the use of biomass fuel has been one of the countries' policies to reduce environmental problems. In [12], a stochastic optimal scheduling framework for a biogas-based EH under uncertainty is presented. This EH converts biomass fuel into a valuable biogas fuel using a digester. Then, this fuel is converted to other energy carriers according to internal needs and participation in the day-ahead (DA) market using other energy converters.

As mentioned above, due to the structure of EHs, these units to participate in energy markets face various uncertainties such as weather parameters (i.e., wind speed and solar radiation for RESs), market prices (e.g., electricity market price), and behavior (e.g., load pattern). Therefore, one of the most important factors in the bidding of MESs is the issue of uncertainty and how to deal with it [13]. In the bidding strategy and operation of EHs with different structures to energy markets, relatively much research has been conducted. Table 1 summarizes the literature review results in this field, emphasizing uncertainty modeling. This table is provided based on uncertain parameters, the approach used to the optimization problem, and uncertainty modeling methods. In other words, the purpose of applying Table 1 is to investigate the major researches of the past in the field of EH in two main areas as follows:

- Uncertain parameters: In this context, the research is investigated to determine items such as the situation of considering the uncertainty issue, the type of uncertain parameters such as weather, the price of energy carriers as well as the behavior of connected loads.
- Problem modeling: The format of the operation problem and the planning of the EH is investigated in this field. These templates are among five categories, including stochastic optimization, robust

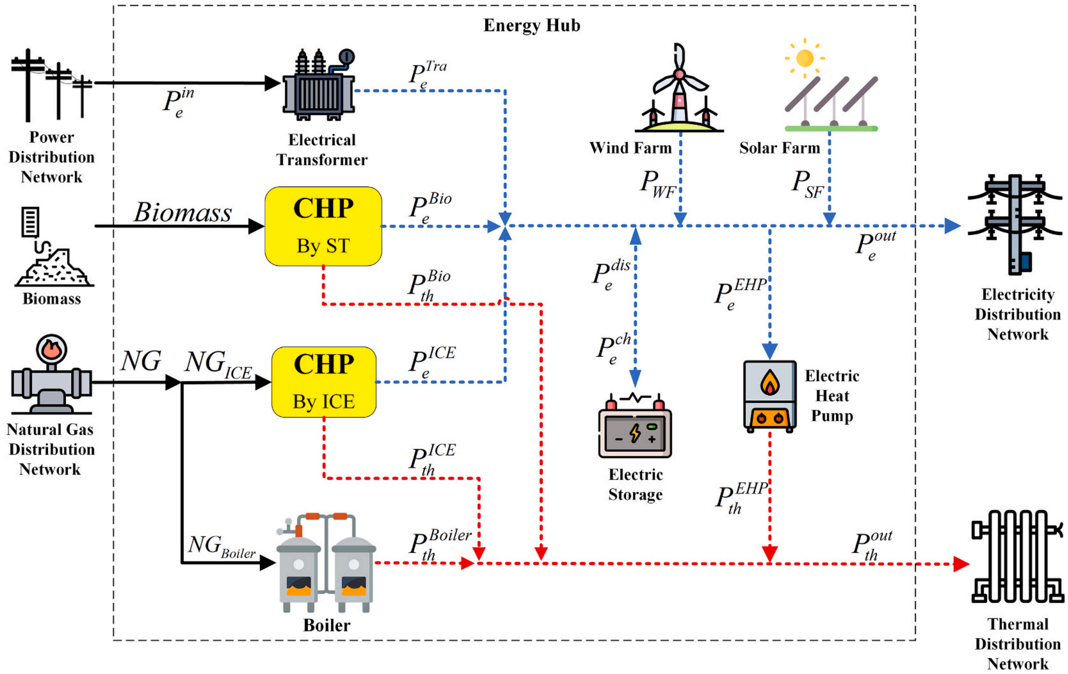

Fig. 1. Schematic of the proposed structure for the EH.

optimization, IGDT, hybrid methods, and the two-point estimate method (2PEM).

Using these indicators to compare past research shows what weaknesses existed in modeling EH utilization under uncertainty and what aspects of the research should be used to strengthen them.

From Table 1, it can be concluded that the most common method for modeling the problem of optimal operation of EHs is stochastic optimization. The parameters considered in these optimizations as quantities with uncertainty only included wind speed, solar radiation, energy market prices, and energy carrier demand. To model these parameters in the form of a stochastic optimization problem, researchers have preferred to use the Monte Carlo (MC) method as a classic and popular method for generating scenarios. However, they have not implemented any innovations or improvements on it. One aspect that needed to be improved and used rationally was the selection and application of probability distribution functions (PDFs), which researchers followed without further reason and approach to modeling the behavior of wind speed, solar radiation, price, and energy carriers. Also, using the ARIMA method to scenario generation has been traditional, and innovation has been less done in this method. In fact, comparing uncertainty modeling methods and investigating their efficiency have been less considered. In many of the references in Table 1, electricity, heat, and gas markets have not been simultaneously considered.

The use of biomass fuels (such as municipal and industrial wastewater, forest waste, and municipal solid waste) to supply EHs has been considered very little in past research related to the operation of these units. However, using these fuels has many advantages such as low cost of energy production, greater distributability in different geographical locations, reduction of pollution production per energy production, and increased stability and flexibility of the network compared to other RESs [54,55].

In general, the use of EHs in energy markets is dependent on their geographical and strategic conditions. For example, geographical conditions can include areas where there is cold or hot weather at long times of the year (such as cold countries like Scandinavia). Strategic conditions also refer to the actors' decision to use MESs due to fluctuations in energy carrier prices and profitability opportunities from the exchange of energy carriers in energy markets. According to the above explanations, Finland is used as a suitable case study in this paper due to its special geographical conditions (cold air temperature and air-light duration), the existence and abundance of energy network infrastructures such as thermal distribution networks, as well as the existence and common use of biomass fuels for CHP units. Considering the mentioned explanations and challenges, the overall purpose of this research is to provide an optimal operation framework for an EH with a new and meaningful structure along with new uncertainty modeling methods. In fact, this paper performs the development of EH in terms of energy carriers such as biomass, electricity, heat, and natural gas in the structural field as well as modeling uncertainty as a very influential parameter in bidding strategy. Therefore, the optimal operation strategy of an EH considering biomass fuel for participation in electricity, heat, and natural gas markets is proposed. On the other hand, with various methods of uncertainty modeling in MATLAB, R, EasyFit, and Python software packages, it is tried to investigate the effect of the accuracy of modeling the uncertain parameters on the above problem based on the actual data. In this regard, four proposed methods have been presented to forecast uncertain parameters and generate scenarios. In summary, the contributions of this paper are as follows:

- An optimal operation strategy for a new EH structure is developed to participate in electricity, heat, and natural gas markets considering biomass unit;
- Using the LSTM model of deep learning and TBATS model, as new methods for scenario generation of uncertain parameters;
- Improving the scenario generation process by the methods of MC based on the Kolmogorov-Smirnov test (MC-KS), and ARIMA model based on Akaike Information Criterion (ARIMA-AIC);
- Comprehensive studies are done to compare the proposed uncertainty modeling methods based on various aspects, such as the EH behavior, EH operator's expected profit, and electrical energy storage behavior;
- A new scenario reduction technique based on the Kantorovich Distance method is presented.

The rest of this paper is organized as follows: In Section 2, the

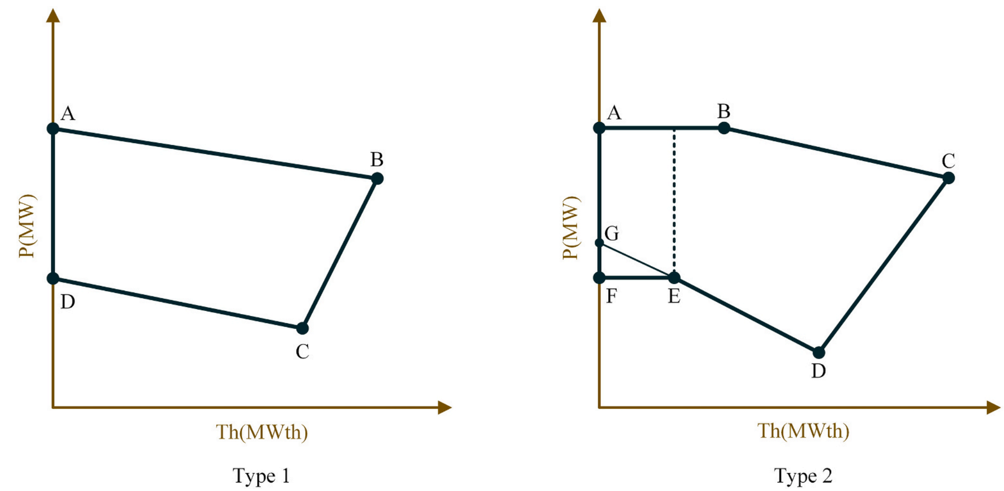

Fig. 2. FOR type1 and type2 of CHP (by ST) unit.

optimal operation strategy of the desired EH is formulated. Section 3 presents how to model uncertain parameters based on the proposed methods. Simulation and its results are expressed in Section 4. Finally, the conclusion is allocated to Sections 5.

2. Optimal operation strategy framework for EH

In this section, a framework for the optimal operation strategy of an EH to the energy markets of the DA electricity, heat, and natural gas is proposed considering the biomass burner CHP unit. The proposed structure of the EH is shown in Fig. 1. This EH is supplied by electricity and natural gas distribution networks, and its outputs are connected to electricity and heat distribution networks. The structure of the intended EH includes CHP with prime mover of steam turbine and biomass fuel (CHP by ST), CHP with prime mover of internal combustion engine and natural gas fuel (CHP by ICE), natural gas burner boiler, electric heat pump (EHP), wind farm (WF), solar farm (SF) and electric energy storage (EES). Besides, the integration of these elements causes not only a much more complete and newer structure of the research mentioned in Table 1 to be formed but also makes the subject of operation strategy and its contrast with uncertain parameters more understandable based on various modeling.

Considering that the elements located in the structure of the EH can have one input and one or more outputs, so the connection of these elements is very effective in determining the energy management system and energy flux [56]. For this reason, (1) is used to model energy flux in the EH.

$$\underbrace{\begin{bmatrix} L_1 \\ L_2 \\ \vdots \\ L_n \end{bmatrix}}_{L} = \underbrace{\begin{bmatrix} C_{11} & C_{21} & \dots & C_{n1} \\ C_{12} & C_{22} & \dots & C_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ C_{1n} & C_{2n} & \dots & C_{nn} \end{bmatrix}}_{C} \times \underbrace{\begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_n \end{bmatrix}}_{P} \tag{1}$$

where L is the output energy vector, C is the coupling matrix, and the input energy vector P.

To model the optimal operation problem of such an EH, which is faced with various uncertainties, a stochastic scenario-based optimization approach is used. The assumptions of the operation strategy framework are as follows:

- Uncertain parameters include wind speed, sunlight, and DA market price.
- The purchase of electricity by the EH from upstream is in the form of participation in the DA market.
- The price of natural gas and thermal markets is determined by tariffs and per season.
- The maintenance costs of wind and solar farms and EES are neglected.

2.1. Objective function

The objective function of the optimal operation problem from the viewpoint of an EH operator can be described by the expected profit maximization, according to (2). In this objective function, (3) and (4) are revenues from electricity and heat sales in the energy markets of DA electricity and heat sales, respectively. Also, (5) and (6) describe the costs of purchasing natural gas and electricity, respectively. The operation cost function of the CHP unit with biomass fuel is shown in (7). Considering that this unit is equipped with the prime mover of the steam turbine, its feasible operation region (FOR) would be explained in Subsection 2.2.3 [57].

$$\begin{aligned} Max\ OF :\pi_s \sum_{s=1}^{N_s} \sum_{t=1}^{24} \Big[& Re{\cdot}P_e^{out}(t,s) + Re{\cdot}P_{th}^{out}(t,s) - Ex{\cdot}NG(t,s) - Ex{\cdot}P_e^{in}(t,s) \\ & - Ex{\cdot}P_{e,th}^{Bio}(t,s) \Big] \end{aligned} \tag{2}$$

$$Re{\cdot}P_e^{out}(t,s) = P_e^{out}(t,s){\cdot}C_{DA}(t,s) \tag{3}$$

$$Re{\cdot}P_{th}^{out}(t,s) = P_{th}^{out}(t,s){\cdot}C_{th} \tag{4}$$

$$Ex{\cdot}NG(t,s) = (NG_{ICE}(t,s) + NG_{Boiler}(t,s)){\cdot}C_{NG} \tag{5}$$

$$Ex{\cdot}P_e^{in}(t,s) = P_e^{in}(t,s){\cdot}C_{DA}(t,s) \tag{6}$$

$$\begin{aligned} Ex{\cdot}P_{e,th}^{Bio}(t,s) = {} & a + b{\cdot}P_e^{Bio}(t,s) + c{\cdot}P_e^{Bio^2}(t,s) + d{\cdot}P_{th}^{Bio}(t,s) + e{\cdot}P_{th}^{Bio^2}(t,s) \\ & + f{\cdot}P_e^{Bio}{\cdot}P_{th}^{Bio} \end{aligned} \tag{7}$$

2.2. Problem constraints

2.2.1. Input energy carriers

Constraints (8)–(9) express the conditions related to the input energy carriers of electricity ($P_e^{in}(t,s)$) and natural gas ($NG(t,s)$) to the desired EH. The total natural gas consumed by CHP (by ICE) and the boiler is expressed in (10).

$$P_{e,min}^{in}(t,s) \le P_e^{in}(t,s) \le P_{e,max}^{in}(t,s) \tag{8}$$

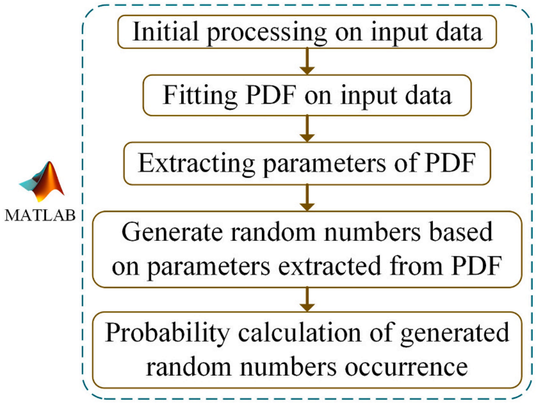

Fig. 3. Scenario generation process by the MC classic method.

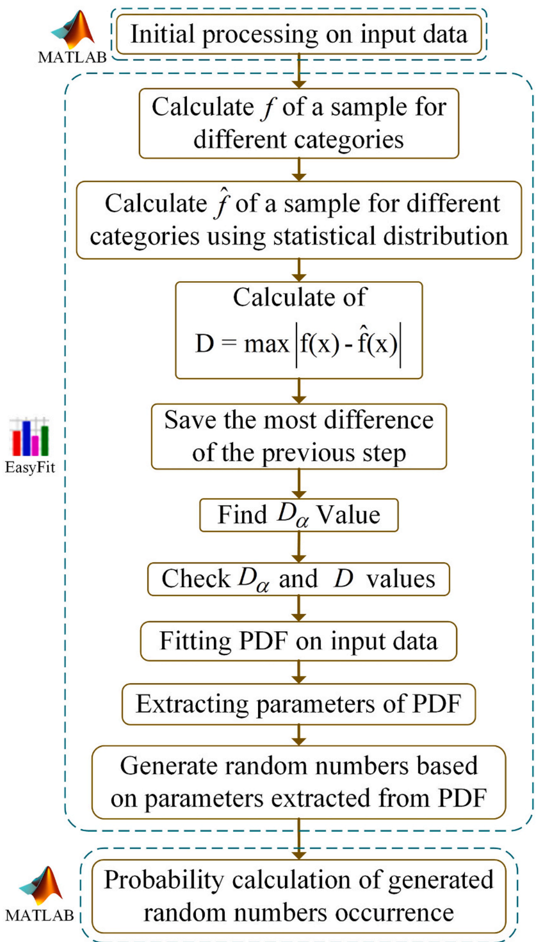

Fig. 4. Proposed scenario generation process using the MC method based on the KS test.

$$NG_{\min}(t,s) \le NG(t,s) \le NG_{\max}(t,s) \tag{9}$$

$$NG(t,s) = NG_{ICE}(t,s) + NG_{Boiler}(t,s) \tag{10}$$

2.2.2. CHP (by ICE)

Constraints (11)–(12) indicate the conversion of natural gas into electricity and heat by CHP unit with the prime mover of the internal combustion engine, respectively. Also, (13)–(14) have been used to observe the range of electricity and heat generation by this unit [58].

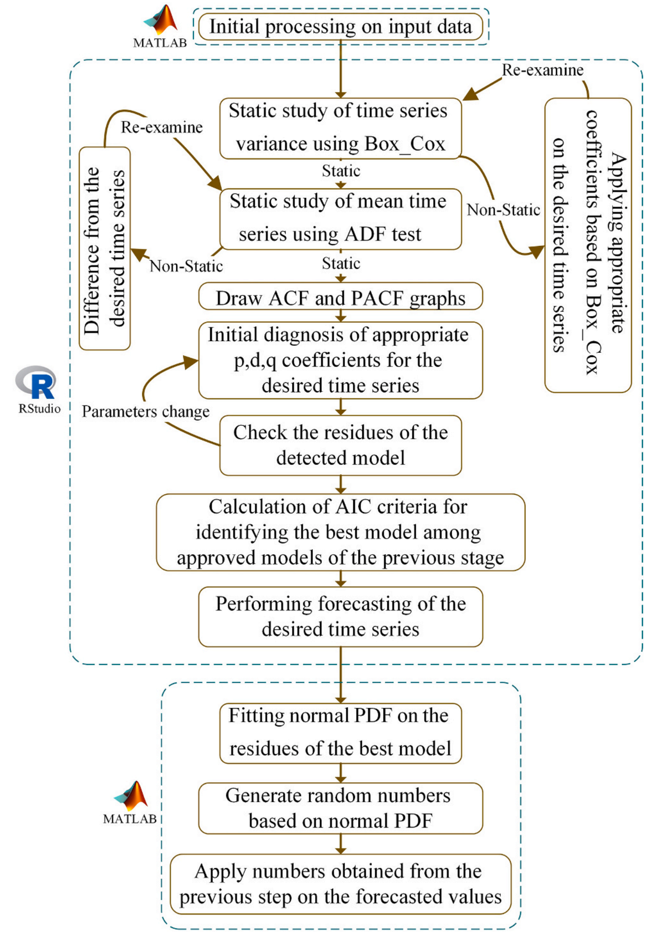

Fig. 5. Proposed scenario generation process with the ARIMA model based on the remainder of the best model selected based on AIC.

$$P_e^{ICE}(t,s) = \eta_e^{ICE} \cdot NG_{ICE}(t,s) \tag{11}$$

$$P_{th}^{ICE}(t,s) = \eta_{th}^{ICE} \cdot NG_{ICE}(t,s) \tag{12}$$

$$P_{e,min}^{ICE} \le P_e^{ICE}(t,s) \le P_{e,max}^{ICE} \tag{13}$$

$$P_{th,min}^{ICE} \le P_{th}^{ICE}(t,s) \le P_{th,max}^{ICE} \tag{14}$$

2.2.3. CHP (by ST)

Most of the units for simultaneous production of electricity and heat are equipped with the prime mover of steam turbine and gas turbine and given that the electricity and heat generated in such units are not separated, so these two parameters depend on each other. Accordingly, for steam turbine and gas turbine units, the relationship between electricity and heat produced as well as the feasible region of operation are modeled in two types [59]. In this paper, based on Fig. 2, the first type is used according to (15)–(17).

$$P_e^{Bio}(t,s) - P_{ST,A}^{Bio} - \frac{P_{ST,A}^{Bio} - P_{ST,B}^{Bio}}{H_{ST,A}^{Bio} - H_{ST,B}^{Bio}}\left(P_{th}^{Bio}(t,s) - H_{ST,A}^{Bio}\right) \le 0 \tag{15}$$

$$P_e^{Bio}(t,s) - P_{ST,B}^{Bio} - \frac{P_{ST,B}^{Bio} - P_{ST,C}^{Bio}}{H_{ST,B}^{Bio} - H_{ST,C}^{Bio}}\left(P_{th}^{Bio}(t,s) - H_{ST,B}^{Bio}\right) \ge 0 \tag{16}$$

$$P_e^{Bio}(t,s) - P_{ST,C}^{Bio} - \frac{P_{ST,C}^{Bio} - P_{ST,D}^{Bio}}{H_{ST,C}^{Bio} - H_{ST,D}^{Bio}}\left(P_{th}^{Bio}(t,s) - H_{ST,C}^{Bio}\right) \ge 0 \tag{17}$$

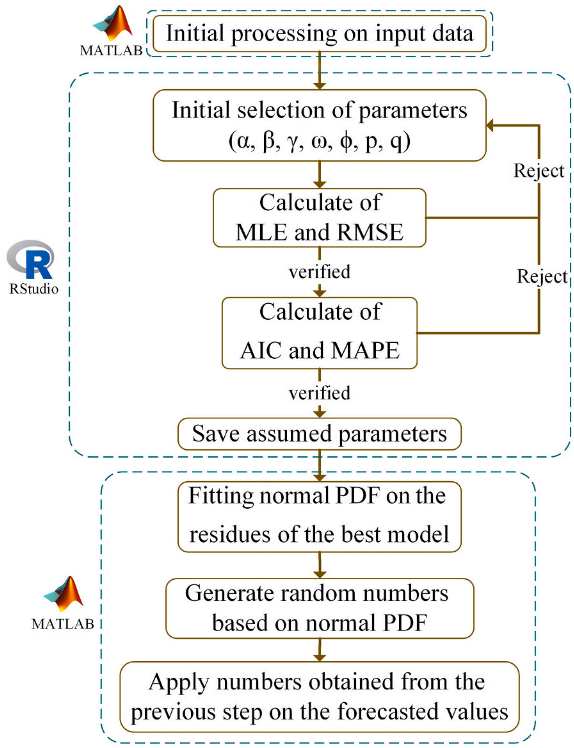

Fig. 6. Proposed scenario generation process with TBATS model considering the remainder of the best model selected based on AIC.

2.2.4. Boiler constraints

In the boiler, (18) is used to model the conversion of natural gas into heat. Also, to observe the heat range produced by this unit, (19) is applied [60].

$$P_{th}^{Boiler}(t,s) = \eta_{th}^{Boiler} \cdot NG_{Boiler}(t,s) \tag{18}$$

$$P_{th,min}^{Boiler} \le P_{th}^{Boiler}(t,s) \le P_{th,max}^{Boiler} \tag{19}$$

2.2.5. Electrical heat pump

One of the most widely used elements in the preparation of residential and industrial heating is electric heat pumps. To describe the heat produced by the EHP and observe its range, (20) and (21) are used, respectively [61].

$$P_{th}^{EHP}(t,s) = COP \cdot P_{e}^{EHP}(t,s) \tag{20}$$

$$P_{th,min}^{EHP} \le P_{th}^{EHP}(t,s) \le P_{th,max}^{EHP} \tag{21}$$

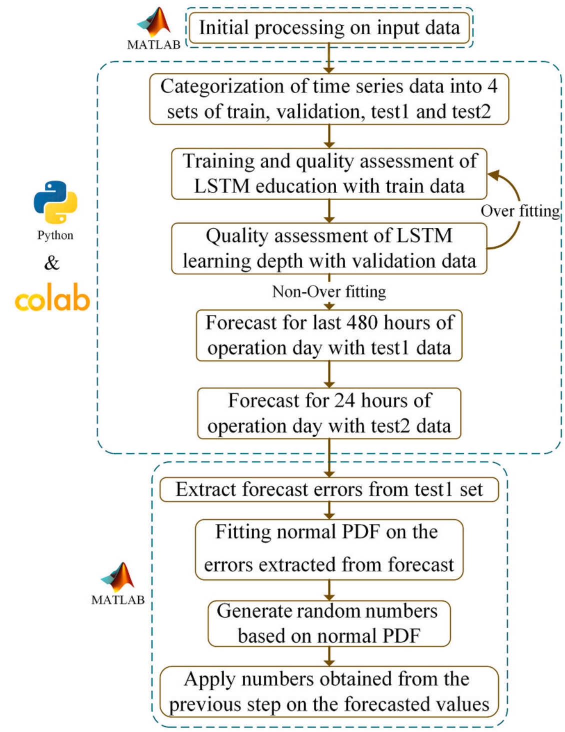

Fig. 8. Proposed scenario generation process with LSTM model of deep learning.

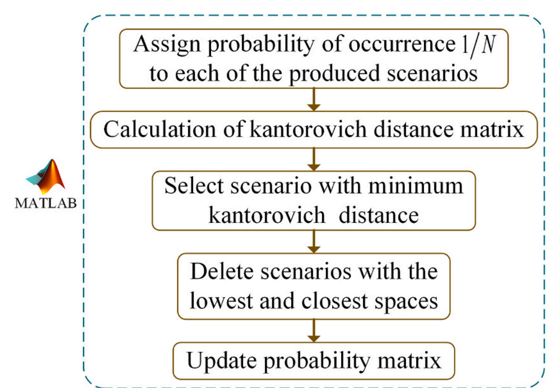

Fig. 9. Proposed scenario reduction process by Kantorovich distance method.

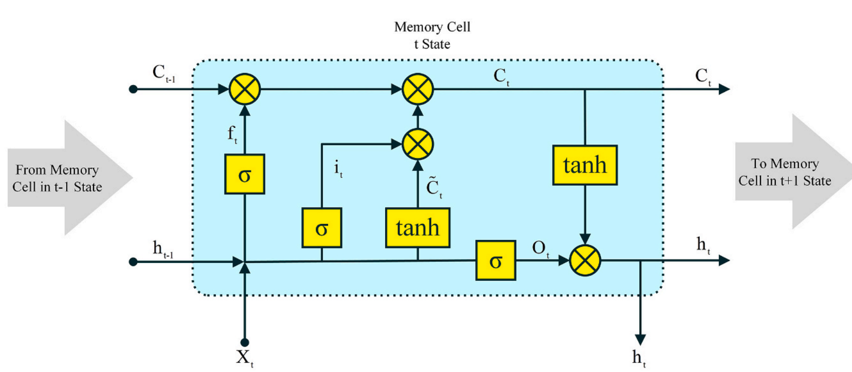

Fig. 7. LSTM block architecture.

Table 2
EH parameters introduced in Fig. 1.

Parameters	Values	Parameters	Values	Parameters	Values	Parameters	Values
η_e^{Tra}	0.9	c	0.0435	$P_{th,\ max}^{EHP}$	0.45 MW	I_{MPP}	7.35%/°C
$P_{e,\ min}^{Tra}$	0 MW	d	0.6002	η_e^{ch}	0.9	V_{MPP}	30.5%/°C
$P_{e,\ max}^{Tra}$	1.5 MW	e	0.027	η_e^{dis}	0.9	K_I	0.00037
NG_{min}	0 MW	f	0.0409	$P_{e,\ 0}^{SOC}$	0.1 MW	K_v	0.00273
NG_{max}	1.8 MW	η_e^{ICE}	0.35	P_{Capa}^{ES}	0.5 MW	N_{PV}	4000
$P_{ST,\ A}^{Bio}$	1.5 MW	η_{th}^{ICE}	0.4	α_e^{loss}	0.02	η_{Inv}	88%
$P_{ST,\ B}^{Bio}$	1.2 MW	$P_{e,\ min}^{ICE}$	0.05 MW	$\alpha_e^{\min}$	0.1	$C_{NG,\ Winter}$	34 €
$P_{ST,\ C}^{Bio}$	0.3 MW	$P_{e,\ max}^{ICE}$	0.7 MW	$\alpha_e^{\max}$	0.9	$C_{NG,\ Spring}$	32 €
$P_{ST,\ D}^{Bio}$	0.5 MW	$P_{th,\ min}^{ICE}$	0.1 MW	$N_{turbine}$	10	$C_{NG,\ Summer}$	34 €
$H_{ST,\ A}^{Bio}$	0 MWth	$P_{th,\ max}^{ICE}$	0.5 MW	$P_{WT-rated}$	200 kW	$C_{NG,\ Autumn}$	36 €
$H_{ST,\ B}^{Bio}$	2.5 MWth	η_{th}^{Boiler}	0.85	$v_{cut-off}$	25 m/s	$C_{th,\ Winter}$	38 €
$H_{ST,\ C}^{Bio}$	1 MWth	$P_{th,\ min}^{Boiler}$	0 MW	v_{cut-in}	3.5 m/s	$C_{th,\ Spring}$	36 €
$H_{ST,\ D}^{Bio}$	0 MWth	$P_{th,\ max}^{Boiler}$	0.8 MW	v_{rated}	11.5 m/s	$C_{th,\ Summer}$	38 €
a	65	COP	2.5	G_0	1000	$C_{th,\ Autumn}$	40 €
b	36.0012	$P_{th,\ min}^{EHP}$	0.003 MW	N_{OT}	4000		

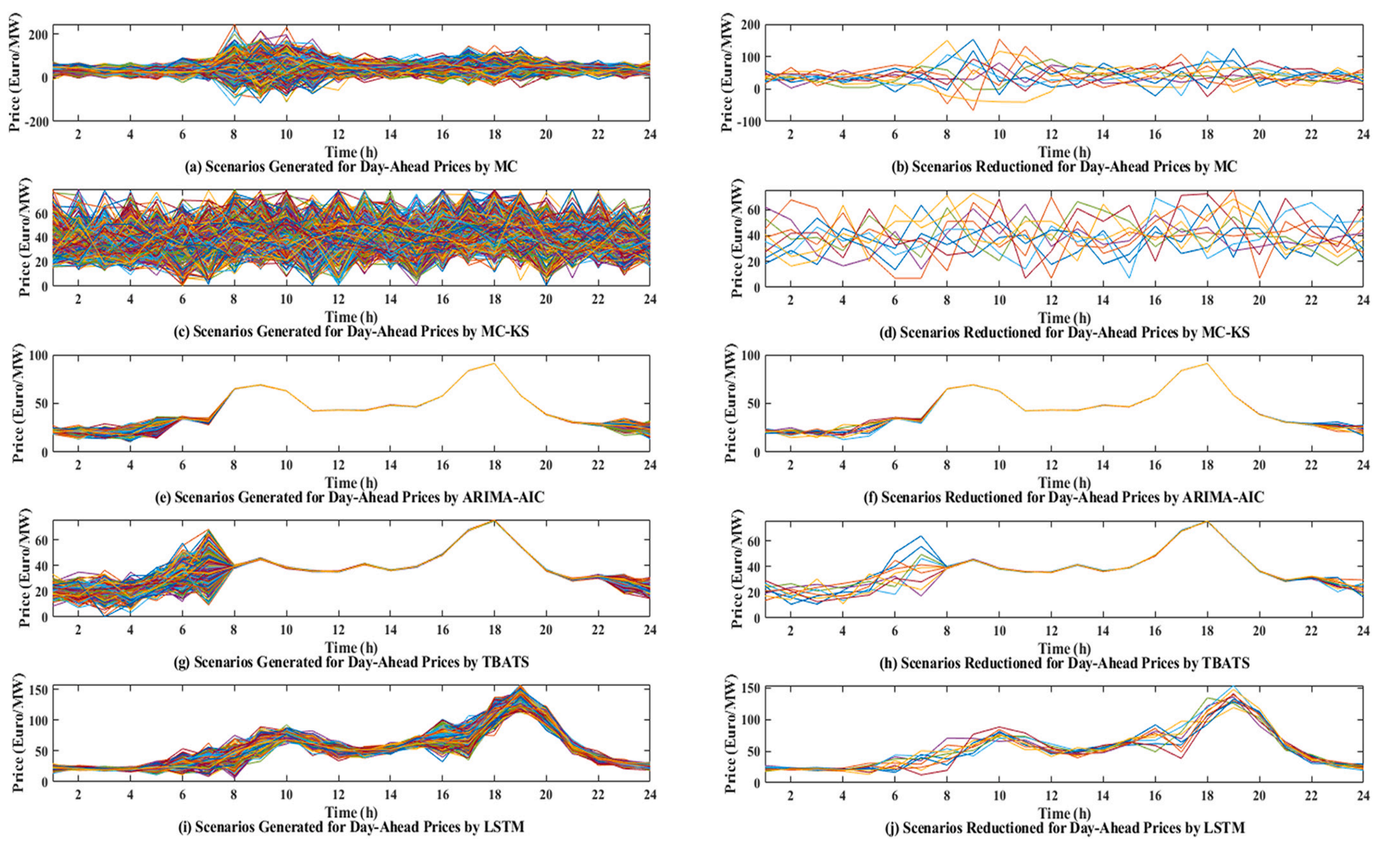

Fig. 10. Results of scenario generation by proposed methods and scenario reduction for DA electricity market price in winter.

Table 3
The best PDFs selected of DA market price in each hour for the winter season based on the KS test.

01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00
Log-Gamma	Log-Pearson3	Log-Gamma	Gumbel max	Figure life	Cauchy	Cauchy	Log-Logistic	Log-Logistic	Log-Logistic	Cauchy	Cauchy
13:00	**14:00**	**15:00**	**16:00**	**17:00**	**18:00**	**19:00**	**20:00**	**21:00**	**22:00**	**23:00**	**24:00**
Dagum	Gen. Logistic	Cauchy	Log-Logistic	Burr	Log-Gamma	Log-Logistic	Cauchy	Log-Logistic	Log-Logistic	Chi-Squared	Lognormal

2.2.6. *Electrical storage*

Electrical storage devices are used to cover uncertainty, increase reliability, and increase participation in profitability opportunities in the EHs. Constraints (22)–(27) that model the electric storage behavior relatively perfect according to [17], are considered in this paper. The level of stored energy in electrical storage is modeled as (22). Eq. (23) expresses the electrical energy wasted in the storage. Constraints (24)–(26) take into place the levels of energy stored, charged, and discharged

Table 4
The best PDFs selected of wind speed and their parameters in each hour for the winter season based on the KS test.

01:00	Parameters:		02:00	Parameters:		03:00	Parameters:		04:00	Parameters:	
Erlang	m	4	Fatigue life	α	0.5927	Fatigue life	α	0.596	Lognormal	σ	0.599
	β	1.7217		β	5.4412		β	5.456		μ	1.707
	γ	−0.405		γ	0		γ	0		γ	0

05:00	Parameters:		06:00	Parameters:		07:00	Parameters:		08:00	Parameters:	
Wakeby	α	201.39	Lognormal	σ	0.596	Lognormal	σ	0.629	Gamma	α	2.888
	β	109.99		μ	1.712		μ	1.703		β	2.159
	γ	6.706		γ	0		γ	0		γ	0.292
	δ	−0.436									
	ξ	0									

09:00	Parameters:		10:00	Parameters:		11:00	Parameters:		12:00	Parameters:	
Gen. Gamma	k	1.331	Fatigue life	α	0.446	Log-Pearson 3	α	12.254	Johnson SB	γ	1.220
	α	1.601		β	7.674		β	−0.174		δ	1.2
	β	4.499								λ	22.98
	γ	0.483		γ	−1.874		γ	3.848		ξ	−0.169

13:00	Parameters:		14:00	Parameters:		15:00	Parameters:		16:00	Parameters:	
Beta	1α	2.253	Lognormal	σ	0.589	Fatigue life	α	0.586	Pearson 5	α	3.142
	2α	6.43		μ	1.71		β	5.480		β	14.646
	a	−0.005		γ	0		γ	0		γ	0
	b	25.115									

17:00	Parameters:		18:00	Parameters:		19:00	Parameters:		20:00	Parameters:	
Pearson 5	α	3.308	Pearson 5	α	3.281	Pearson 5	α	3.011	Pearson 5	α	3.099
	β	15.656		β	15.508		β	13.923		β	14.383
	γ	0		γ	0		γ	0		γ	0

21:00	Parameters:		22:00	Parameters:		23:00	Parameters:		24:00	Parameters:	
Lognormal	σ	0.577	Lognormal	σ	0.627	Lognormal	σ	0.579	Fatigue life	α	0.606
	μ	1.695		μ	1.676		μ	1.692		β	5.333
	γ	0		γ	0		γ	0		γ	0

Table 5
The best PDFs selected of sunlight and their parameters at 9:00 to 14:00 for the winter season based on the KS test.

09:00	Parameters:		10:00	Parameters:		11:00	Parameters:		12:00	Parameters:	
Johnson SB	γ	1.2292	Log-Logistic	α	1.0894	Weibull	α	0.50479	Burr	k	0.01059
	δ	0.30627		β	46.77		β	83.125		α	52.374
	lam	418.05								β	6.9105
	ξ	1.5097		γ	0		γ	7.16		γ	0

13:00	Parameters:		14:00	Parameters:		–	–		–	–	
Burr	k	0.0383	Power function	α	0.10472	–	–	–	–	–	–
				a	0		–	–		–	–
	α	15.294		b	599.28		–	–		–	–
	β	4.1204					–	–		–	
	γ	0									

Table 6
Comparison of proposed methods of modeling uncertainty in the optimal bidding strategy of EH to energy markets.

Season	Parameters		Methods of uncertainty modeling				
			MC	MC-KS	ARIMA-AIC	TBATS	LSTM
Winter	RMSE	Wind power	0.8588	0.9499	0.4762	0.4260	0.0532
		Solar power	0.0249	0.0352	0.0342	0.0458	0.0127
		DA price	34.738	36.839	22.7409	30.2225	21.1982
	EES	Charging time (h)	12	12	15	11	11
		Discharging time (h)	12	12	9	12	12
		Continuity of Ch/Dis states (h)	9	10	10	9	11
		Number of status change	14	13	13	14	11
	Profit of EH bidding (€)		2378.8	2025.3	2772.0	2367.9	4057.8
Spring	RMSE	Wind power	0.8489	0.8674	1.15	1.0895	1.3589
		Solar power	0.1695	0.1752	0.2	0.1894	0.0836
		DA price	9.3598	9.1296	4.0708	2.5492	1.8623
	EES	Charging time (h)	10	10	12	11	15
		Discharging time (h)	12	14	11	13	9
		Continuity of Ch/Dis states (h)	9	12	5	8	6
		Number of status change	12	12	17	16	18
	Profit of EH bidding (€)		1719.5	1642.7	985.1	1105.0	951.1
Summer	RMSE	Wind power	0.5978	0.5878	0.5804	0.5955	0.1156
		Solar power	0.1112	0.1220	0.0560	0.0670	0.0606
		DA price	4.9037	4.0999	3.2236	3.0676	2.4084
	EES	Charging time (h)	10	12	13	12	13
		Discharging time (h)	12	11	11	11	11
		Continuity of Ch/Dis states (h)	6	8	4	7	8
		Number of status change	15	15	20	16	16
	Profit of EH bidding (€)		1750.9	1739.2	1943.3	2016.3	1811.3
Autumn	RMSE	Wind power	0.7568	0.7414	0.6414	0.6998	0.2542
		Solar power	0.0941	0.0801	0.0469	0.0798	0.0321
		DA price	6.4702	6.2041	6.2383	5.2898	7.8129
	EES	Charging time (h)	12	10	12	13	14
		Discharging time (h)	12	13	12	11	10
		Continuity of Ch/Dis states (h)	12	10	10	8	6
		Number of status change	12	13	14	16	18
	Profit of EH bidding (€)		2363.8	2248.9	2012.9	2147.7	1700.8

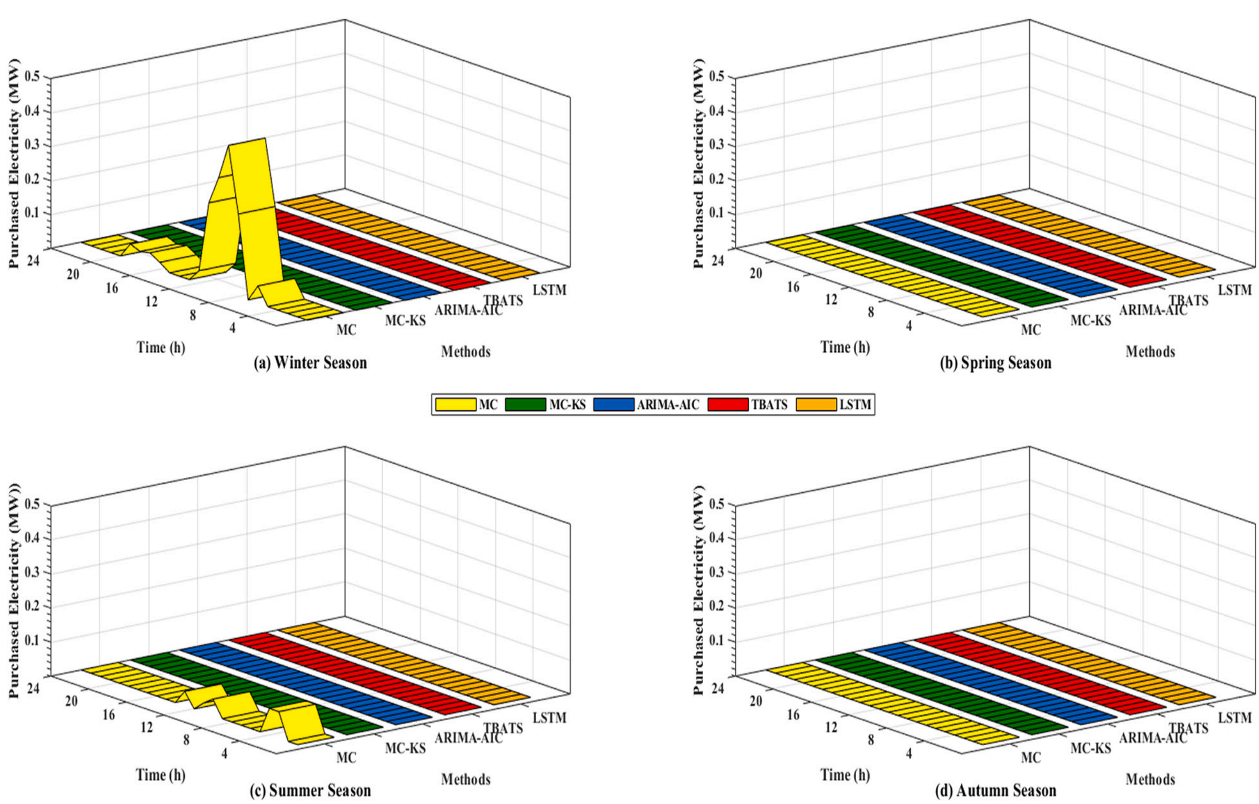

Fig. 11. Expected values of electricity purchased by EH from DA market based on proposed uncertainty modeling methods expressed in different seasons.

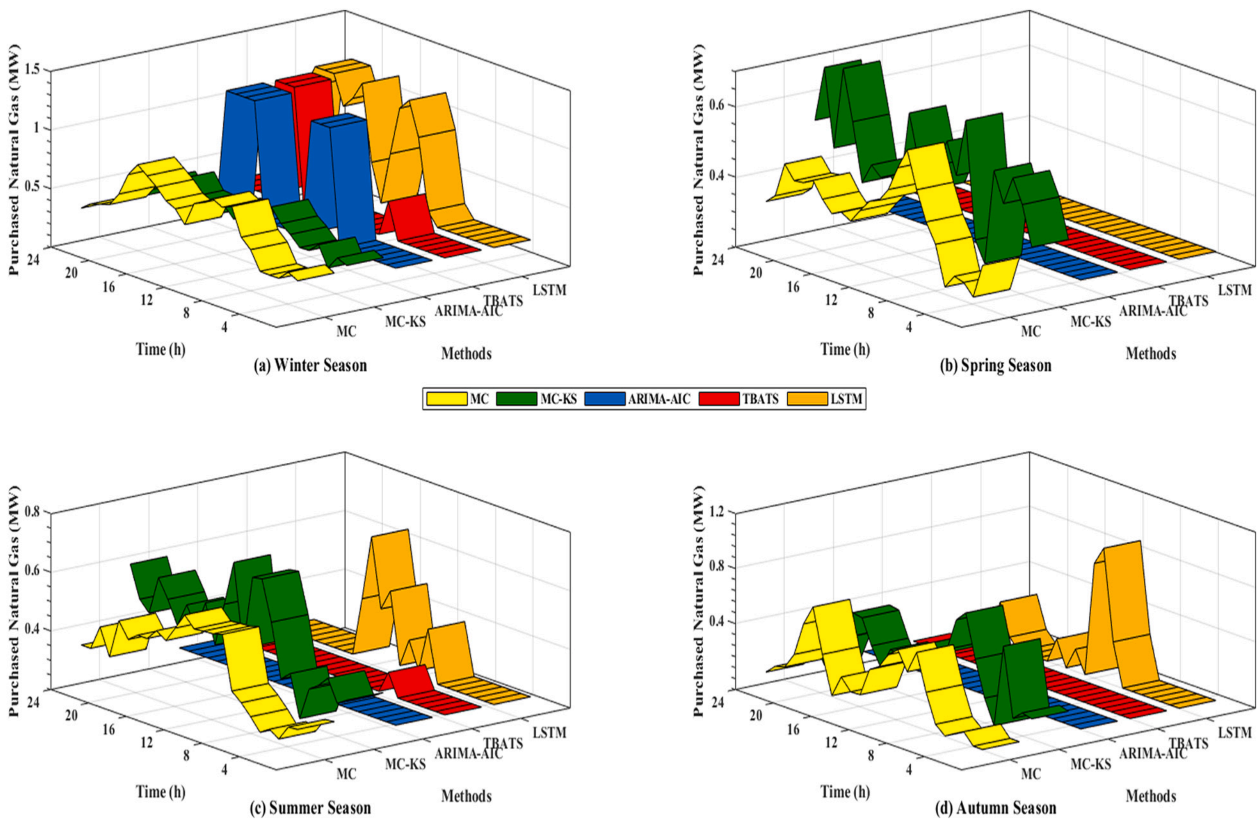

Fig. 12. Expected values of natural gas purchased by EH based on proposed uncertainty modeling methods expressed in different seasons.

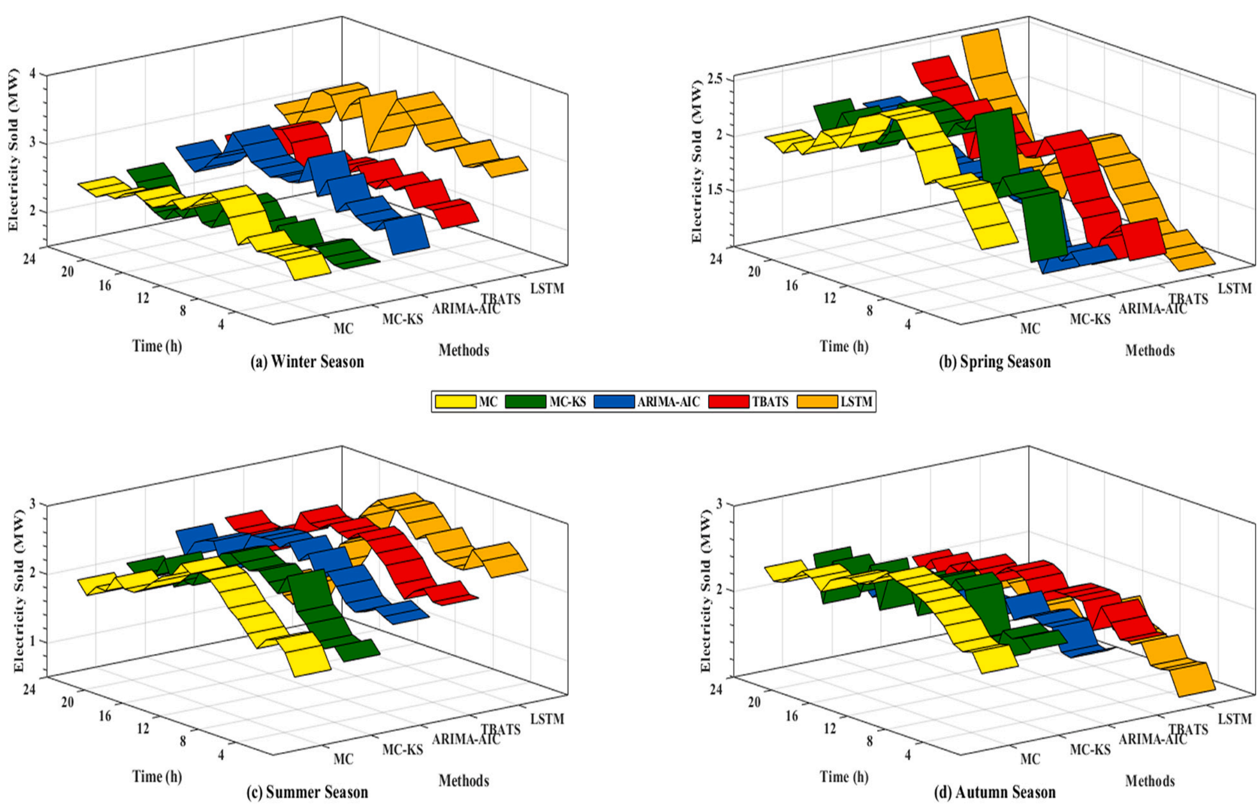

Fig. 13. Expected values of electricity energy sale by EH to the DA market based on proposed uncertainty modeling methods in different seasons.

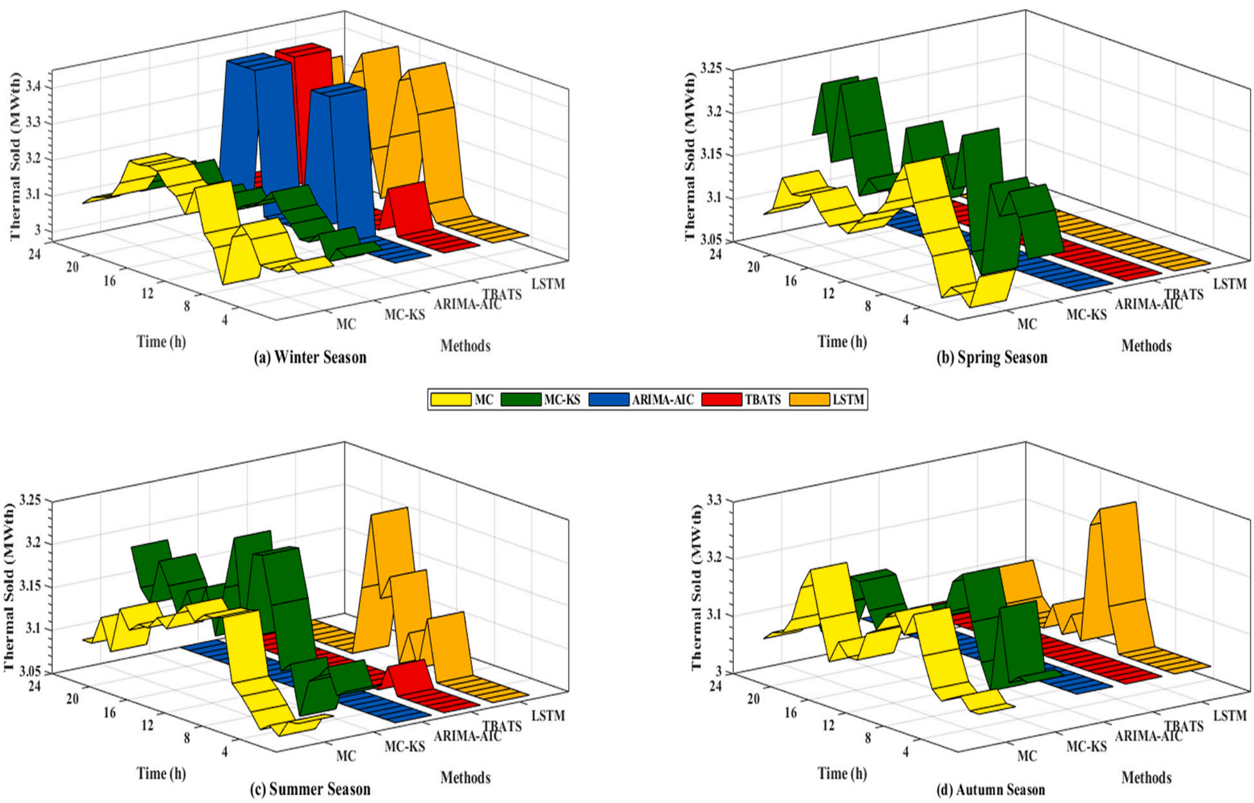

Fig. 14. Expected values of thermal energy sale by EH to thermal market based on proposed uncertainty modeling methods in different seasons.

by the electric storage, respectively. Moreover, (27) is applied to prevent simultaneous charging and discharge in the storage.

$$P_e^{SOC}(t) = P_e^{SOC}(t-1) + P_e^{ch}(t) - P_e^{dis}(t) - P_e^{loss}(t) \tag{22}$$

$$P_e^{loss}(t) = \alpha_e^{loss} \cdot P_e^{SOC}(t) \tag{23}$$

$$\alpha_e^{\min} \cdot P_{Capa}^{ES} \leq P_e^{SOC}(t) \leq \alpha_e^{\max} \cdot P_{Capa}^{ES} \tag{24}$$

$$\alpha_e^{\min} \cdot (1/\eta_e^{ch}) \cdot P_{Capa}^{ES} \cdot I_e^{ch}(t) \leq P_e^{ch}(t) \leq \alpha_e^{\max} \cdot (1/\eta_e^{ch}) \cdot P_{Capa}^{ES} \cdot I_e^{ch}(t) \tag{25}$$

$$\alpha_e^{\min} \cdot \eta_e^{dis} \cdot P_{Capa}^{ES} \cdot I_e^{dis}(t) \leq P_e^{dis}(t) \leq \alpha_e^{\max} \cdot \eta_e^{dis} \cdot P_{Capa}^{ES} \cdot I_e^{dis}(t) \tag{26}$$

$$0 \leq I_e^{ch}(t) + I_e^{dis}(t) \leq 1 \tag{27}$$

2.2.7. *Wind power modeling*

The electrical energy generated from the wind farm based on wind speed scenarios is obtained by (28) [62].

$$P_{WF}(t,s) = \begin{cases} P_{WT-rated} \times N_{turbine} & v_{rated} \leq v(t,s) \leq v_{cut-off} \\ \dfrac{v(t,s) - v_{cut-in}}{v_{rated} - v_{cut-in}} \times P_{WT-rated} \times N_{turbine} & v_{cut-in} \leq v(t,s) \leq v_{rated} \\ 0 & else \end{cases} \tag{28}$$

2.2.8. *Solar power modeling*

Eqs. (29)–(33) model the power generation of the solar farm. Indeed, (29)–(30) are used to calculate the clearness index and cell temperature, respectively. Also, (33) calculates the power produced by the solar farm considering the current and voltage computations in (31)–(32) [63].

$$k_t(t,s) = G(t,s)/G_0 \tag{29}$$

$$T_c(ts) = T_a(ts) + (G(ts) \times (N_{OT} - 20)/800 \tag{30}$$

$$I(t,s) = k_t(t,s) \times (I_{MPP} + (T_c(t,s) - T_a(t,s)) \times K_I) \tag{31}$$

$$V(t,s) = V_{MPP} - T_c(t,s) \times K_v \tag{32}$$

$$P_{SF}(t,s) = I(t,s) \times V(t,s) \times N_{PV} \times \eta_{Inv} \tag{33}$$

2.2.9. *Electrical and heat balance*

Considering that the amount of supply and demand for electrical energy should be equal at all hours and scenarios, therefore, (34) is used. Also, (35) is applied to balance thermal energy.

$$P_e^{in}(t,s).\eta_e^{Tra} + P_e^{Bio}(t,s) + P_e^{ICE}(t,s) + P_e^{dis}(t) + P_{WF}(t,s) + P_{SF}(t,s) = P_e^{out}(t,s) + P_e^{ch}(t) + P_{EHP}(t,s) \tag{34}$$

$$P_{th}^{Bio}(t,s) + P_{th}^{ICE}(t,s) + P_{th}^{Boiler}(t,s) + P_{th}^{EHP}(t,s) = P_{th}^{out}(t,s) \tag{35}$$

3. Proposed uncertainty modeling methods

In this paper, a stochastic scenario-based optimization framework is used to design the optimal operation strategy of the mentioned EH. Therefore, to model the parameters with uncertainty such as wind speed, solar radiation, and the DA electricity market price, it is necessary to generate stochastic scenarios. The methods used in this paper include the classic MC, the MC-KS, the ARIMA-AIC, the TBATS, and the LSTM model of deep learning, based on forecasted values. The MC method is considered as a basic method like most research in this paper. MC-KS method is used as a new method which is a more optimal developer of the MC method. ARIMA-AIC and TBATS-AIC were considered as two new methods for modeling uncertainty in this paper due to the lack of development of these time series models for scenario generation. Also, the LSTM model, as a powerful method based on artificial intelligence, is used in the field of scenario generation.

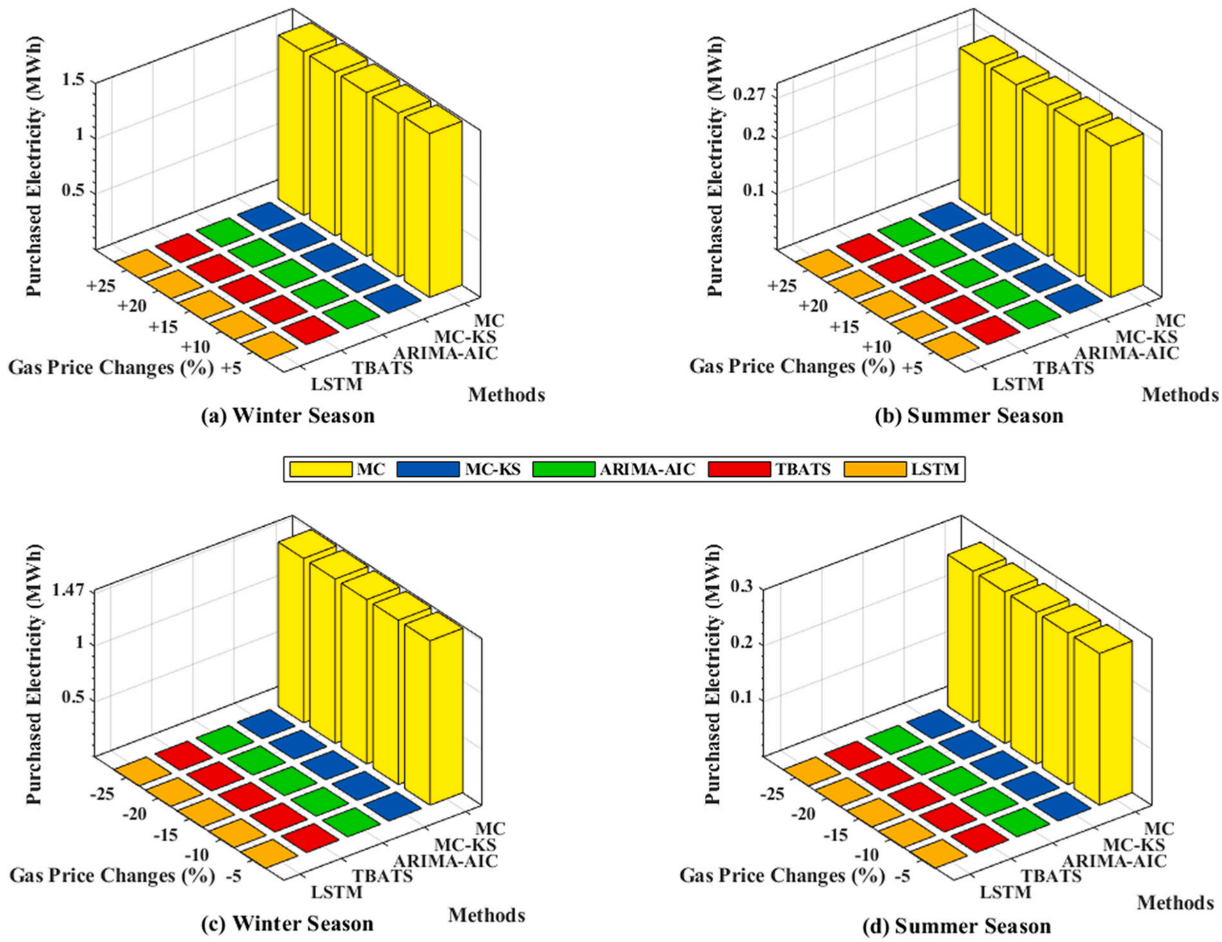

Fig. 15. Expected amounts of electricity purchase from the DA market by EH with changes in gas prices.

3.1. Monte Carlo classic method

The MC classic method can be introduced as the most widely used scenario generation method in stochastic optimization problems. The foundation of the MC is based on a PDF that is either obtained from historical data or a PDF that already exists and behaves similarly to the data. In modeling uncertain parameters, including wind speed, sunlight, and energy market prices, this procedure is common to use the PDFs of Weibull or Rayleigh, Beta and Normal, respectively. In this section, the same process is followed based on the PDF mentioned in (36)–(38) [38] and the flowchart expressed in Fig. 3.

$$PDF(WS) = \left(\frac{k}{c}\right)\left(\frac{WS}{c}\right)^{k-1} e^{\left(-\frac{WS}{c}\right)^{k}} \tag{36}$$

$$PDF(SL) = \begin{cases} \dfrac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)+\Gamma(\beta)} \times S_i^{\alpha-1} \times (1-S_i)^{\beta-1}, for\ 0 \le S_i \le 1, \alpha, \beta \ge 0 \\ 0 \qquad\qquad else \end{cases} \tag{37}$$

$$PDF(Price) = \frac{1}{\sqrt{2\pi\sigma^2 Price}} e^{-\frac{(Price-\mu_{Price})^2}{2\sigma^2 Price}} \tag{38}$$

where, the coefficients k and c in (36), α and β in (37), σ and μ in (38) are parameters of PDFs Weibull (wind speed), Beta (solar radiation), and Normal (price), respectively.

In all methods for modeling uncertainty in this paper, the initial preprocessing is on historical data to identify missing values to remove or replace them and normalize. The second and third stages of Fig. 3 relate to the PDFs fitting of Weibull, Beta, and Normal for historical data of wind speed, solar radiation, and energy market price, which is used by maximum likelihood estimation (MLE) to obtain parameters related to each PDF [64]. In this method, to generate scenarios, n random numbers are generated based on the parameters of PDFs obtained from the previous stage. Finally, to calculate the occurrence probability of each scenario, the created areas of discrete cumulative distribution function (CDF) have been used. This paper uses MATLAB software to implement all the steps described.

3.2. Monte Carlo method based on KS test

As mentioned in Section 3.1, most research that uses the MC method for scenario generation considers Weibull, Beta, and Normal PDFs for wind speed, sunlight, and energy market prices, respectively. This is explained as if some researchers are confident in the same wind speed behavior in different geographical locations, and there are no fundamental drawbacks to these assumptions. In this paper, the KS test [65,66] is used to reject such behavioral assumptions in past research and to investigate the effect of more accurate modeling of these parameters on generation scenario results. The main purpose of presenting this method in this paper is to determine the best PDFs from more than sixty PDFs, based on the behavior that historical data of each parameter of uncertainty from the past to the present have shown. In Fig. 4, the generation scenario process is demonstrated by the MC method based on the KS test, and the above process has been performed in EasyFit and MATLAB statistical software packages.

As seen in Fig. 4, after preprocessing the input data, the actual

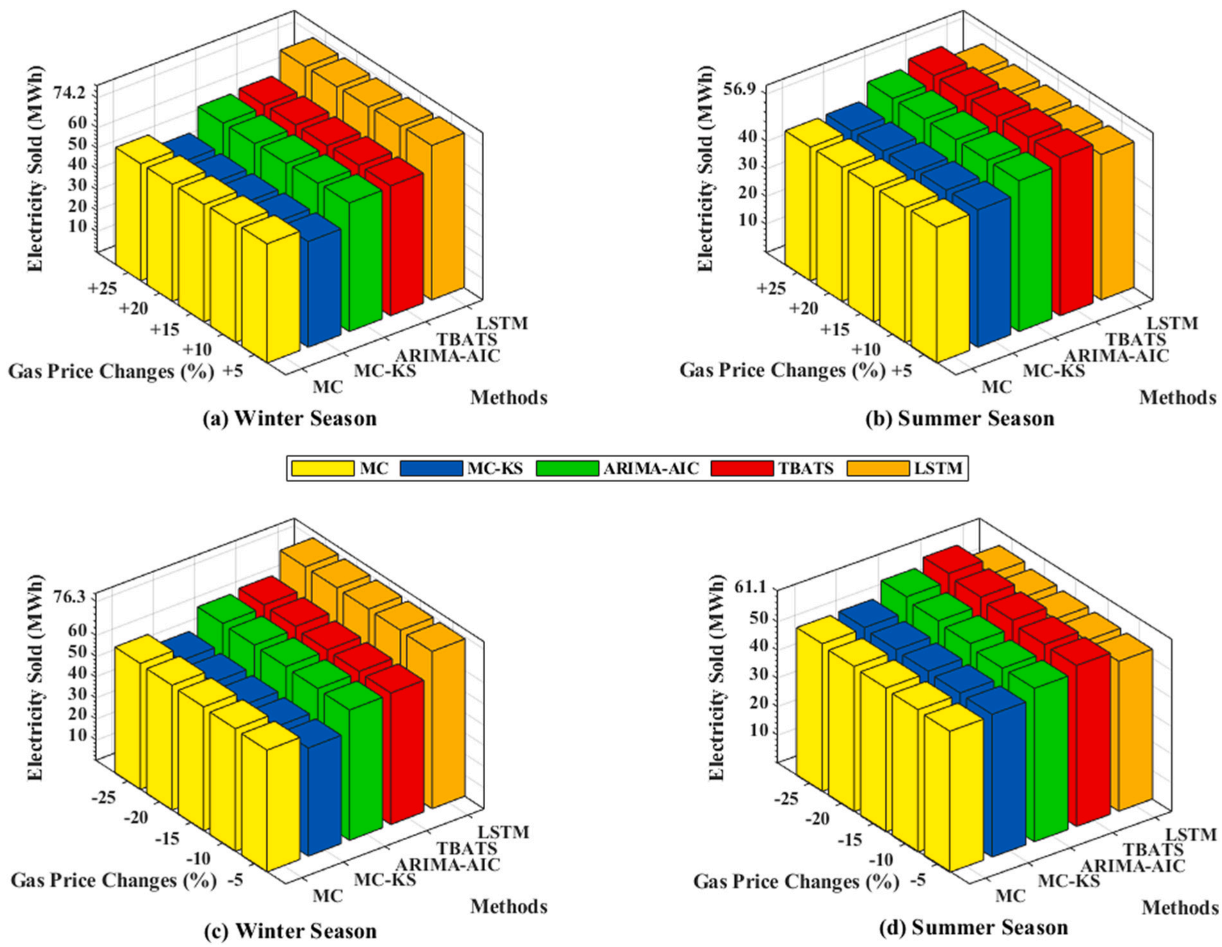

Fig. 16. Expected amounts of electricity sales from the DA market by EH with changes in gas prices.

cumulative relative frequency (f) and the expected cumulative relative frequency ($\hat{f}$) are calculated to compute the statistics of KS (D). The D value is obtained from the highest difference value obtained in each interval. The value is read from the corresponding tables by selecting α as the error rate and for the number of n samples. If the D value is less than the D_α value obtained from the tables, the knowledgeable assumption of sample adherence to the intended distribution is accepted and otherwise rejected. After determining the best PDF based on the described process, it produces a scenario similar to the process expressed in Fig. 3.

3.3. ARIMA-AIC method

ARIMA is one of the classic and popular methods for analyzing and forecasting time series that was used by Box and Jenkins in 1970 introduced. The ARIMA model is a mathematical language that represents a time series and a combination of non-static models AR with p and MA with q order and according to Eqs. (39)–(41), respectively, which is converted to ARMA by differentiating to d-order from ARIMA mode to ARMA [67].

The AR model expresses the relationship between one observation and other observations based on p order (39).

$$X_t = C + \sum_{i=1}^{p} \varphi_i \times X_{t-i} + \varepsilon_t \tag{39}$$

The MA model shows the correlation between an observation and the remainder of the error term by q order and Eq. (40).

$$X_t = \mu + \sum_{i=0}^{q} \theta_i \times \varepsilon_{t-i} \tag{40}$$

By combining the above two non-static models, the ARIMA model with p, d, q orders can be shown as Eq. (41).

By static and combining AR and MA models expressed in (39) and (40), the static ARIMA model with p, d, q orders can be expressed as (41). Of course, due to static (41), the order d is zero, and as a result, an ARMA model is obtained.

$$X_t = C + \varepsilon_t + \sum_{i=1}^{p} \varphi_i \times X_{t-i} + \sum_{i=1}^{q} \theta_i \times \varepsilon_{t-i} \tag{41}$$

In this paper, the process presented in Fig. 5 is used for scenario generation by the ARIMA model. After analyzing and forecasting the time series in the proposed method, the remaining values of the best model determined based on AIC are used for scenario generation. Uncertainty modeling in the above models uses the forecast package in R software and MATLAB.

3.4. TBATS method

TBATS is one of the methods of modeling the analysis and forecasting of time series with multiple seasonality that is composed of trigonometric seasonal, box-cox transformation, ARMA residuals, trend, and seasonality [68]. This model is rooted in exponential smoothing methods and is expressed by (42)–(51). In Fig. 6, the process of forecasting and scenario generation is expressed using R and MATLAB statistical software packages.

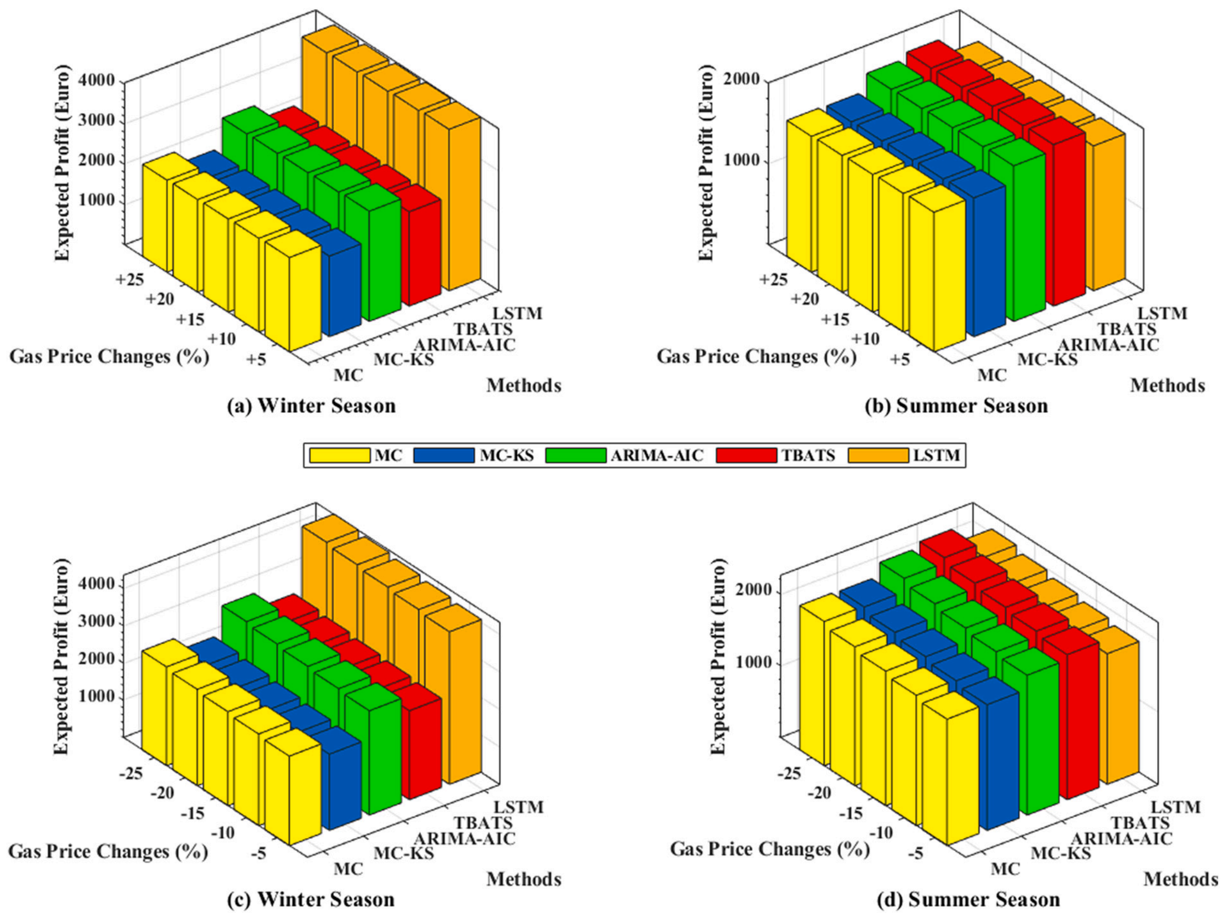

Fig. 17. Expected profits from EH operation with changes in gas prices.

$$y_t^{(\omega)} = \begin{cases} \dfrac{y_t^{\omega} - 1}{\omega}, & \omega \neq 0 \\ \log y_t, & \omega = 0 \end{cases} \tag{42}$$

$$y_t^{(\omega)} = \ell_{t-1} + \phi b_{t-1} + \sum_{i=1}^{T} s_{t-m_i}^{(i)} + d_t \tag{43}$$

$$\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha d_t \tag{44}$$

$$b_t = (1-\phi)b + \phi b_{t-1} + \beta d_t \tag{45}$$

$$s_t^{(i)} = s_{t-m_i}^{(i)} + \gamma_i d_t \tag{46}$$

$$d_t = \sum_{i=1}^{p} \varphi_i d_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{47}$$

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)} \tag{48}$$

$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} cos\lambda_j^{(i)} + s_{j,t-1}^{*(i)} sin\lambda_j^{(i)} + \gamma_1^{(i)} d_t \tag{49}$$

$$s_{j,t}^{*(i)} = -s_{j,t-1} sin\lambda_j^{(i)} + s_{j,t-1}^{*(i)} cos\lambda_j^{(i)} + \gamma_2^{(i)} d_t \tag{50}$$

$$\lambda_j^{(i)} = 2\pi \big/ m_i \tag{51}$$

where, $y_t^{(\omega)}$ is time series at t moment, $s_t^{(i)}$ is the ith seasonal component, I_t is local level, b_t is the trend by damping, d_t is ARMA(p,q) is processed for residuals, e_t is Gaussian white noise. Also parameters, T is the number of seasonalities, m_i is the length of the seasonal period, k_i is harmonics value for the ith seasonal period, λ is box-cox transformation, α, and β smoothing parameters, ϕ is trend damping, φ_i and θ_i coefficients of ARMA(p,q), γ_1 and γ_2 seasonal smoothing (two for each period).

3.5. LSTM method form deep learning

Over time, with the advancement of software systems and, more importantly, the development of machine learning algorithms, new models have been proposed to forecast time series after classical models such as ARIMA. ARIMA models, due to some limitations, such as the inability to establish a nonlinear relationship between variables [69], made experts more suitable to develop algorithms. One of these algorithms was long short-term memory (LSTM), developed by Hochreiter and Schmidhuber in 1979 [70]. This model is a special type of recurrent neural network (RNN) that, due to the difficulty of training and its application, had an important capability that increased its popularity day by day and is equipped with memory [71]. The existence of this memory improves forecasting if the neural network fails to learn and understand from several of its previous data by referring to the behavior of the desired time series in the farther past. These types of neural networks are composed of sets of cells or modules, and each cell is composed of 3 types of gates, including forget, memory, and output. The use of such gates causes the neural network to make decisions in selecting data for the forecasting process and have an elimination, selective, or filtering behavior with each data. Accordingly, Fig. 7 can be introduced as the general structure of LSTM.

Undoubtedly, many methods can be offered to implement such neural networks, but the Keras package is more popular and valid in Python software. It is noted that training and using these networks

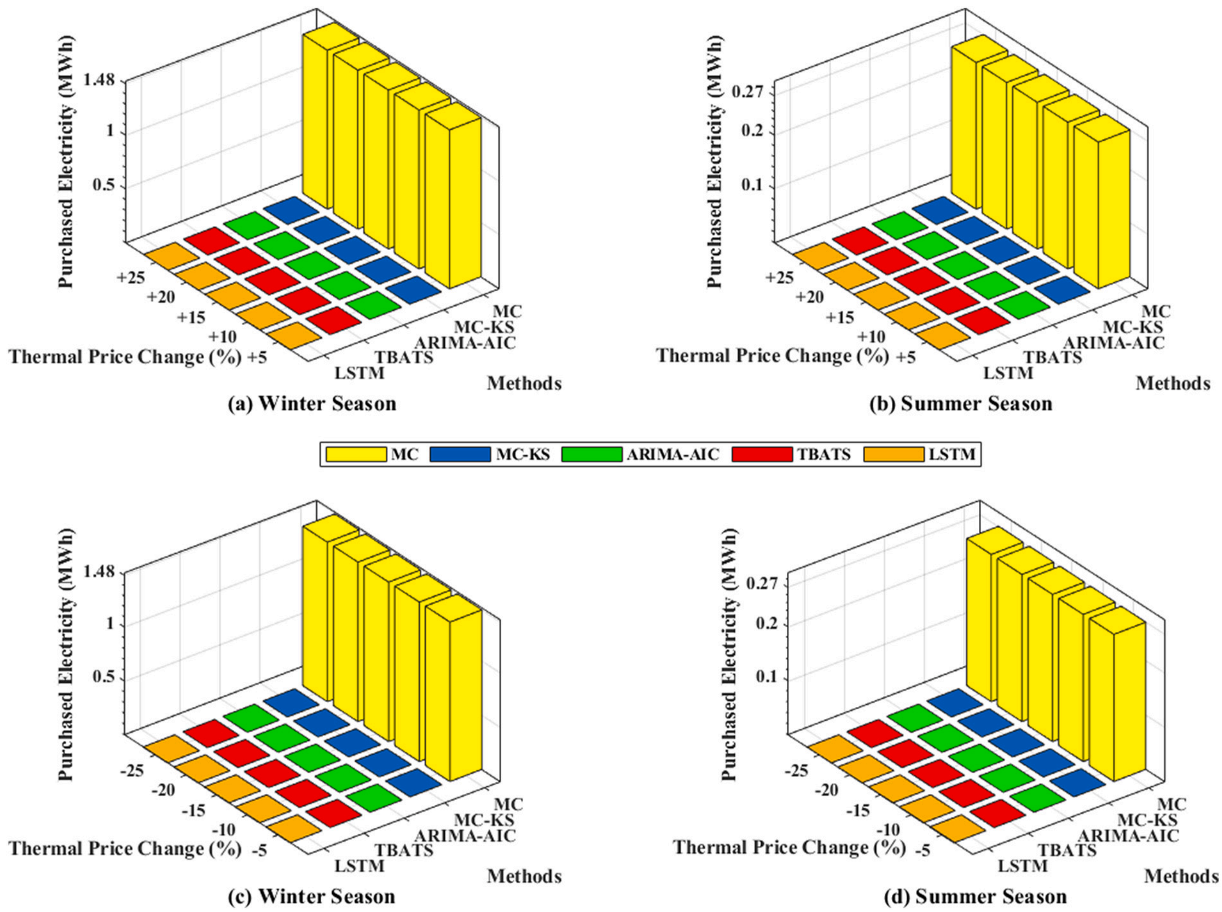

Fig. 18. Expected amounts of electricity purchase from the DA market by EH with changes in thermal prices.

requires strong hardware, so in this article, the Colab implementation environment is used in Google's servers [72].

To use the LSTM model to forecast time series related to uncertain parameters, like many other neural networks, the data of each time series must be divided into 3 parts: train, validation, and test. In this paper, train, validation, and test data include 70, 15, and 15% of total input data, respectively. Also, the test data were divided into two categories: test1 and test2. Test1 data includes the total data assigned to the test set other than the last 480 data, and test2 data includes test set data in addition to the last 480 data. The forecasting and scenario generation processes in Python and MATLAB have been carried out in Fig. 8.

3.6. Proposed method for scenario reduction

The previous subsections presented how to generate random scenarios for each of the uncertain parameters (including wind speed, solar radiation, and DA market price) with the proposed methods. In this paper, 500 scenarios per hour for each of the three uncertain parameters are considered. However, due to the concept of the scenario tree construction in the proposed stochastic optimization problem, the number of outcome scenarios increases greatly by combining the three mentioned parameters. Accordingly, the computational burden of the optimization problem is significantly increased. Thus, a scenario reduction method is useful to make a trade-off between computational burden and the accuracy of the problem. In general, clustering scenarios with a similar or very low probability of occurrence is an action done by scenario reduction methods. One of the effective methods in scenario reduction is the Kantorovich distance method [73]. This method has not already been used in the field of EH operation. The Kantorovich distance matrix contains the probable distance between the set of generated scenarios. The less the distance between the two scenarios, the more likely behaviors that are similar to each other have been found. When similar scenarios are found, they are assigned zero probability, and their values are added to the probability of residual scenarios. The proposed process of how to reduce the scenario by this method is shown in Fig. 9.

4. Simulation results and discussion

In this section, the optimal operation of the EH introduced in Fig. 1 in the energy markets for the DA horizon is done based on the parameters assumed in Table 2. In this paper, to do the least damage to the correlation between uncertain parameters and rich data, all historical data of uncertain parameters are selected from one place (region Varsinais_Suomi due to having wind farms and access to electricity, natural gas, heat distribution networks, and biomass fuel) and at the specified time (2005–2016) extracted from Finland [74–77]. As mentioned in Section 1, it is reasonable to assume that the proposed structure of the EH is located in Finland, given this country's circumstances.

Studies have been conducted on the 14th working and non-holiday days of January, April, July, and October to examine the optimal operation strategy of EH in different seasons with different weather conditions and energy carrier prices.

Considering that part of CHP (by ST) unit cost function model in (7) has nonlinear terms and their effect on the bidding strategy process of EH is very low, they were eliminated to increase the speed and decrease the volume of calculations. This led to the proposed EH problem in the form of a MILP problem to be solved by the CPLEX salver in the GMAS software. Simulation results obtained from the optimal operation problem of EH introduced in this paper can be divided into three categories, including scenario generation by proposed methods, outcomes

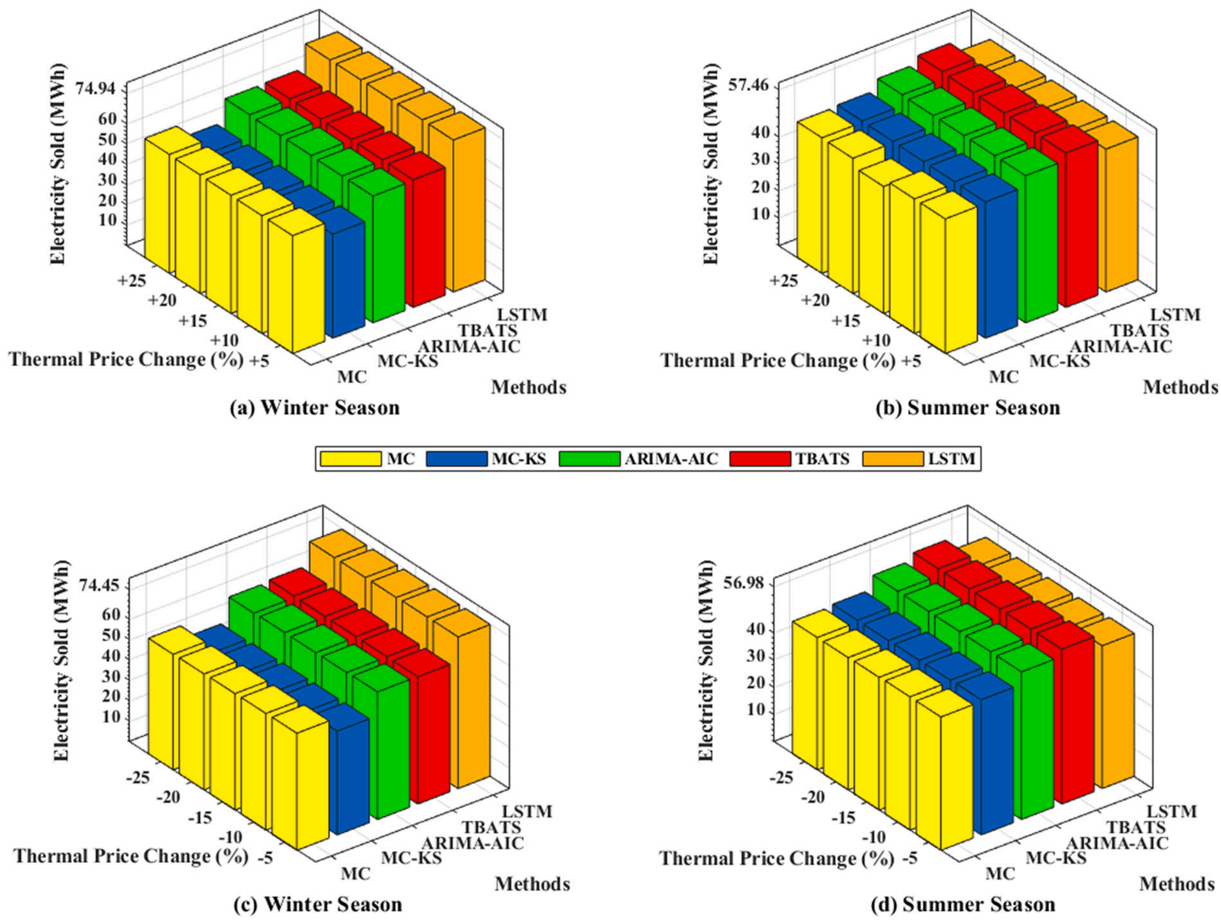

Fig. 19. Expected amounts of electricity sales from the DA market by EH with changes in thermal prices.

from the operation of EH, and sensitivity analysis.

4.1. Results of scenario generation by proposed methods

As stated previously, to model uncertain parameters such as wind speed, sunlight, and DA price, five methods with different scenario-making accuracy for four seasons have been used. Moreover, based on sensitivity analysis, 10 scenarios have been selected for reduction. In Fig. 10, as an example, 500 scenarios generated for the DA price parameter and the reduction to 10 scenarios by the Kantorovich distance method in winter have been shown.

As is evident from the shape of scenarios plotted by the classic MC method, some of the values of scenarios generated during the day and night have values very close to zero, negative, or even very high. This happened while none of Finland's historical DA prices data from 2005 to 2016 had negative values. This could be due to the inappropriate of the Normal PDF for modeling historical energy market price data. Because according to the surveys to find the best PDF out of more than 60 PDFs, the items in Table 3 have been achieved. As seen from the scenarios generated by the MC method based on the KS test in Fig. 10, the interval of scenarios has been such that it does not have negative or inappropriate values.

The scenarios produced with ARIMA-AIC and TBATS models have acted in such a way that the higher the residuals values of the best model based on the recognition of the AIC at hours, the greater the range of values occupied by them, and the lower the values in the residuals, the more confident the forecasted values are, the less range they are occupied. Moreover, in modeling performed by LSTM at different times, different areas are considered to cover uncertainty, the amount of which is related to the past prediction error values of the LSTM model.

The use of the Kantorovich distance method to reduce the scenarios generated by five methods, according to Fig. 10, has shown that the intrinsic behavior of scenarios during different hours is well summarized in 10 scenarios, which indicates that the reduced scenarios have entered the EH operation problem by maintaining their behavioral nature and the least damage to the behavior considered in the production process of their scenario has been done. To further investigate the explanations expressed about the use and logic of the MC-KS method, the best PDF along with its parameters for wind speed and sunlight in winter are expressed in Tables 4 and 5, respectively. As visible, it can be concluded that the wind speed did not follow the Weibull PDF in any of the hours. It is also shown in Table 5 that the sunlight behavior does not follow the Beta PDF. It should be noted that sunlight is available in the selected region of Finland and in winter only from 9 AM–2 PM.

4.2. Results from the operation of EH

In this subsection, the results related to the accuracy of modeling the parameters of uncertainty, the performance of the EES, and the profits from the proposed EH to the energy markets using 5 methods and in 4 seasons are presented. Table 6 shows these results. Here, to investigate the accuracy of modeling uncertain parameters using the methods expressed, the index of root mean square error (RMSE) is used. In addition to the number of charges and discharges, other factors such as the continuity of charging or discharge states and the number of status changes have been used to investigate the performance of the EES.

As shown in Table 6, in general, the accuracy of modeling uncertain parameters such as wind speed, solar radiation, and DA market price using the LSTM model has the highest value. The ARIMA-AIC and TBATS models are located at almost the same level, but they are more accurate

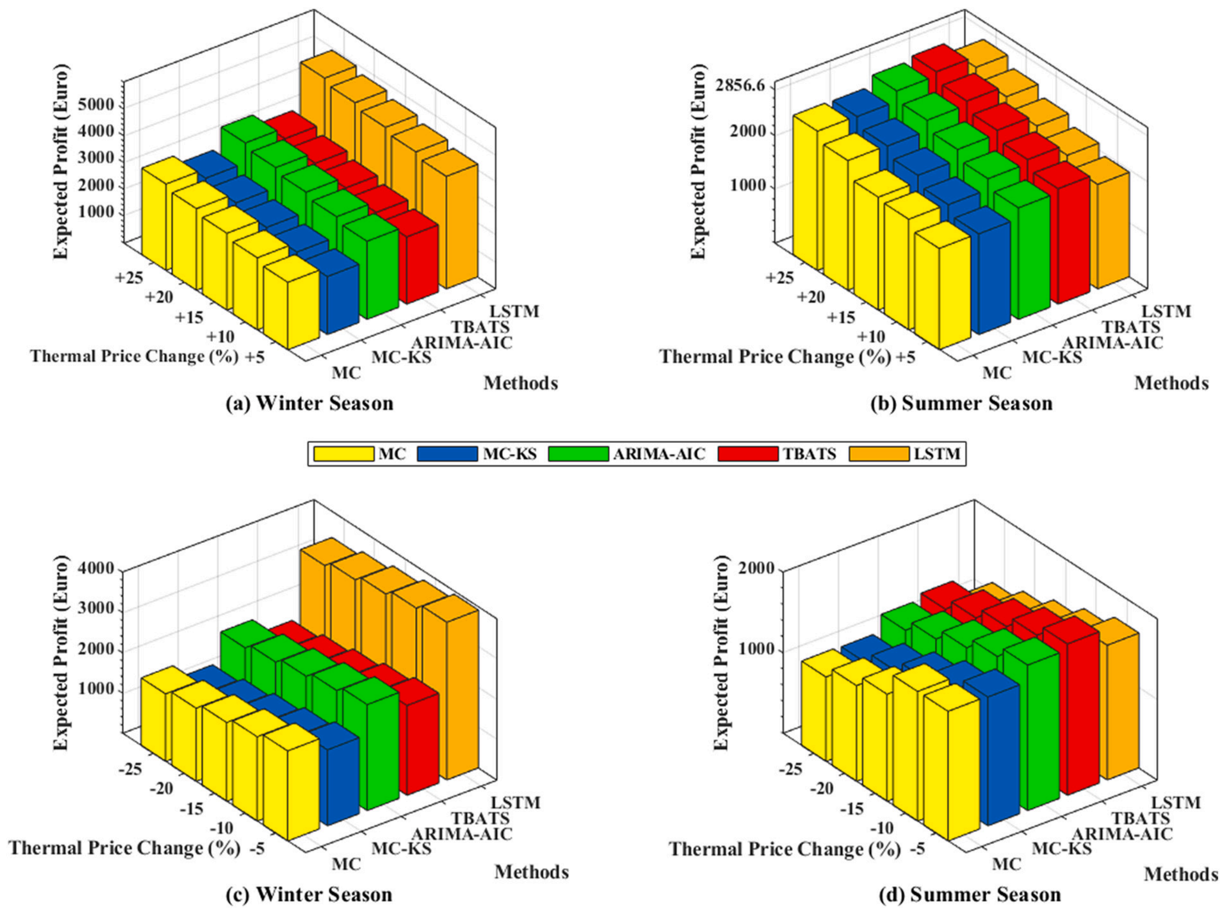

Fig. 20. Expected profits from EH operation with changes in thermal prices.

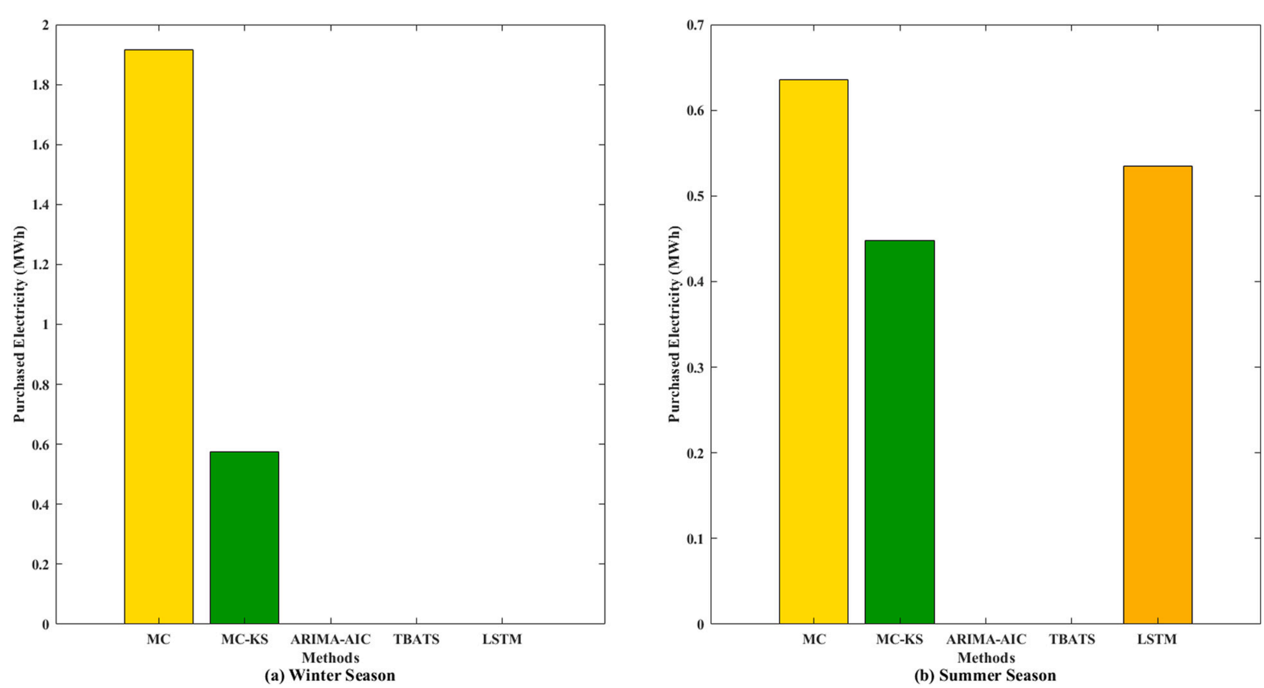

Fig. 21. Expected amounts of electricity purchase by EH with the absence of CHP (by ST) unit.

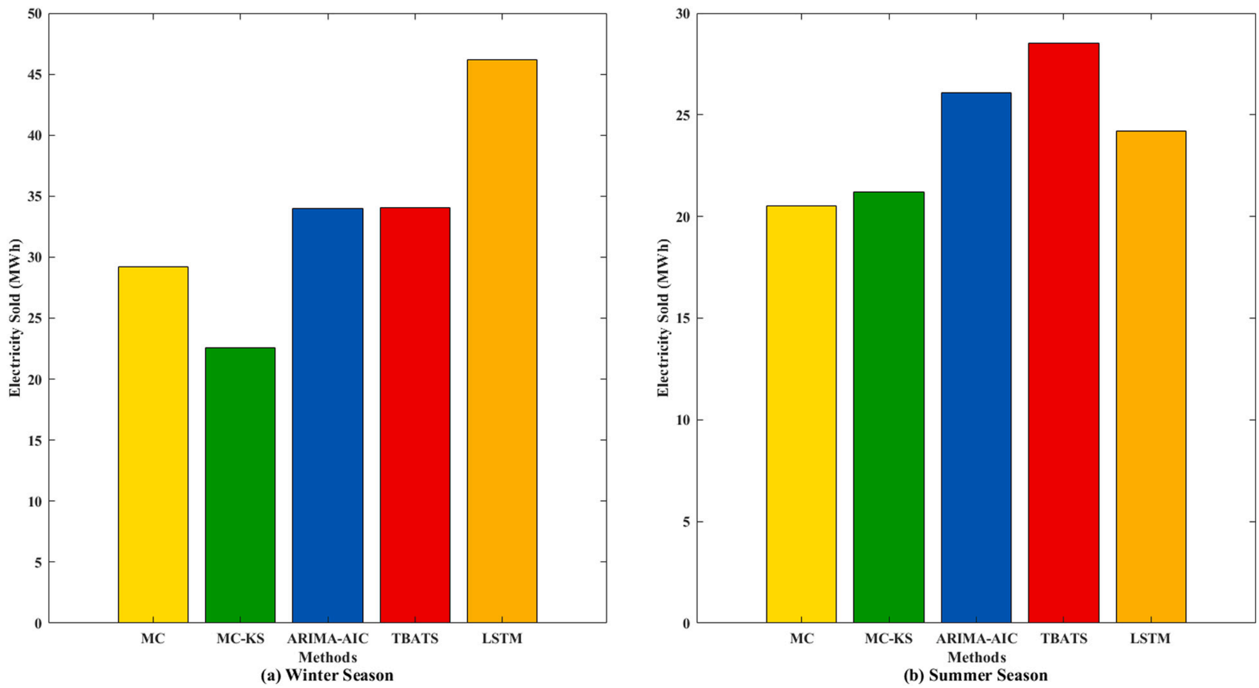

Fig. 22. Expected amounts of electricity sales by EH with the absence of CHP (by ST) unit.

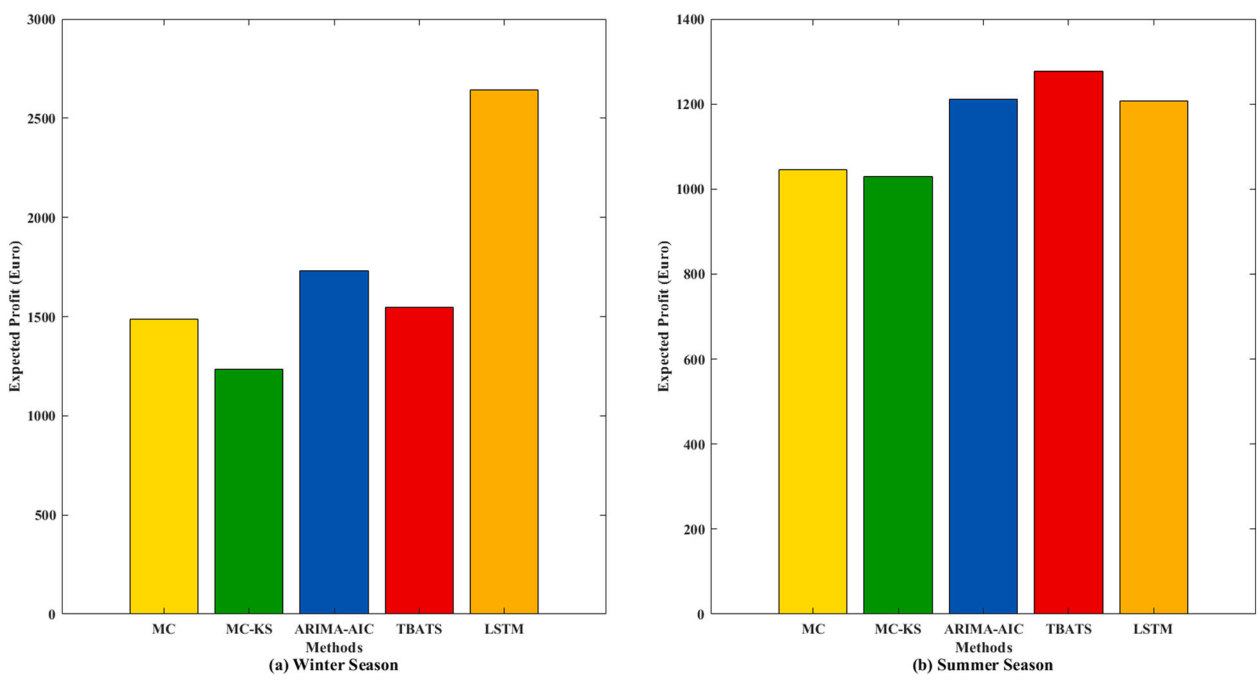

Fig. 23. Expected profits from EH operation with the absence of CHP (by ST) unit.

than the classic MC and MC-KS methods. In addition to the above, the results show that the scenarios generated by MC-KS are of higher accuracy than MC, and their values have a more rational performance; moreover, by assigning a different probability of occurrence in scenarios reduced by the Kantorovich distance matrix, this method can have better accuracy than the MC in summer and autumn.

The behavior and application of EES depend on the EH operator's decisions in the bidding process, and these decisions are a function of the set of parameters that include uncertainties and operation conditions. In this paper, the behavior of the EES has been evaluated and measured in the aspect of application during the charging and discharge process, as well as the number of change statuses. Because the operation of the EES is a function of the optimization problem, considering uncertain parameters, especially DA market price and operating conditions such as FOR in CHP (by ST), at any time and opportunity that the operation of EH is profitable, the number of charge and discharge of the EES can increase relative to its optimal rule. If there is a cost of the ESS operation, the number of status changes can also be improved.

Moreover, the expected benefit of the EH is an important criterion that can be used to compare the various uncertainty modeling methods. The LSTM model has been introduced as the best method for modeling uncertain parameters in this research. On the other hand, the behavior of EH in this method than other methods is closer to actuality. For example, in winter, the EH operator is able to obtain more 1286 EUR than the next profitable method.

Since the EH is fed by two electricity and natural gas distribution networks, the purchase and use of these two energy carriers in the operation process based on uncertainty modeling methods have been relatively different in the four seasons. In Figs. 11 and 12, the expected amounts of electricity and natural gas energy carriers are shown, respectively. According to Fig. 11, the expected amounts of electricity purchased from the DA market, which has been performed by methods with higher modeling accuracy, have been zero in all seasons. As seen in Fig. 12, by more precise modeling of uncertain parameters, the amount of natural gas energy carrier purchase could reduce in the EH.

In the proposed EH, EES plays an important role. In fact, in addition to covering wind speed behaviors, sunlight, and electricity market prices that have uncertainty, increased operation, and this element also does energy productivity. The purposes of increasing productivity are to increase the EH's flexibility and the benefits of participation in EMs, respectively. If this element is removed from the EH, more pressure should be applied to other elements of the EH. This pressure is performed according to the objective function and constraints of the operation problem. However, the biomass burner CHP unit can fill this void due to its flexible and optimal performance in producing electrical and thermal energies.

Figs. 13 and 14 exhibit the expected results of electricity and heat sold from the EH to the electricity and heat markets, respectively.

4.3. Sensitivity analysis

To further study the effect of the uncertainty modeling method on the problem of EH optimal operation strategy and to investigate the performance of the methods introduced in this paper, extensive sensitivity analyses have been performed. Due to the weather conditions in Finland, winter (very low air temperature, high wind speed, and low air light hours) and summer (moderate air temperature, low wind speed, and high daylight hours) seasons have been selected for sensitivity analysis studies.

4.3.1. Natural gas price changes

In this sensitivity analysis, by changing the gas price in steps of 5% compared to the base values, buying and selling electricity to the DA market and the expected profit from the bidding of the EH to the energy markets have been investigated. The results of these studies for different methods of modeling uncertainty are shown in Figs. 15 and 16. In these figures, the vertical axis expresses the values of cumulative daily energy. Fig. 17 also shows the expected profits from EH operation with changes in gas prices.

4.3.2. Thermal price changes

In this sensitivity analysis, instead of the price of gas, the price of thermal is changed step by step. Figs. 18 to 20 show the results of these analyses.

4.3.3. Absence of CHP (by ST) unit from EH structure

This sensitivity analysis is conducted to reduce the flexibility of the EH and investigate the effect of uncertainty modeling on the operation and its bidding to energy markets. The results of this study are shown in winter and summer as Figs. 21 to 23.

According to the analysis performed in this subsection, it can be concluded that increasing the accuracy of uncertainty modeling would have a significant impact on the dependence of the EH on the incoming electricity carrier, the sale of electricity carriers, and the amount of profit earned from participation in energy markets. The results of the third sensitivity analysis show that even by reducing the flexibility of the EH operation to participate in energy markets, the issue of uncertainty modeling has a special place. In fact, the use of appropriate uncertainty modeling methods in various network operating conditions can influence the EH operator's decision and profit.

5. Conclusion

In this article, an optimal operation framework for the participation of a sample EH with a new structure considering biomass fuel in DA electricity, natural gas, and heat energy markets has been presented. In the suggested framework, we have tried to investigate the EH operation strategy by proposing four uncertainty modeling methods, including MC-KS, ARIMA-AIC, TBATS models, as well as LSTM model of deep learning. The results presented in this paper can be divided into two general categories, including the results of modeling uncertainty parameters as well as the results of EH participation in EMs as follows.

1- Uncertainty modeling:
- In this study, the performance of the MC as a classical method was investigated. Detailed studies showed that using Weibull, Beta, and Normal PDFs for modeling behavior with the uncertainty of wind speed, sunlight, and EMs prices at all hours, seasons, and geographical conditions is a false assumption. This hypothesis eventuated in the output results of modeling having irrational behavior away from reality. This increases the risk of EH operation and greatly reduces the quality of optimal decision-making. In the sample studies, it was shown that uncertainty modeling using this method leads to negative scenarios in the DA EMs prices at almost all hours, whereas in all historical data, this has not been the case;
- The performance of the proposed MC-KS method due to the selection of the best PDF according to historical data and based on the Kolmogorov Smirnov test has much better accuracy and logical behavior than the classic MC method;
- ARIMA-AIC and TBATS-AIC were used as time series models to forecast future behavior. In addition to forecasting the scenario based on AIC, these models showed that they are working properly and are much more accurate than the common MC method and MC-KS. Using AIC as a guide in scenario generation showed that it can be a suitable leader for determining future behavior status of uncertainty parameter;
- In this research, in general, the best modeling method of uncertain parameters was done by using the LSTM model based on artificial intelligence. In this method, the main challenge was the need for a powerful computer system and increased computational time used by the Google Colab environment for this field. The scenarios generated in this method were based on the prediction errors of the past few periods and applying to Normal PDF and applying to future predictions. The results and studies showed that this method, in addition to logical behavior, had a worthy accuracy compared to time series and classical methods;
- Moreover, the scenario reduction by the Kantorovich distance method has a good quality, and the intrinsic behavior of the generated scenarios can be found in the reduced scenarios.

2- Operation of EH in EMs:
- The results showed that the quality of modeling of uncertain parameters would have a direct impact on the operator's decision-making for the future day;
- Optimal use of elements located in MES, such as EES, is an issue that improves the operational performance and reduces its depreciation. The results demonstrated that this issue is achieved by increasing the modeling accuracy;
- Increasing flexibility and better awareness of the future, reducing the risk of operation and dependence on imports of energy carriers, increasing reliability in supplying connected loads, increasing the profitability of the operation, and also satisfying users can be considered as among the issues related to increased accuracy in the operation of EHs;

- Increasing flexibility is an important issue that is not only significant in the field of EH operation but also covers an essential task in the design of energy systems;
- In the proposed EH structure, it was shown that the use of CHP units with biomass fuel could increase the flexibility of the EH energy supply in addition to increasing profits and reducing operating costs;

Finally, if the EH participates in other markets (such as intra-day and real-time markets) and the bidding strategy is expressed as a multi-stage optimization model, the effectiveness of the proposed uncertainty modeling methods can become more transparent. This issue can be considered in future works.

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