Stochastic Optimal Operation Framework of an Integrated Methane-Based Zero-CO2 Energy Hub in Energy Markets

Author(s): Tavakoli, Alireza; Karimi, Ali; Shafie-khah, Miadreza

Title: Stochastic Optimal Operation Framework of an Integrated Methane-Based Zero-CO2 Energy Hub in Energy Markets

Year: 2022

Version: Accepted manuscript

Please cite the original version:

Tavakoli, A., Karimi, A. & Shafie-khah, M. (2022). Stochastic Optimal Operation Framework of an Integrated Methane-Based Zero-CO2 Energy Hub in Energy Markets. *Electric Power Systems Research* 209, 108005. https://doi.org/10.1016/j.epsr.2022.108005

Stochastic Optimal Operation Framework of an Integrated Methane-Based Zero-CO_2 Energy Hub in Energy Markets

Alireza Tavakoli[a], Ali Karimi[a*], Miadreza Shafie-khah[b]

[a] Faculty of Electrical and Computer Engineering, University of Kashan, 6 km Ghotbravandi Blvd, postal code: 8731753153, Kashan, Iran (e-mails: alireza_tavakoli@grad.kashanu.ac.ir, a.karimi@kashanu.ac.ir),

*Corresponding Author

[b] School of Technology and Innovations, University of Vaasa, Vaasa, Finland (e-mail: miadreza.shafiekhah@uwasa.fi)

Abstract

Energy hubs (EHs) are couplers between different energy carriers in smart grids. The optimal participation of these actors in energy markets (EMs) as active and helpful actors is essential. This paper presents a new structure of methane-based EH considering biomass fuel to participate in the EMs of electricity, heat, and natural gas (NG). For this purpose, we propose an optimal bidding framework for the EH as a MILP stochastic optimization problem. The EH does not inject any CO_2 pollution into the air (zero-CO_2) and converts it into valuable methane (CH_4) fuel using the CH_4 production unit. To model uncertain parameters, electricity market price, wind speed, and solar radiation, an LSTM-based model of deep learning is proposed for scenario generation. Moreover, the Kantorovich distance matrix method reduces the generated scenarios. Since the proposed EH structure is compatible with Finland's infrastructure, simulation studies using actual data of this country are performed on selected days. The results show that in addition to profitable operation, high flexibility, environmental friendliness, and high accuracy of uncertainty modeling, the EH has no dependence on the purchase of energy carriers.

Keywords: Energy hub, Zero-CO_2, Biomass, Methane, Uncertainty modeling, Deep learning.

Nomenclature

Indices

s	Scenario index
T,t	Set and index of hours in the time horizon
j	CHP_{ST} & CHP_{ICE} units

Acronyms

MES	Multi-energy system

EH	Energy hub
DA	Day-ahead
MC	Monte Carlo
EES	Electrical energy storage
CHP_{ICE}	Combined heat and power by prime mover of the internal combustion engine
CHP_{ST}	Combined heat and power by prime mover of steam turbine
EHP	Electric heat pump
WF	Wind farm
SF	Solar farm
NG	Natural gas
FOR	Feasible operation region
PDF	Probability distribution function
LSTM	Long short-term memory

Parameters

π_s	Probability of scenarios
C_{th}, C_{NG}	Heat/NG prices
$P_{e,\min/\max}^{in/out}$	Min/max electricity input/output to/from the EH (MW)
$NG_{\min/\max}^{in/out}$	Min/max NG input/output to/from the EH (MW)
$\eta_e^{ICE}, \eta_{th}^{ICE}$	NG to electricity/heat efficiency of CHP_{ICE} (%)
$P_{e,\min/\max}^{ICE}$	Min/max amount of electricity generation by CHP_{ICE} (MW)
$P_{th,\min/\max}^{ICE}$	Min/max amount of heat generation by CHP_{ICE} (MW)
$a, b, ..., f$	CHP_{ST} cost function coefficients
$P_{ST,x}^{Bio}$	Permissible amounts of electricity generation in FOR of CHP_{ST} (MW) - x=[A,…, D]
$H_{ST,x}^{Bio}$	Permissible amounts of heat generation in FOR of CHP_{ST} (MW) - x=[A,…, D]
$CCSU(j)$	Cost coefficient of *j* unit start-up (€)
$CCSD(j)$	Cost coefficient of *j* unit shut-down (€)
M	A large number
$L(j), F(j)$	Number of hours unit *j* must be on & off
$U(0, j)$	Periods unit has been on at the beginning of the *j* unit planning horizon (hour)
$S(j)$	Periods that *j* unit has been shut-down at the hour (hour)

η_{th}^{Boiler}	NG to heat efficiency of the boiler (%)
$P_{th,\min/\max}^{Boiler}$	Min/max value of boiler heat generation (MW)
EF_{CO_2/SO_2}	CO_2/SO_2 pollution emission factor (kg/MW)
$PAPP_{SO_2}$	The permissible amount of SO_2 pollution production (kg)
N_{turb}	Number of turbines in the wind farm
P_{WT-r}	Rated wind power for wind turbine (kW)
v_r	Rated wind speed for wind turbine (m/s)
$v_{cut-in/off}$	Cut-in/cut-off speed of wind turbine (m/s)
G_0	Standard solar irradiance (W/m^2)
N_{OT}	Nominal operating temperature (°C)
T_c, T_a	Solar cell/ambient temperature (°C)
I/V_{MPP}	Max power point current/voltage (A), (V)
$K_{I/v}$	Current/voltage temperature coefficient (A/°C), (V/°C)
N_{PV}	Number of photovoltaic arrays
η_{Inv}	Electricity efficiency of the inverter (%)
η_e^{Tra}	Electricity efficiency of the transformer (%)
η^{EL}	Electricity efficiency of the electrolyzer (%)
LHV_{H2}	The lower heating value of H_2 (kJ/kg)
$N_{H2,max}^{EL}$	Max produced H_2 by electrolyzer (molar)
α, β, λ	Coefficient of H_2, CO_2 & CH_4 in methanation reaction

Variables

$Re.x$	EH revenue terms (€) - $x=[P_e^{out}, P_{th}^{out}, NG_{out}]$
$Ex.x$	EH expense terms (€) - $x=[P_e^{in}, P_{e,th}^{Bio}, NG_{in}, SU, SD]$
P_e^{out}, P_{th}^{out}	Electric/heat power sold to the EMs (MW)
P_e^{in}, NG_{in}	Total electricity/NG purchased from the EMs (MW)
C_{DA}	Day-ahead electricity market price (€/MWh)
NG_{Gen}	Total gas produced by the methane unit (MW)
NG_{ICE}	NG consumed by CHP_{ICE} (MW)
NG_{Boiler}	NG consumed by the boiler (MW)

P_e^{Bio}, P_{th}^{Bio}	Electricity/heat generated by CHP_{ST} biomass burner (MW)
P_e^{ICE}, P_{th}^{ICE}	Electricity/heat generated by CHP_{ICE} (MW)
P_{th}^{Boiler}	The heat generated by the boiler (MW)
U_{Bio}	Binary variable to on/off unit of CHP_{ST}
U_{ICE}	Binary variable to on/off unit of CHP_{ICE}
$v(j)$	Binary variable for the commitment of *j* unit
$UT(j), DT(j)$	MUT/MDT of *j* unit (hour)
$y(j), z(j)$	Binary variable to start-up/shut-down the *j* unit
$Generated_x$	Total of CO_2/SO_2 pollutions produced (kg)- $x = [CO_2, SO_2]$
H_{Gen}	H_2 produced by electrolyzer (kg)
N_{H2}^{EL}	H_2 produced by electrolyzer (molar)
NG_{Gen-in}	NG generated & injected into the EH (MW)
$NG_{Gen-out}$	NG sold (MW)
P_{EL}	Electrolyzer power consumption (MW)
U_{EL}	Binary variable to on & off of electrolyzer
P_{WF}, P_{SF}	Electric power generated by the wind/solar farm (MW)
v, G	Wind speed/Solar irradiance (m/s, W/m^2)
k_t	Clearness index
I, V	Output current/voltage of PV (A, V)

1. Introduction

Environmental compatibility, productivity, and flexibility are the most critical policy priorities of governments, organizations, and research laboratories engaged in energy systems. The use of multi-energy systems (MESs) brought advantages, including the priorities expressed for the operation of energy systems [1]. With the development of these systems in the context of smart grids and the attractiveness of profitability opportunities in the energy markets (EMs), actors have been introduced who, in addition to buying energy carriers, are also active in selling them (called prosumer) [2]. One of these actors is the energy hub (EH), which as multi-energy actors, has a function as a black-box and generally performs three types of operations, including conversion, transmission, and storage, on the energy carriers at its input [2]-[3]. One of the most important issues for the proper and profitable performance of the EH in EMs is having an optimal bidding strategy that depends on the structure and components assumed in the EH participation. In fact, proposing EH is a matter for optimal management and operation of EHs to participate in EMs.

In [4], the optimal bidding of an EH is introduced to the electricity markets, taking into account the uncertainty of electricity prices and wind power generation. The intended EH only can buy electricity and natural gas (NG) and sell electricity and heat. In [5], how to bidding a prosumer controlled by a computational device is presented. In fact, this device has a function similar to that of an agent, which also forecasts in addition to bidding. This agent seeks to maximize profits and minimize risk. Rui Li et al. in [6] modeled the participation of a sample EH in the electricity and heat markets as a mathematic program with equilibrium constraints problem and then approximated a mixed-integer linear programming (MILP) model using binary expansion technique and KKT. Researchers [7] have explored a bilevel game between energy retailers and consumers in a multi-carrier energy system and simple EHs. In [8], the solution to the interdependence of electricity and NG systems for integration with wind resources using the demand side management of EHs has been investigated.

In [9], an optimal two-level operation framework for an EH with electricity, NG, and heat energy carriers is presented. In general, the results of this study can be noted that exploiter risk aversion in future scheduling causes the costs of operation to decrease under costly scenarios. In [10], a robust framework for the optimal operation of an H_2-based micro EH is presented. In this EH, there has been pollution production, and methane-fueled behavior has been carried out as an incoming and consumable energy carrier. Researchers [11], similar to researchers [10], have presented a framework for optimal participation of an EH in terms of electric vehicles (EVs) in day-ahead (DA) and real-time (RT) electricity markets. Looking at the issue of pollution as well as dealing with methane fuel is similar to the previous reference. In this research, conditional value at risk (CVaR) was used in terms of uncertainties related to wind speed, electricity prices, and the behavior of EVs. M. Oskouei et al. in [12] introduced a planning framework for the MES, which consists of networking multiple EHs. Researchers have modeled wind speed uncertainty using the information gap decision theory (IGDT) in their problem. However, the costs associated with CO_2 emissions as well as the cost of EH operation have been mentioned as the most important cost-dependent semesters of this optimization problem. The results of this study have shown that EH networking and their operation as a MES have reduced energy costs.

An RT scheduling problem for EHs in a dynamic pricing market is presented in [13]. Moreover, the interaction of EHs is modeled as a potential game to optimize the payment of each EH to the electricity and NG markets and customer satisfaction of energy consumption.

The use of H_2, heat, and electricity storage systems and CHP and boilers has created an EH in [14] that its researchers can investigate the optimal operation of this element with multiple energy sources under uncertainty of the electricity market prices and electricity and heat loads. Also, operation limitations such as minimum uptime (MUT)/downtime (MDT) are investigated in this article. In [14], despite the carriers of electricity, heat, and H2, EH operation has been studied using IGDT to deal with the wind speed and solar radiation uncertainties. The issue of energy sharing as an alternative solution to the high cost of energy storage systems has made this issue attractive and valuable in smart grids. Bei Li et al. in [15] have presented a coordinated scheduling method for a microgrid that comprises NG, electricity, and heat energy carriers. This microgrid functions for DA scheduling like an EH.

Accordingly, in [16], a method for sharing energy between electricity and H_2 in the presence of electric storage, PV, and PH2EV vehicles has been introduced. The studies have shown that by dividing the integrated energy of H_2 and electricity, the system's total cost has decreased, and social welfare has increased. Due to the increasing extent of EHs in power systems and considering the benefits of these elements in current energy structures, in [17], a demand response model for an EH is introduced as a multi-objective optimization problem. In the presence of uncertainty parameters in such EH, the results indicate an increase in economic aspects and reduce other negative aspects. In [18], considering the advantage of reducing pollution under dependence conditions between different energy carriers, a two-level model is presented to help it consider the cost of producing CO_2, the low-carbon operation in coordination with the level of transmission and distribution integrated energy-carbon prices. The presented model allows both levels to operate independently and coordinates these two levels effectively to operate the various energy systems in larger dimensions. Alipour et al. at [19] have presented an optimal probabilistic scheduling model for operating an EH, taking into account load response plans in the form of an MINLP model. The considered uncertainties include market price and load, modeled by Monte Carlo (MC) and 2PEM methods. A chance-based optimization framework is provided to manage the optimal scheduling of an EH in the presence of electric demands, heat and cool, and renewable power generation in [20]. A robust chance-constrained optimization method is presented in this paper to model hourly demands and renewable energy generation. In [21], the operation of an EH generated by the coupling of renewable wind, solar, biogas, and other heat exchangers have been investigated. In addition to selling the generated electricity and heat, the EH under study in this paper can sell biogas. The results show that the cost of operation and the use of electrical storage increase its life. Another very influential issue in the planning and operation of the EH is the constraints related to greenhouse gas emissions.

Yuan et al. in [22] have presented the optimal scheduling framework of an EH composed of CHP units, wind turbines, energy storage systems, and moveable loads. Researchers have used gas conversion technology to control and make the most of wind renewable energy due to the uncertain nature of wind speed, demand, and electricity prices. The results have shown that the purchase of electricity from the energy market has decreased by coupling between energy carriers in this framework. As a result, the cost of operation has also taken a decreasing trend. As mentioned above, one of the roles in which the EH can be used is energy retailing. With that in mind, the authors in [23] have introduced a multi-energy retailer hybrid robust-stochastic model in terms of demand accountability plans to implement this role. This framework aims to maximize profit regarding uncertain parameters of electricity market prices and energy demands. The results of this work have shown that using EH in the role of retailer and demand response program in terms of the traditional mode will benefit the actor more.

Considering the support that biogas fuels have provided in production and use, we presented in [24] a linearized DA operation framework of an EH that provided all its internal electrical and thermal loads and participation in EMs based on the production and use of biogas fuels. In this EH, the local biomass fuel energy in that area is converted to biogas fuel by a chemical process in the digester converter. Also, uncertainties of electricity market price and solar radiation are modeled. This study showed that local production and use of biogas fuels compared to NG-dependent energy converters increase profits and flexibility, reduce pollution production, and depend on the purchase of energy carriers. One of the significant issues for an actor in operation and bidding to EMs is uncertainty modeling. The relationship between increasing the modeling accuracy of uncertain parameters and the amount of EH profit from participation in EMs is a direct relationship. The authors of this article have already proposed four new uncertainty modeling methods in [25] to improve the accuracy of estimating the behavior of uncertain parameters. The results showed that the presented methods have led to lower operating costs, reduced dependence on the purchase of energy carriers, increased flexibility and reduced the use of energy converters such as electrical storage.

Another very influential issue in the planning and operation of the EH and MES is the constraints related to greenhouse gas emissions. According to the world health organization (WHO), more than 7 million people die annually due to air pollution [26]. Such incidents on a global scale led governments to commit to reducing CO_2 emissions and other greenhouse gases; the Paris agreement, ratified on November 4, 2016, was among those measures [27]. These agreements led energy industry operators to look for ways to respond positively to these plans. One of the best cases, when RES was introduced, was supporting and developing energy converters with lower pollution levels and higher efficiency. However, considering relatively high investment costs, increasing generation uncertainty, and spending considerable time can be considered the challenges of constructing these producers.

The use of technology and engineering techniques and the complexities they bring to their beneficiaries can be a suitable or temporary solution for responding to the challenges expressed. One of these techniques, which can also be implemented in the EHs, is CH_4 production systems by accessing a suitable level of CO_2 produced in generating electricity, heat, etc., in the body of the EH. These units prevent the emissions of the bulk of greenhouse gases. However, they can also purchase and depend on the EH into the NG distribution network low or needlessly and introduce it as a producer with an acceptable production level. The main reason for such capability in this structure is the dependence between different energy carriers.

In the research that has been done so far in the field of EH operation, biomass fuel has rarely been used. This fuel has many advantages, such as low energy production cost and less dependence on weather conditions, and its use is increasing. Therefore, biomass units can reduce pollution, reduce uncertainty and increase flexibility for the participation of EHs in EMS. [28]-[29].

Table 1 summarizes the differences between this study and previous studies. In this Table, the mentioned references in terms of items such as the type of energy carriers used, non-pollution production and use of CO_2 in the energy production process, structure based on production and local use of CH_4, application of proven chemical and laboratory relationships in production CH_4, conversion of electrical energy into H_2 fuel and CH_4 as well as the characteristics of the optimization model in the operation of the EH are compared with each other.

Table 1: Comparison among the studied references and the framework of this article

Year-Ref	Energy carriers							Zero-CO_2 target	Methane-based	Methane composition coefficients	Power to H_2	Power to CH_4	Framework Stochastic
	Electricity	Thermal	NG	H_2	Biomass	Wind	Solar						
[4]-2018	✓	✓	✓	×	×	✓	×	×	×	×	×	×	✓
[5]-2018	✓	×	×	×	×	×	×	×	×	×	×	×	✓
[6]-2018	✓	✓	✓	×	×	×	×	×	×	×	×	×	✓
[7]-2018	✓	✓	✓	×	×	×	×	×	×	×	×	×	×
[8]-2020	✓	✓	✓	×	×	✓	×	×	×	×	×	×	✓
[9]-2018	✓	✓	✓	×	×	×	×	×	×	×	×	×	✓
[10]-2020	✓	✓	✓	✓	×	✓	×	×	×	×	✓	×	×
[11]-2021	✓	✓	✓	×	×	✓	×	×	×	×	×	×	✓
[12]-2021	✓	✓	✓	×	×	✓	×	×	×	×	×	×	✓
[13]-2017	✓	✓	✓	×	×	×	×	×	×	×	×	×	×
[30]-2018	✓	✓	✓	✓	×	×	×	×	×	×	✓	×	✓
[14]-2019	✓	✓	✓	✓	×	✓	✓	×	×	×	✓	×	✓
[15]-2018	✓	✓	✓	✓	×	×	×	×	×	×	✓	×	✓
[16]-2020	✓	✓	✓	✓	×	✓	✓	×	×	×	✓	×	×
[17]-2018	✓	✓	✓	×	×	✓	×	×	×	×	×	×	×
[18]-2019	✓	✓	✓	×	×	✓	×	×	×	×	×	×	×
[19]-2017	✓	✓	✓	×	×	×	×	×	×	×	×	×	✓
[20]-2020	✓	✓	✓	×	×	×	✓	×	×	×	×	×	✓
[21]-2018	✓	✓	✓	×	✓	✓	✓	×	×	×	×	×	✓
[22]-2020	✓	✓	✓	×	×	✓	×	×	×	×	×	✓	✓
[23]-2021	✓	✓	✓	×	×	×	×	×	×	×	×	✓	✓
[24]-2021	✓	✓	✓	×	✓	×	✓	×	✓	×	×	×	✓
[25]-2022	✓	✓	✓	×	✓	✓	✓	×	×	×	×	×	✓
This paper	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

From Table 1, it can be concluded that in the EH structure studied in past research, energy carriers such as electricity, heat, NG, H_2, biomass, wind, and sunlight are not simultaneously considered a stochastic optimization problem. There has been the challenge of producing CO_2 as an environmental issue in many previous works. This causes the operator to either consider restrictions on CO_2 production or pay its production penalty. However, not only does the EH as a multi-energy and environmentally friendly element distance itself from its nature, but it also reduces its flexibility and also affects its profits and offers to EMs. In none of the research mentioned, there has been no full and direct use of CO_2 produced by energy converters located in the EH for chemical composition with H_2-based on proven laboratory relationships. In fact, the actual conditions and limitations for producing CH_4 by a special converter using H_2 and CO_2 must be considered.

In summary, in previous research, it can be mentioned that the modeling of methane production has been done simply and away from the actual situation. Moreover, the CH_4 energy carrier has not been considered a pivotal fuel that could directly evaluate all EH productions and partnerships in the EM. The simultaneous conversion of electrical energy to CH_4 and H_2 is another case that can be trusted due to the high penetration of renewable energy sources in the structure of the EH and the improvement of their energy management. This issue has also been less considered in previous works.

Accordingly, in this article, the optimal operation of an EH with CHP's biomass fuel and prime mover of the steam turbine (CHP_{ST}) and NG with prime mover of the internal combustion engine (CHP_{ICE}), boiler with NG, wind and solar farms, electrolyzer and CH_4 production units, respectively, are studied in the EMs of DA electricity, heat, and NG without CO_2 emissions. Since modeling uncertain parameters, such as solar radiation, wind speed, and electricity market price is very effective in EH operation, a method based on the long-short term memory (LSTM) model of deep learning is introduced for scenario generation with higher accuracy. Also, to reduce the volume of generated scenarios, the Kantorovich distance matrix method, which had high accuracy, is applied. Moreover, Finland has been selected as a case study due to having two specific features (geographical and strategic conditions) that can increase the significant level and advantage of using the EH in these conditions as a case study and, of course, under actual conditions. The main advantages of this study are the existence of entirely different climatic conditions in different seasons, high prices of energy carriers such as NG and heat, and extensive distribution networks of heat, NG, and electricity. In addition to the cases mentioned above, the abundance of biomass-fuel CHP units in this country can be considered an attractive option.

Considering the research gaps and challenges mentioned in Table 1, the innovations of this article can be expressed as follows:

- Developing a new EH structure for modeling CH_4 production from CO_2 and H_2, taking into account biomass fuel;
- Proposing an optimal operation framework of the introduced EH to the EMs of electricity, heat, and NG, without CO_2 emissions.

In addition, considering that in our recent research in [25], the LSTM method showed a better performance than other methods (especially compared to the classic Monte Carlo), in this paper, this method is also applied to generate a scenario. Therefore, another contribution of this paper is the implementation of LSTM in the proposed EH structure.

The rest of this article is organized as follows. Section II contains the model description in which the proposed structure of the EH and the optimal strategy problem framework are presented. The scenario generation and scenario reduction to model the uncertainties are carried out by the proposed method in Section III. In Section IV, simulation results based on the actual data in Finland are presented, and finally, conclusions are given in Section V.

2. Model Description

In this section, first, a description of the proposed methane-based EH structure is presented. Then, the proposed optimal operation framework for the EH to participate in EMs is formulated as a stochastic optimization problem.

2.1. Proposed Structure of Energy Hub

In the structure of EHs since their emergence, CHP units with natural gas fuel, wind farms, and solar have been the most commonly used. Typically, the participation of EHs as vendors in the electricity and heat EMs has only been investigated. If researchers wanted to consider the issue of CO_2 pollution produced in the operation of EHs, they would have to set constraints for it. As seen in Fig. 1, the proposed EH uses biomass fuel as a valuable and environmentally friendly fuel in this paper. However, it also transfers all CO_2 produced from internal units in the proposed EH to the CH_4 production unit after collection. In the CH_4 production unit, after the chemical reaction of CO_2 with H_2 (produced from the electrolyzer unit), valuable CH_4 fuel is produced. The produced CH_4 can be sold directly to the NG market or injected into the EH. Even in the case of profitable opportunities from the sale of electricity and heat, it can be injected into the CHP unit with NG and boiler to produce heat and electricity. Also, to better understand the proposed EH structure, the single-line diagram of Fig. 1 is shown as Fig. 2.

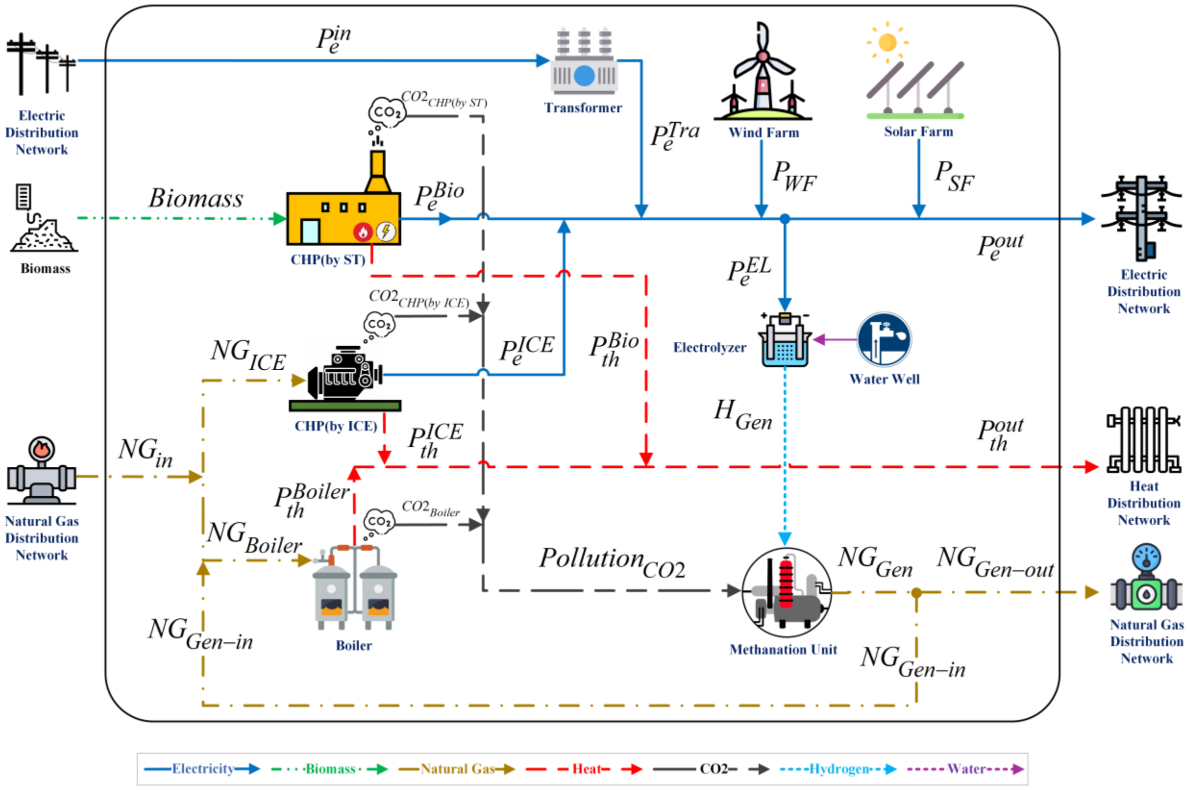

Fig. 1. Structure of the proposed EH understudy.

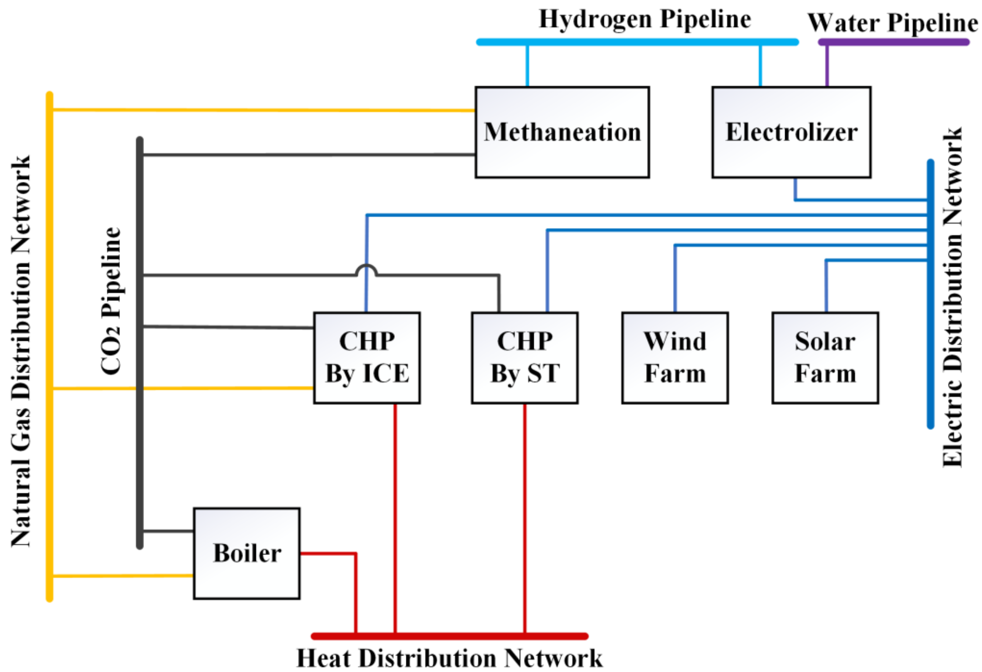

Fig. 2. Single line diagram of the proposed EH.

Many studies that have examined CH_4 production, such as references [31] and [32], have made CH_4 production very simple and without the operational and chemical challenges that exist for such a chemical reaction. This paper has tried to model methane production under conditions close to reality, based on valid articles' laboratory results.

2.2. Objective Function of Operation Problem

The objective function of the operation strategy problem is in the form of profit maximization, according to (1), and its terms are revenue from the sale of electrical energy (2), revenue from the sale of heat (3), and revenue from the sale of NG (4) are expressed. Cost terms include the cost of purchasing electricity (5), the cost of operating the CHP-ST biomass burner unit (6) [33], the cost of purchasing NG (7), the cost of setting up and shutting down the CHP_{ST} and CHP_{ICE} units (8)-(9).

$$Max\ OF\ :\ \pi_s \sum_{s=1}^{N_s}\sum_{t=1}^{24}\begin{bmatrix} Re.P_e^{out}(t,s)+Re.P_{th}^{out}(t,s)+ \\ Re.NG_{out}(t,s)-Ex.P_e^{in}(t,s)- \\ Ex.P_{e,th}^{Bio}(t,s)-Ex.NG_{in}(t,s)- \\ Ex.SU(t,s)-Ex.SD(t,s) \end{bmatrix} \tag{1}$$

$$Re.P_e^{out}(t,s)=P_e^{out}(t,s).C_{DA}(t,s) \tag{2}$$

$$Re.P_{th}^{out}(t,s)=P_{th}^{out}(t,s).C_{th} \tag{3}$$

$$Re.NG_{out}(t,s)=NG_{Gen-out}(t,s).C_{NG} \tag{4}$$

$$Ex.P_e^{in}(t,s)=P_e^{in}(t,s).C_{DA}(t,s) \tag{5}$$

$$Ex.P_{e,th}^{Bio}(t,s)=a+b.P_e^{Bio}(t,s)+c.P_e^{Bio^2}(t,s)+d.P_{th}^{Bio}(t,s)+e.P_{th}^{Bio^2}(t,s)+f.P_e^{Bio}.P_{th}^{Bio} \tag{6}$$

$$Ex.NG(t,s)=NG_{in}(t,s).C_{NG} \tag{7}$$

$$EX.SU(t,s)=CCSU_j\times y_j(t,s) \tag{8}$$

$$EX.SD(t,s)=CCSD_j\times z_j(t,s) \tag{9}$$

2.3. Constraints of Operation Problem

The EH as an energy coupling system can include several elements, each with one or more inputs and outputs. Therefore, the energy flow in the EH is significant for energy management [34], which is given in (10).

$$\underbrace{\begin{bmatrix} L_1 \\ L_2 \\ \vdots \\ L_n \end{bmatrix}}_{L}=\underbrace{\begin{bmatrix} C_{11} & C_{21} & \cdots & C_{n1} \\ C_{12} & C_{22} & \cdots & C_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ C_{1n} & C_{2n} & \cdots & C_{nn} \end{bmatrix}}_{C}\times\underbrace{\begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_n \end{bmatrix}}_{P} \tag{10}$$

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

2.3.1. Electricity and NG distribution networks

Constraints related to the input/output port of the EH with electricity and NG distribution networks are stated in (11-14). Also, for both gas and electricity networks, the limitations of the input and output energy ports are the same.

$$P_{e,\min}^{in}(t,s) \le P_{e}^{in}(t,s) \le P_{e,\max}^{in}(t,s) \tag{11}$$

$$P_{e,\min}^{out}(t,s) \le P_{e}^{out}(t,s) \le P_{e,\max}^{out}(t,s) \tag{12}$$

$$NG_{\min}^{in}(t,s) \le NG^{in}(t,s) \le NG_{\max}^{in}(t,s) \tag{13}$$

$$NG_{\min}^{out}(t,s) \le NG^{out}(t,s) \le NG_{\max}^{out}(t,s) \tag{14}$$

2.3.2. CHP by biomass fuel

The prime mover of biomass-fuel CHP units is usually a steam turbine. Due to the dependence of electricity and heat on each other, it is possible to operate in one of the two types of feasible operating regions (FORs). CHP with FOR type I is used in this paper, and its modeling is by (15)-(17). Also, for the CHP_{ST} unit, (18) and (19) are used the heat and power generation to zero [25].

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

$$P_{e}^{Bio}(t,s) - P_{ST,B}^{Bio} - \frac{P_{ST,B}^{Bio} - P_{ST,C}^{Bio}}{H_{ST,B}^{Bio} - H_{ST,C}^{Bio}} \times \left(P_{th}^{Bio}(t,s) - H_{ST,B}^{Bio}\right) \ge -(1 - U_{Bio}(t,s)) \times \mathrm{M} \tag{16}$$

$$P_{e}^{Bio}(t,s) - P_{ST,C}^{Bio} - \frac{P_{ST,C}^{Bio} - P_{ST,D}^{Bio}}{H_{ST,C}^{Bio} - H_{ST,D}^{Bio}} \times \left(P_{th}^{Bio}(t,s) - H_{ST,C}^{Bio}\right) \ge -(1 - U_{Bio}(t,s)) \times \mathrm{M} \tag{17}$$

$$0 \le P_{e}^{Bio}(t,s) \le P_{ST,A}^{Bio}(t,s) \times U_{Bio}(t,s) \tag{18}$$

$$0 \le P_{th}^{Bio}(t,s) \le H_{ST,B}^{Bio}(t,s) \times U_{Bio}(t,s) \tag{19}$$

2.3.3. CHP by NG fuel

The electricity and heat generated by CHP_{ICE} are calculated according to (20)-(21) and within the framework of the constraints specified in (22)-(23) [35].

$$P_{e}^{ICE}(t,s) = \eta_{e}^{ICE}.NG_{ICE}(t,s) \tag{20}$$

$$P_{th}^{ICE}(t,s)=\eta_{th}^{ICE}.NG_{ICE}(t,s) \tag{21}$$

$$P_{e,\min}^{ICE}\times U_{ICE}(t,s)\le P_{e}^{ICE}(t,s)\le P_{e,\max}^{ICE}\times U_{ICE}(t,s) \tag{22}$$

$$P_{th,\min}^{ICE}\times U_{ICE}(t,s)\le P_{th}^{ICE}(t,s)\le P_{th,\max}^{ICE}\times U_{ICE}(t,s) \tag{23}$$

2.3.4. Minimum up/downtime

Considering that the on/off of CHP_{ST} and CHP_{ICE} units, in addition to the cost, MUT and MDT operation limitations are used, in this paper, (24)-(27) are used for MUT modeling and (28)-(31) for MDT [36].

$$\sum_{t=1}^{L(j)}\left[1-v(t,s,j)\right]=0,\forall s,\forall j \tag{24}$$

$$\sum_{t=k}^{k+UT(j)-1}v(t,s,j)\ge UT(j)y(t,s,j),\forall s,\forall j,\forall k=L(j)+1...T-UT(j)+1 \tag{25}$$

$$\sum_{t=k}^{T}\left[v(t,s,j)-z(t,s,j)\right]\ge 0,\forall s,\forall j,\forall t=T-UT(j)+2...T \tag{26}$$

$$L(j)=Min\left[T,(UT(j)-U(0,j)v(0,j)\right] \tag{27}$$

$$\sum_{t=1}^{F_j}v(t,s,j)=0,\forall s,\forall j \tag{28}$$

$$\sum_{i=k}^{k+DT(j)-1}\left[1-v(t,s,j)\right]\ge DT(j)z(t,s,j),\forall s,\forall j,\forall k=F(j)+1...T-DT(j)+1 \tag{29}$$

$$\sum_{t=k}^{T}\left[1-v(t,s,j)-z(t,s,j)\right]\ge 0,\forall s,\forall j,\forall t=T-DT(j)+2...T \tag{30}$$

$$F(j)=Min\left\{\ T,\left[DT(j)-s(0,j)\right]\ \left[1-v(0,j)\right]\ \right\} \tag{31}$$

In (24), the initial status of the jth unit is checked that if the j unit is turned on at zero-hour, the number of fewer hours of MUT is clear, one of the conditions has been met. (25)-(26) has been used to check MUT adverbs during consecutive hours and the last $UT(j)$, respectively. Also, (27) expresses the mathematical relationship of the number of hours the j unit should be turned on. The constraints related to MDT are similarly described in (28)-(30) that also the mathematical relationship of the number of hours that the j unit should be turned off is mentioned in (31).

2.3.5. Boiler by NG fuel

Equations (32-33) are used to express the heat generated by the boiler and the constraints related to its product range, respectively [37].

$$P_{th}^{Boiler}(t,s)=\eta_{th}^{Boiler}.NG_{Boiler}(t,s) \tag{32}$$

$$P_{th,\min}^{Boiler}\le P_{th}^{Boiler}(t,s)\le P_{th,\max}^{Boiler} \tag{33}$$

2.3.6. Pollution

The highest limitation of organizations in the world is for the production of CO_2 and Sulfur dioxide (SO_2), which in this paper is used to calculate their production levels (34) and (35), respectively. Furthermore, the maximum emission of SO_2 determined by Finnish environmental law must always be observed in (36) as a condition.

Due to the use of all CO_2 produced in the EH to produce CH_4 (the methane-based zero-CO_2 EH), no amount of it is released into the environment, and accordingly, no additional constraints are defined for it.

$$Generated_{CO2}(t,s)=EF_{CO2}\times\left[P_e^{Bio}(t,s)+P_e^{ICE}(t,s)+P_{th}^{Boiler}(t,s)\right] \tag{34}$$

$$Generated_{SO2}(t,s)=EF_{SO2}\times\left[P_e^{Bio}(t,s)+P_e^{ICE}(t,s)+P_{th}^{Boiler}(t,s)\right] \tag{35}$$

$$Generated_{SO2}(t,s)\le PAPP_{SO2} \tag{36}$$

2.3.7. Solar and wind farm

Equation (37) is used to model the power generated by the wind farm [38]. Also, (38-42) to calculate the power generated from the solar farm have been applied [39]. It should be noted that, due to the relatively small capacity of the considered solar farm, the effect of partial shading conditions has been neglected.

$$P_{WF}(t,s)=\begin{cases} P_{WT-r}\times N_{turb} & v_r\le v(t,s)\le v_{cut-off} \\ \dfrac{v(t,s)-v_{cut-in}}{v_r-v_{cut-in}}\times P_{WT-r}\times N_{turb} & v_{cut-in}\le v(t,s)\le v_r \\ 0 & else \end{cases} \tag{37}$$

$$k_t(t,s)=G(t,s)/G_0 \tag{38}$$

$$T_c(t,s)=T_a(t,s)+(G(t,s)\times((N_{OT}-20)/800) \tag{39}$$

$$I(t,s)=k_t(t,s)\times(I_{MPP}+(T_c(t,s)-T_a(t,s))\times K_I) \tag{40}$$

$$V(t,s)=V_{MPP}-T_c(t,s)\times K_v \tag{41}$$

$$P_{SF}(t,s)=I(t,s)\times V(t,s)\times N_{PV}\times\eta_{Inv} \tag{42}$$

2.3.8. CH_4 production unit

CH_4 is naturally underground and is usually produced through biological and geological processes. Also, this is high-consumption gas can be obtained from the reaction $CO_2 + 4H_2 \rightarrow CH_4 + 2H_2O$. A certain amount of CO_2 and H_2 is used in this chemical reaction, producing CH_4 and water. One of the main elements for the preparation of CH_4 at a meager cost is the reduction of injectable air pollution. In this paper, CO_2 produced by CHP_{ST}, CHP_{ICE}, and boiler units are transferred to the CH_4 production unit after the screening of exhaust, each of which is dependent on pollution produced from fuel consumed and under operational constraints. CH_4 produced in the EH unit is obtained from (43) the condition of establishing constraints [40]. According to [41] and considering laboratory research in [42], a combination of 2.272 kg of CO_2 and 0.4131 kg of H_2, 0.933 kg of CH_4 is formed.

To balance the H_2 and CO_2 injected into the CH_4 production unit and obtain the zero-CO_2 EH, (44) is used. Also, since 85 to 95 percent of NG is CH_4, in this paper, it is assumed that the thermal value of CH_4 by domestic energy converters as well as NG distribution network is the same as NG. The second constituent element of CH_4 is H_2, which in this paper is caused by the chemical activity of electrolyzer in water according to (45) [43]. Moreover, the constraints related to the range of electricity consumed by the electrolysis unit (MW) and the H_2 produced (molar) are expressed in (46) and (47), respectively [43].

$$NG_{Gen}(t,s) \times \lambda = H_{Gen}(t,s) \times \alpha + Generated_{CO2}(t,s) \times \beta \quad (43)$$

$$Generated_{CO2}(t,s) = H_{Gen}(t,s) \times (\beta / \alpha) \quad (44)$$

$$N_{H2}^{EL}(t,s) = \frac{\eta^{EL} \times P_{EL}(t,s)}{LHV_{H2}} \quad (45)$$

$$P_{min}^{EL} \times U_{EL}(t,s) \le P_{EL}(t,s) \le P_{max}^{EL} \times U_{EL}(t,s) \quad (46)$$

$$N_{H2}^{EL}(t,s) \le N_{H2,max}^{EL} \times U_{EL}(t,s) \quad (47)$$

2.3.9. Balance of electricity, heat, NG

To balance and implement appropriate behavior within a specific framework of electricity generation, heat, and NG in the EH understudy, (48-51) are used, respectively.

$$P_e^{in}(t,s).\eta_e^{Tra} + P_e^{Bio}(t,s) + P_e^{ICE}(t,s) + P_{WF}(t,s) + P_{SF}(t,s) = P_e^{out}(t,s) + P_e^{EL}(t,s) \quad (48)$$

$$P_{th}^{Bio}(t,s) + P_{th}^{ICE}(t,s) + P_{th}^{Boiler}(t,s) = P_{th}^{out}(t,s) \quad (49)$$

$$NG_{in}(t,s) + NG_{Gen-in}(t,s) = NG_{ICE}(t,s) + NG_{Boiler}(t,s) \quad (50)$$

$$NG_{Gen}(t,s) = NG_{Gen-in}(t,s) + NG_{Gen-out}(t,s) \tag{51}$$

3. Uncertainty modeling

The operation problem of the EH understudy, considering that it has been proposed in the form of a stochastic optimization problem like much other research, therefore, appropriate scenarios are needed to model uncertain parameters, including solar radiation, wind speed, and the DA market price. This paper proposes the LSTM model based on forecasting to generate the scenario, and the Kantorovich distance matrix method is also presented to reduce the scenarios.

3.1. Scenario Generation

Long-short term memory (LSTM) is the name of one of the most famous models available in deep learning, proposed by Hochreiter and Schmidhuber [44]. Due to their advantages, such as memory, ability to establish a relationship between nonlinear variables, and accuracy, deep learning models paved the way for displaying their high ability against classical methods such as the ARIMA family [45].

The use of the LSTM for modeling uncertain parameters in different applications has been paid special attention in these years. One of these applications is scenario generation by it in different ways. For example, in [46], a three-step process involving a class allocation component, an LSTM-based productive element, and an automated reduction method with variance-based continuity criteria is presented. Scenario generation in this model has been done without forecasting past data and their error based on layers assigned to the neural network and determining its parameters for scenario generation. In [47], scenario generation for a hydro-PV power system has been done to correlate spatial and temporal data without forecasting past parameters. By examining input data related to southwestern China, the researchers announce the acceptable results of their approach. Based on our recent research in [25], we proposed four methods for modeling uncertainty. The results showed that the proposed LSTM method in comparison with other three methods (i.e., Monte Carlo based on Kolmogorov Smirnov test, ARIMA based on AIC statistic, and TBATS based on AIC statistic) has higher efficiency and accuracy to generate scenarios of uncertain parameters of wind speed, solar radiation, and electricity market price. Accordingly, we use the LSTM in this research.

The process of the proposed LSTM-based model for the scenario generation is shown in Fig. 3. After determining and removing the missing values from historical data sets, the total data is categorized into three categories: training (70%), validation (15%), and test (15%) are divided. Also, the test data are divided into two categories: test1 (except the last 480 data) and test2 (all data). Test1 data is used to forecast and extract forecast errors in recent days to determine the forecast error's normal probability distribution function (PDF) for the scenario generation process. one of the ways to increase the quality of machine learning is to adjust the hyperparameters of the model used. Usually, determining the best hyperparameters is very hard and, in most cases, impossible. For this reason, researchers are more looking to determine the optimal hyperparameters. We used the Grid Search method in the LSTM learning process. This method is based on applying an input to the black box, receiving the results, and examining them to reset the parameters. The apparent advantage of this method compared to other methods is that all possible combinations are examined, so high computational and processing power will be needed in some instances. However, the significant disadvantage of this method is the speed of its performance and processing. The high growth rate of search time relative to the number of parameters makes using this method in massive data practically impossible or costly.

Python and MATLAB program codes have been applied to perform all the preprocessing, forecasting, and scenario generation processes. Considering that using the LSTM model with higher speed requires robust computer hardware, Google Colab servers have been used [48].

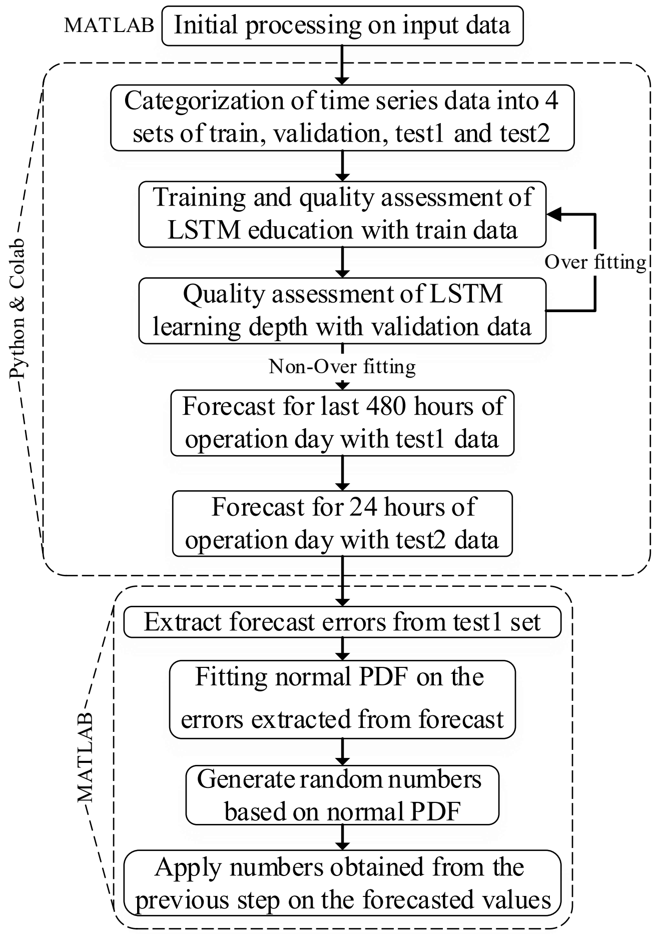

Fig. 3. Proposed scenario generation process with LSTM model.

3.2. Scenario Reduction

Usually, the scenarios generated for modeling uncertainty parameters have a large number because of the behavioral coverage of the parameter under study in different aspects. Performing calculations related to optimization problems with this large number of scenarios leads to an increase in the resolution time or even the computer's inability to perform it. For this reason, scenario reduction methods are used to transfer parameter behavior to a smaller number of scenarios. The main operation of these methods is to remove generated scenarios that are close to each other or that the probability of their occurrence is very low. The dimensions of the remaining scenarios can be up to the appropriate number. The desired basis of sensitivity analysis performed is reduced. In this paper, the Kantorovich distance matrix method is used, according to Fig. 4, as a reducer of scenarios generated by the LSTM model [49].

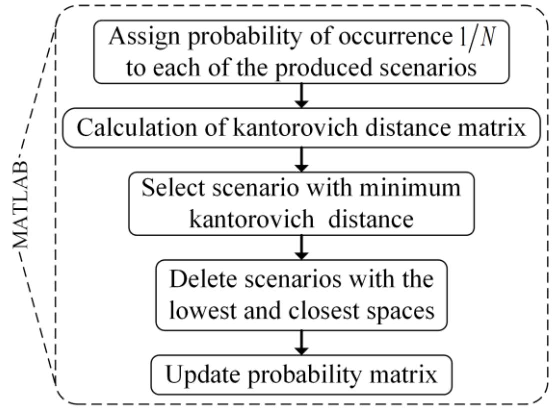

Fig. 4. Used scenario reduction process by Kantorovich distance method.

According to Fig. 4, the basis of this method is the use of a matrix in which the probable distance of the generated scenarios is placed. Like other clustering methods, this method tries to divide scenarios and generally input data into their own in different clusters. The primary purpose of this method is to determine a representative with a specific probability of occurrence from the data located in each cluster. For this purpose and determining the remaining scenarios, its probability interval is used. In general, the greater the probability distance between the two scenarios, the more likely it is to behave in the same scenario. Also, if the value is equal to zero, it means behaving quite similarly to those two scenarios. By identifying similar scenarios by this method, those scenarios are eliminated, and their probability is added to the remaining scenarios. In this way, the scenarios generated by the LSTM model are reduced by the Kantorovich distance matrix method.

4. Simulation & Discussion

In this section, the results related to the optimal operation of the EH introduced in Fig. 1, whose parameters are considered based on Table 2, are stated. Due to the reduction of damage to the correlation between uncertain parameters, all historical data for modeling these parameters from one place (region Varsinais_Suomi due to having wind farms and access to electricity, NG, heat distribution networks, and biomass fuel) and a specific time (from 2005 to 2016) have been extracted [50–53]. Also, two sample working days in winter and summer, including January 14 and July 14, 2016, have been selected for simulation studies. Considering that one of the main terms of the objective function of the optimization problem in this paper, cost function of CHP_{ST} unit and also has nonlinear components, this cost function is assumed linearly. Accordingly, the EH operation problem was modeled as a MILP optimization problem and solved using the CPLEX solver in GAMS. This section presents the results in three sub-sections, including modeling the uncertain parameters, the results of EH optimal operation to EMs, and three sensitivity analyses for completing the studies.

Table 2: EH parameters understudy

Parameter	Value	Parameter	Value
η_{e}^{Tra}	0.98	η^{EL}	0.75
$P_{e,min/\max}^{Tra}$	0 ,4	N_{El}	500
$NG_{min/\max}$	0 ,5	LHV_{H2}	240
$P_{ST,A,B,C,D}^{Bio}$	1.5, 1.2, 0.3, 0.5	$N_{H2,max}^{EL}$	1562.5
$H_{ST,A,B,C,D}^{Bio}$	0, 2.5, 1, 0	$N_{turb/PV}$	10, 4000
b, c, e	36.0012, 65, 0.6002	P_{WT-r}	200
$\eta_{e/th}^{ICE}$	0.35, 0.4	$v_{cut-in/off}$	3.5, 25
$P_{e,min/\max}^{ICE}$	0.05, 0.7	v_{r}	11.5
$P_{th,min/\max}^{ICE}$	0.1, 0.5	G_{0}	1000
$CCSU_{j}, CCSD_{j}$	5, 5	N_{OT}	4000
UT_{ST}, UT_{ICE}	2, 1	I_{MPP}	7.35
DT_{ST}, DT_{ICE}	2, 1	V_{MPP}	30.5
U_{ST}^{0}, U_{ICE}^{0}	1, 1	K_{I}	0.0003
η_{th}^{Boiler}	0.85	K_{v}	0.0027
$P_{th,min/\max}^{Boiler}$	0, 0.8	η_{Inv}	0.88
$EF_{CO2,ST/ICE/Boiler}$	500, 550, 450	$C_{NG,\ winter}$	34
$EF_{SO2,ST/ICE/Boiler}$	0.003, 0.0035, 0.0025	$C_{NG,\ Summer}$	34
$PAPP_{SO2}$	500	$C_{th,\ winter}$	38
α, β, λ	0.4131, 2.272, 0.933	$C_{th,\ Summer}$	38

4.1. Scenarios Generated and Reduced

The process described in Fig. 3 has been used to generate scenarios using the LSTM model. To adequately cover the behavioral aspects of uncertain parameters, 500 scenarios were generated for each parameter. After this step, 500 scenarios were reduced to 10 using the Kantorovich distance method and its stated method in Fig. 4. It should be noted that selecting 10 scenarios to reduce the generated scenarios based on sensitivity analysis and background studies has been a suitable option.

As examples in winter, the generated and reduced scenarios with actual and forecasted values for wind power, solar power, and DA market price parameters are shown in Fig. 5 and Fig. 6. The generated scenarios have not exceeded a specific range and have followed the forecasted values with high accuracy. Also, the reduced scenarios summarize the inherent behavior of the generated scenarios, indicating the appropriate performance of this method.

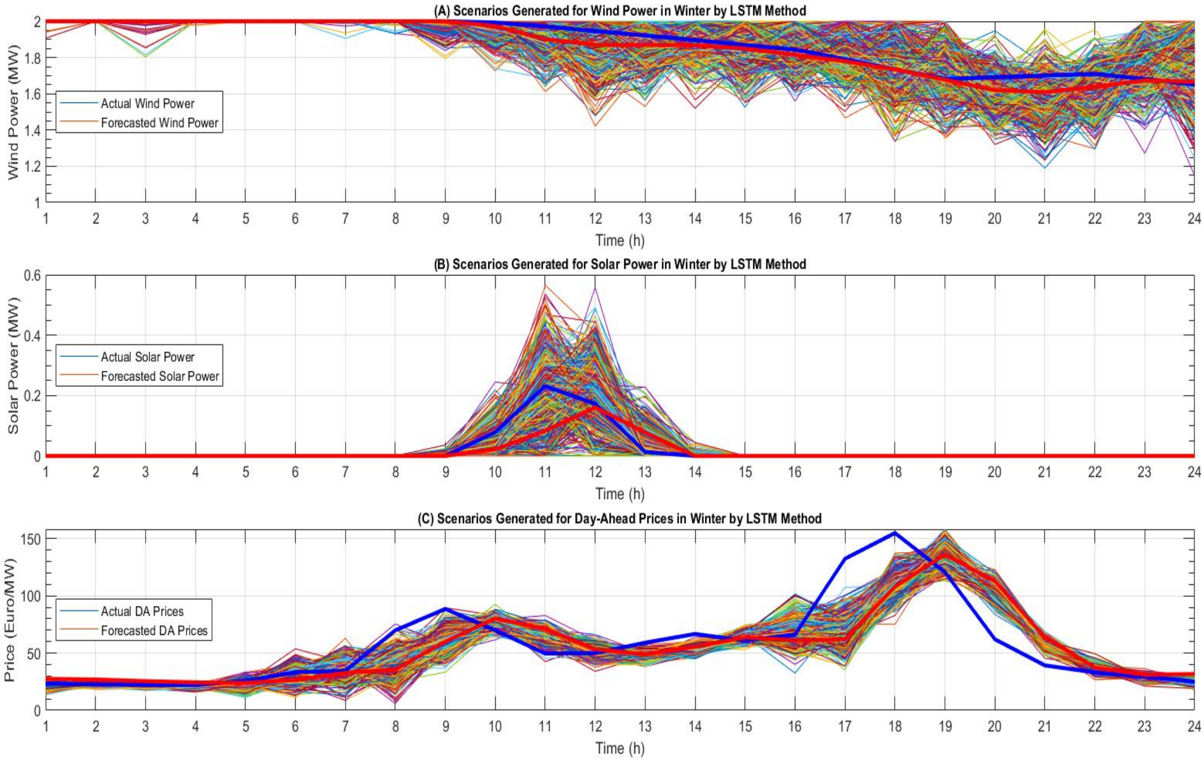

Fig. 5. Generated scenarios for uncertain parameters using the LSTM in winter with actual and forecasted values.

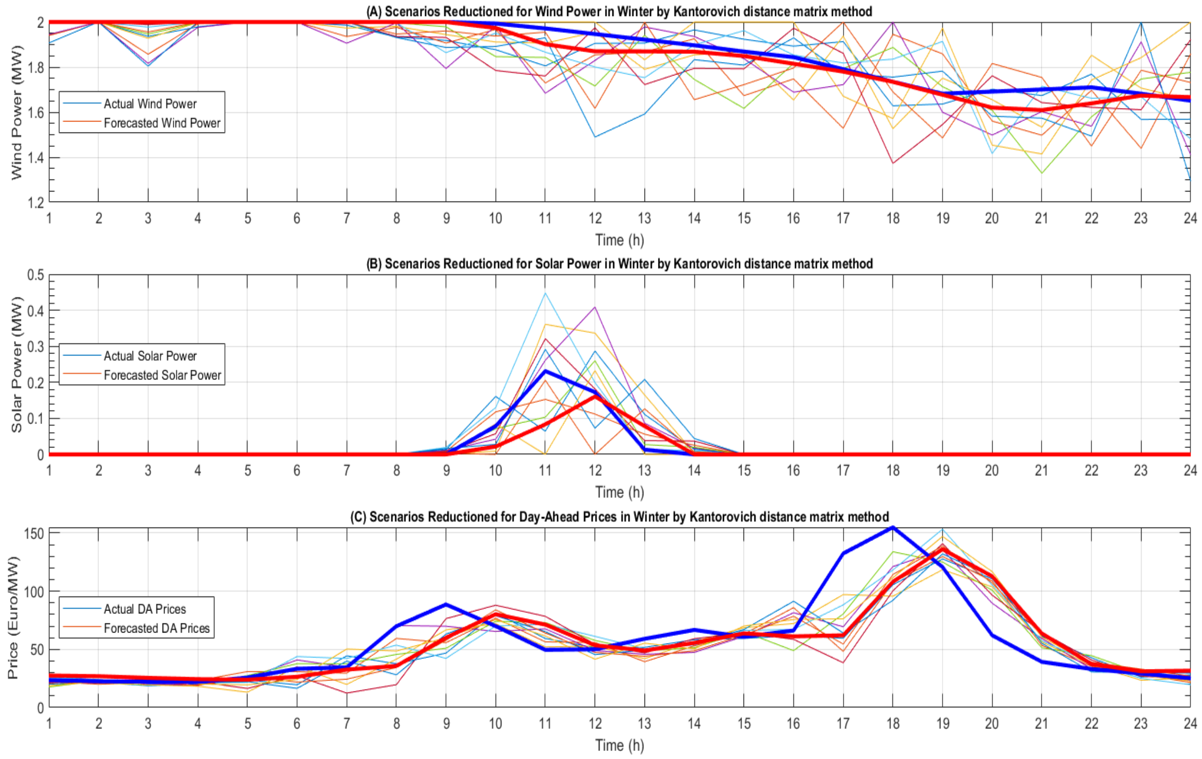

Fig. 6. Reduced scenarios for uncertain parameters using the Kantorovich distance method in winter with actual and forecasted values.

4.2. Results from the Operation of EH and Comparative Studies

Table 3 and Fig. 7 show the expected results of the proposed EH operation during the 24 hours of selected days in the electricity, heat, and NG markets. Table 3 shows the operation results of this EH, including the benefits of operation and exchange of electricity, heat, and NG carriers and the amount of CO_2 injection into the air. In this section, the behavior of two other structures is also investigated for a more thorough investigation and a better understanding of the benefits of EH structure behavior proposed in this research. Accordingly, Table 3 includes the results of the operation of three types of case studies as follows:

- Case study 1: The structure of the proposed EH in this research;
- Case study 2: The EH structure proposed in this study without considering CH_4 production unit and H_2 production; and
- Case study 3: Structure of the second case study without regard to biomass fuel and CHP_{ST} unit.

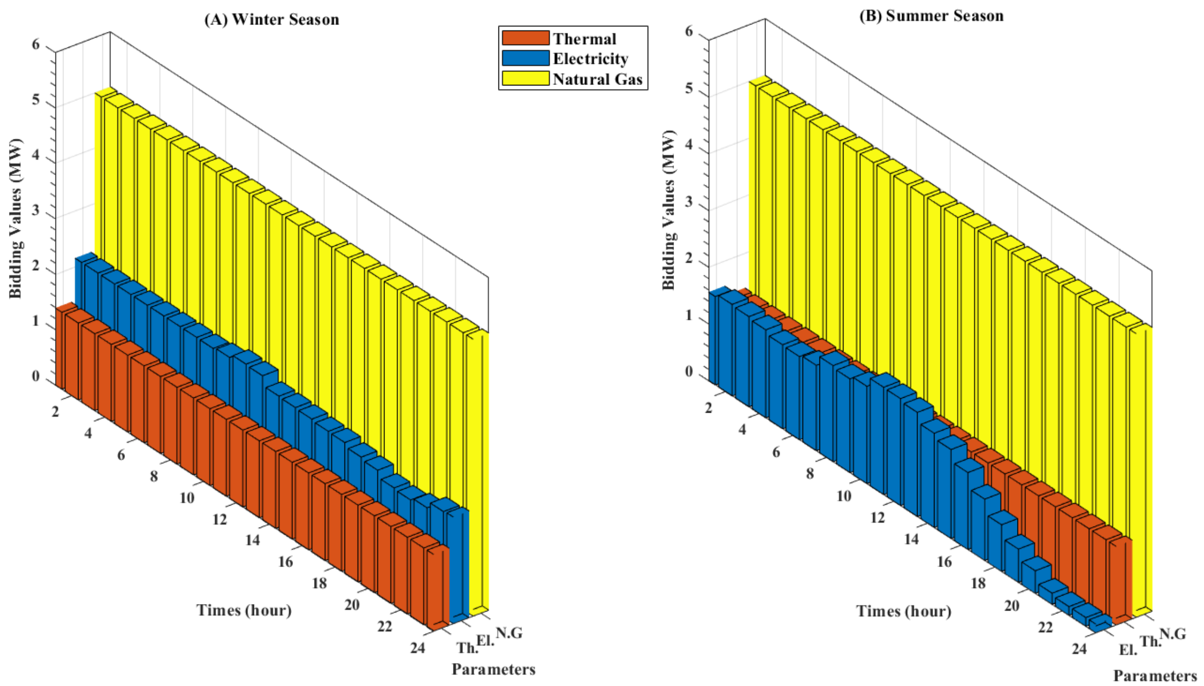

Fig. 7. The results of EH operation to EMs in winter and summer.

Table 3: The results of the proposed EH operation and its comparison with two different structures

	Structure	Purchased electricity (MWh)	Sold electricity (MWh)	Purchased NG (MWh)	Sold thermal (MWh)	CO_2 injected to air (kg)	Operation profit (€)	Revenue from EMs (€)		
								Electricity	Thermal	NG
Winter Season	Case study 1	0	49.073	0	33.327	0	6077.333	2564	1266	4080
	Case study 2	0	79.903	16.286	66.514	17535	3645.824	4304	2527	-553
	Case study 3	0	51.106	16.294	6.517	3136.6	2467.630	2773.957	247.668	-553
Summer Season	Case study 1	0	29.589	0	33.327	0	4511.379	998	1266	4080
	Case study 2	0	57.266	7.278	62.911	15801	1428.405	1918	2390	-247
	Case study 3	0	28.466	7.278	2.911	1401	836.944	973.771	110.625	-247

The results show that the operating income of the proposed EH in this paper, alone from the NG market on the selected winter and summer days, constitutes 51% and 61% of the total income of the proposed EH, respectively. However, this EH does not inject any CO_2 contamination into the air and spends all of it producing CH_4. Also, EH does not need to buy electricity carriers and NG from networks and therefore does not depend on energy distribution networks to purchase energy.

On the contrary, it can be concluded that the removal of biomass fuel, local CH_4 production, and the use of CO_2 produced to convert into more valuable energy lead to a great increase in the purchase of electricity and NG. Also, the amount of profit is significantly reduced, and the beneficiary is faced with a significant amount of pollution that you have to manage during the operation process. All of this indicates the valuable function of the proposed model and adapts to the environment and economic conditions.

Considering that the proposed optimization problem consists of three main parts, including scenario generation, scenario reduction, and determination of bidding decision variables, the time spent on the computer system with the specifications of Core i5 7th Gen and RAM 6 GB is shown in Table 4. According to this Table and the EH DA operation, the calculation time for each sector, i.e., scenario generation and reduction and determination of EH decision variables, is relatively short. Such processing speed makes the proposed framework for using a suitable and fast operator.

Table 4: Simulation time (sec.) for calculations of the proposed model

		Software	Processing environment	Winter season	Summer season
Scenario generation	Wind speed	Python & MATLAB	Google Colab and PC	175	177
	Sunlight			178	176
	Market price			172	174
Scenario reduction	Wind speed	MATLAB	PC	65	62
	Sunlight			70	65
	Market price			59	61
Determining decision variables		GAMS	PC	31	28

4.3. Sensitivity Analysis

In the following, three sensitivity analyses are presented to investigate the impact of EMs price, CO_2 pollution, and limitations related to the NG network port connected to the EH on the behavior and expected profit gained from the EH operation.

4.3.1. Price of Energy Carriers

In this sensitivity analysis, the effect of positive and negative changes in market price in steps of 5% to the base value of energy carriers including electricity, heat, and NG on the operation profit result of the EH has been investigated. As seen from Fig. 8, with energy carriers' prices rising or falling, the EH's profit reaction to these changes would be almost linear. In other words, by increasing or decreasing each energy carrier's price, the profit earned by the EH also increases or decreases, respectively.

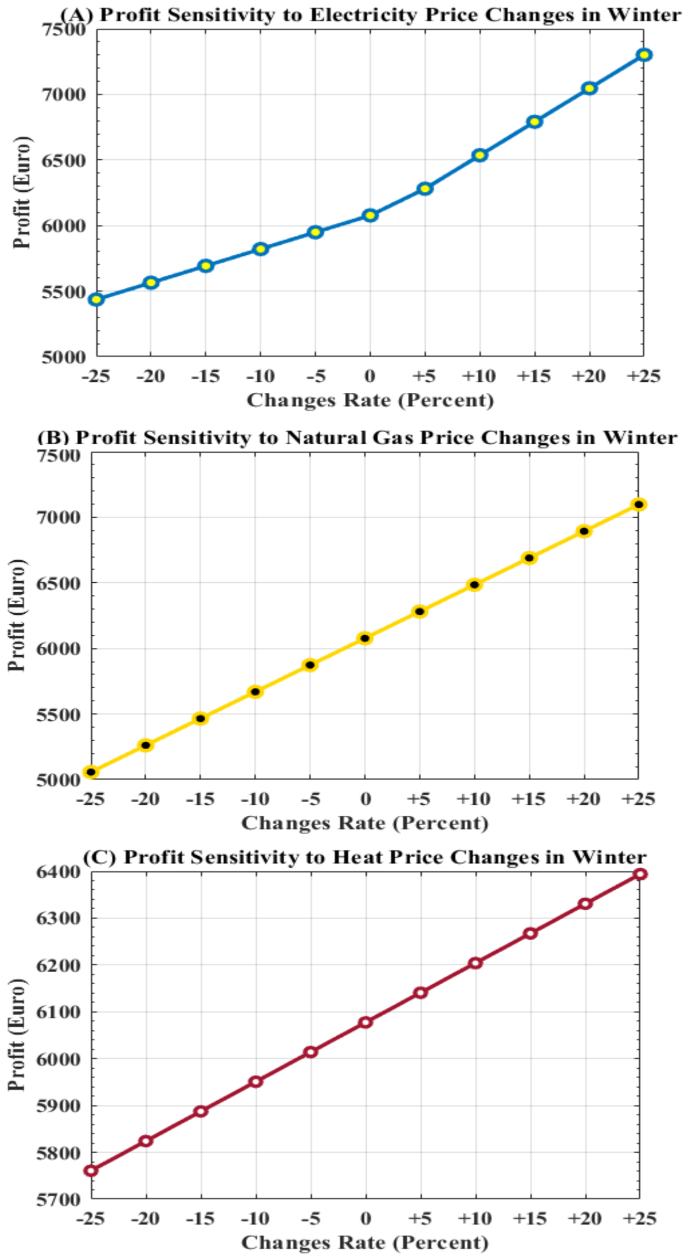

Fig. 8. Results of EH operation profit in the sensitivity analysis of EMs prices.

4.3.2. Emission Factor of CO_2

Considering that CH_4 production in this EH depends on the specific chemical composition of CO_2 and H_2, in this part of sensitivity analysis, the amount of CO_2 produced by CHP units with biomass and NG fuels as well as the boiler unit with NG fuel has been studied. Changes in CO_2 production volume from the mentioned units have been performed by applying 5% incremental and decreasing steps compared to the primary factor values. The results of this analysis, shown in Fig. 9, mean that the total pollution rate increases by increasing the CO_2 emission factor. As a result, the EH is forced to increase the volume of H_2 produced to comply with the operational constraints. Finally, because the EH cannot sell more than 5MW to the NG network, it injects some of the produced gas levels into the domestic units, which causes the EH's profits to be withdrawn from the well-being.

On the other hand, the electricity demand by the electrolyzer increases, which reduces electricity sales and profits. Such a relationship can be expressed between the mentioned parameters regarding reducing CO_2 pollution coefficients. The increasing and decreasing behavior of this analysis has a linear relationship with the profit of the EH.

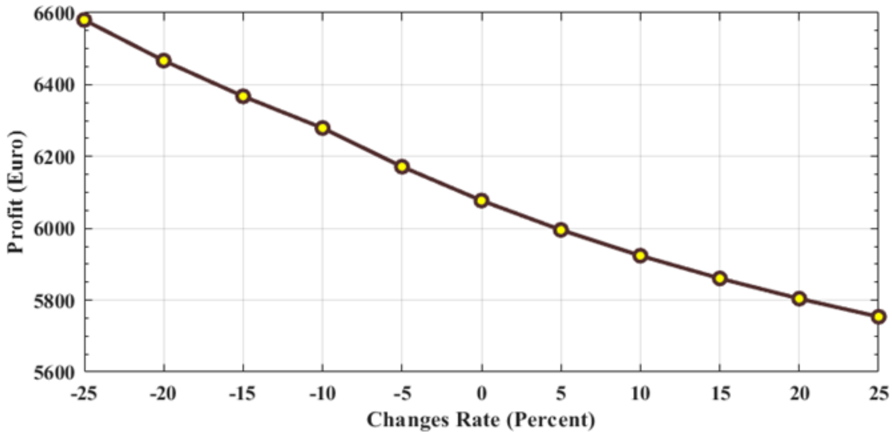

Fig. 9. Results of EH operation profit in the sensitivity analysis of CO_2 emission.

4.3.3. Port Restrictions of NG

Investigating the impact of buying/selling restrictions from/to the NG network is the third analysis studied due to the impact on the EH operation results in energy carriers exchanges. In this analysis, the NG network port's capacity connected to the EH has been accompanied by a 1.5 MW step increase, with the results of exchanges related to the electricity, heat, and NG network along with CO_2 pollution produced and the operating profits of winter are shown in Fig. 10. By changing the structure mentioned in this sensitivity analysis, the EH at each stage is faced with an increase in the sales capacity of NG, which attracts the operator's focus to make more profits towards increasing the sales of this energy carrier. To implement such a decision, the CH_4 generating elements, including H_2 and CO_2, increase production so that the biomass-burning CHP unit has faced an increase in production at each stage. However, in the last stage, the production of NG-burning CHP decreased. The electrolyzer power demand increased, leading to a decrease in electricity sales to the DA power market.

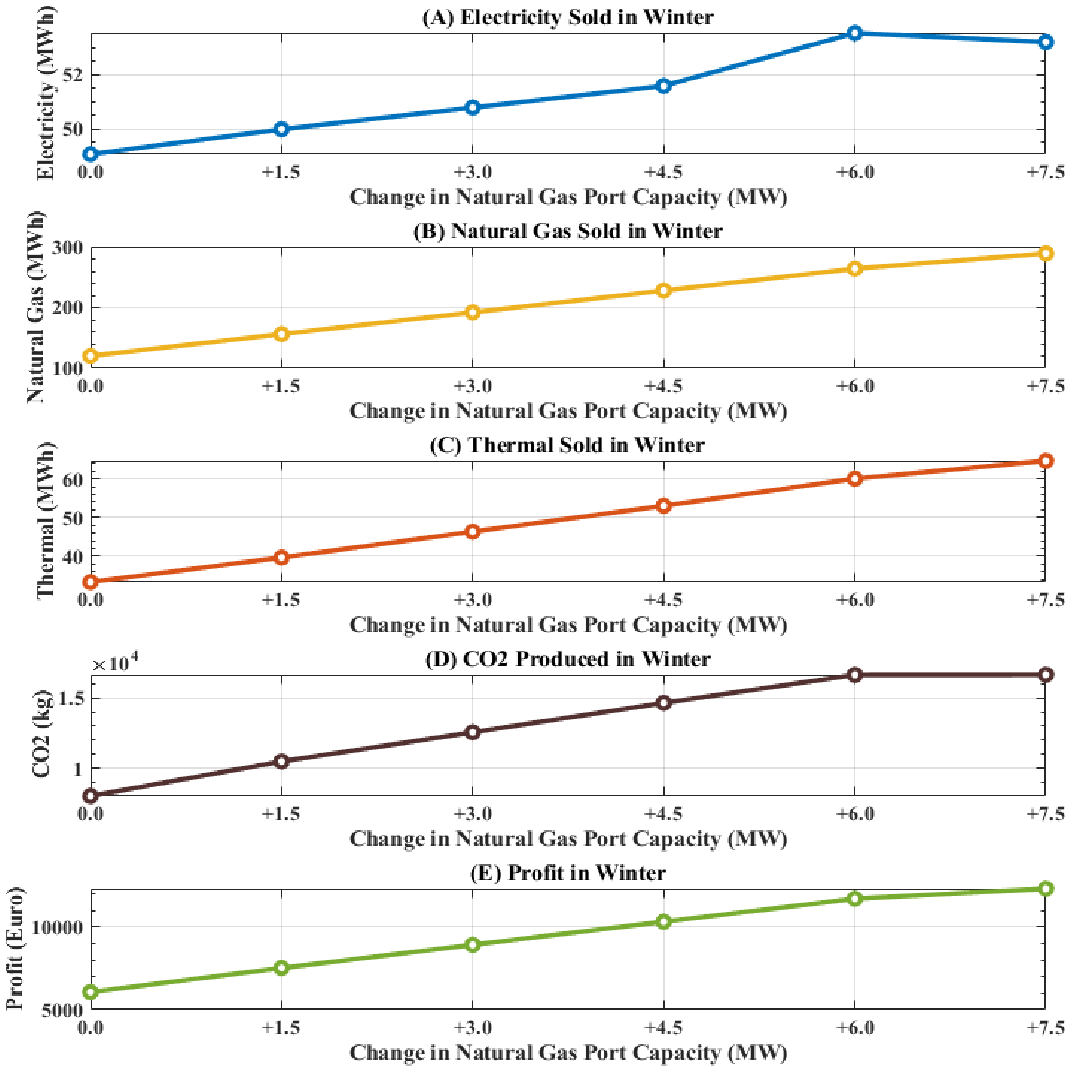

Fig. 10. Results of EH operation profit in the sensitivity analysis of NG port restrictions.

The presence of scalable capability in the presented EH is another valuable and important point that can be concluded in different parts of this research simulation. The main reason for such an advantage in the proposed operation framework is the complete linear structure of the optimization problem.

5. Conclusion

In this article, an optimal operation framework of an EH with a new and attractive structure has been proposed to the electricity, heat, and NG markets along with considering uncertain parameters, including solar radiation, wind speed, and DA power market price. One of the most important features of the presented EH is CH_4 production, CO_2 emissions prevention, and biomass fuel as a usual and clean fuel. Moreover, an LSTM based model of deep learning has been presented to generate scenarios and model the behavior of uncertain parameters. The results showed that this method has high accuracy and has generated scenarios close to the behavioral reality of parameters. Also, the reduced scenarios of the Kantorovich distance method have been very accurate and able to follow the initial scenarios' behavior.

The results of the optimal operation of the EH to EMs showed the EH has no dependence on the purchase of electricity and NG from distribution networks, and it has also been able to become a significant player in the sale of electricity, heat, and NG. Such flexibility and increased energy exchange power can be considered the placement of biomass-burning CHP units and CH_4 production. The EH's profits in the EMs showed how attractive and profitable the operation of such a unit could be. This profitability is due to the cheap or cost-free of one of the main elements of CH_4 production, i.e., CO_2, in which all CO_2 EHs produced from biomass-burning CHPs, NG burners, and boilers were transferred to the CH_4 production unit. In addition to this profitability, the compatibility of such an EH with the environment showed that no CO_2 was injected into the air, which could also result in the sale of pollution permits that would increase the profits of the EH. Sensitivity analyses showed that the EH as a player who couples different energy carriers together could bring many advantages in productivity, which occurs provided that the constraints related to the EH are also met. For example, in this paper, it was shown that by increasing the volume of CO_2 production as a CH_4-making supplement, the EH's profits would not increase because this occurs due to the limitations of energy distribution networks. In this study, to further investigate the performance of the proposed energy hub, we considered two other structures. These two structures are formed by eliminating the methanation unit and removal of biomass fuel, respectively. One of the most important results of this study can be a 40% and 60% increase in winter and 59% and 82% profit of the proposed model compared to the other two structures in summer. The existence of scalability features and reliable results for changing the size dimensions of the presented framework is another advantage of the proposed model.

According to the presented results, finally, the following points can be considered in order to implement the proposed structure in practical applications:

- Existence and proper access of EH to electricity, heat, and NG distribution networks as well as biomass fuel locally in the study location;
- Access to reliable and comprehensive weather information and data on geographical location and EMs;
- Lack of restrictive laws for the participation of multi-energy actors as well as the conversion of H_2, CO_2, and other energy carriers into valuable CH_4 fuels;
- Observing safety rules in the design and operation of converters during the process of energy conversion; and

- Paying attention to the chemical reaction capacity of the CH_4 converter, the existence of constant pressure and temperature of NG, heat, CO_2 produced from the conversion of NG to other energy carriers and H_2 fuel.

References

[1] M. Manfren, B. Nastasi, D. Groppi, D.A. Garcia, Open data and energy analytics-An analysis of essential information for energy system planning, design and operation, Energy. 213 (2020) 118803.

[2] R. Zafar, A. Mahmood, S. Razzaq, W. Ali, U. Naeem, K. Shehzad, Prosumer based energy management and sharing in smart grid, Renew. Sustain. Energy Rev. 82 (2018) 1675–1684.

[3] M. Mohammadi, Y. Noorollahi, B. Mohammadi-Ivatloo, H. Yousefi, Energy hub: from a model to a concept–a review, Renew. Sustain. Energy Rev. 80 (2017) 1512–1527.

[4] V. Davatgaran, M. Saniei, S.S. Mortazavi, Optimal bidding strategy for an energy hub in energy market, Energy. 148 (2018) 482–493.

[5] R. Ghorani, M. Fotuhi-Firuzabad, M. Moeini-Aghtaie, Optimal bidding strategy of transactive agents in local energy markets, IEEE Trans. Smart Grid. 10 (2018) 5152–5162.

[6] R. Li, W. Wei, S. Mei, Q. Hu, Q. Wu, Participation of an energy hub in electricity and heat distribution markets: An MPEC approach, IEEE Trans. Smart Grid. 10 (2018) 3641–3653.

[7] S. Khazeni, A. Sheikhi, M. Rayati, S. Soleymani, A.M. Ranjbar, Retail market equilibrium in multicarrier energy systems: a game theoretical approach, IEEE Syst. J. 13 (2018) 738–747.

[8] C. Shao, Y. Ding, P. Siano, Y. Song, Optimal Scheduling of the Integrated Electricity and Natural Gas Systems Considering the Integrated Demand Response of Energy Hubs, IEEE Syst. J. (2020).

[9] M.H. Shams, M. Shahabi, M.E. Khodayar, Risk-averse optimal operation of Multiple-Energy Carrier systems considering network constraints, Electr. Power Syst. Res. 164 (2018) 1–10.

[10] A. Mansour-Saatloo, M. Agabalaye-Rahvar, M.A. Mirzaei, B. Mohammadi-Ivatloo, M. Abapour, K. Zare, Robust scheduling of hydrogen based smart micro energy hub with integrated demand response, J. Clean. Prod. 267 (2020) 122041.

[11] A. Najafi, A. Tavakoli, M. Pourakbari-Kasmaei, M. Lehtonen, A risk-based optimal self-scheduling of smart energy hub in the day-ahead and regulation markets, J. Clean. Prod. 279 (2021) 123631.

[12] M.Z. Oskouei, B. Mohammadi-Ivatloo, M. Abapour, M. Shafiee, A. Anvari-Moghaddam, Techno-economic and environmental assessment of the coordinated operation of regional grid-connected energy hubs considering high penetration of wind power, J. Clean. Prod. 280 (2021) 124275.

[13] S. Bahrami, M. Toulabi, S. Ranjbar, M. Moeini-Aghtaie, A.M. Ranjbar, A decentralized energy management framework for energy hubs in dynamic pricing markets, IEEE Trans. Smart Grid. 9 (2017) 6780–6792.

[14] S.M. Moghaddas-Tafreshi, M. Jafari, S. Mohseni, S. Kelly, Optimal operation of an energy hub considering the uncertainty associated with the power consumption of plug-in hybrid electric vehicles using information gap decision theory, Int. J. Electr. Power Energy Syst. 112 (2019) 92–108.

[15] B. Li, R. Roche, D. Paire, A. Miraoui, Coordinated scheduling of a gas/electricity/heat supply network

considering temporal-spatial electric vehicle demands, Electr. Power Syst. Res. 163 (2018) 382–395.

[16] Y. Tao, J. Qiu, S. Lai, J. Zhao, Integrated Electricity and Hydrogen Energy Sharing in Coupled Energy Systems, IEEE Trans. Smart Grid. 12 (2020) 1149–1162.

[17] M. Majidi, K. Zare, Integration of smart energy hubs in distribution networks under uncertainties and demand response concept, IEEE Trans. Power Syst. 34 (2018) 566–574.

[18] Y. Cheng, N. Zhang, B. Zhang, C. Kang, W. Xi, M. Feng, Low-carbon operation of multiple energy systems based on energy-carbon integrated prices, IEEE Trans. Smart Grid. 11 (2019) 1307–1318.

[19] M. Alipour, K. Zare, M. Abapour, MINLP probabilistic scheduling model for demand response programs integrated energy hubs, IEEE Trans. Ind. Informatics. 14 (2017) 79–88.

[20] M.S. Javadi, M. Lotfi, A.E. Nezhad, A. Anvari-Moghaddam, J.M. Guerrero, J.P.S. Catalão, Optimal operation of energy hubs considering uncertainties and different time resolutions, IEEE Trans. Ind. Appl. 56 (2020) 5543–5552.

[21] B. Zhou, D. Xu, C. Li, C.Y. Chung, Y. Cao, K.W. Chan, Q. Wu, Optimal scheduling of biogas–solar–wind renewable portfolio for multicarrier energy supplies, IEEE Trans. Power Syst. 33 (2018) 6229–6239.

[22] Z. Yuan, S. He, A. ad Alizadeh, S. Nojavan, K. Jermsittiparsert, Probabilistic scheduling of power-to-gas storage system in renewable energy hub integrated with demand response program, J. Energy Storage. 29 (2020) 101393.

[23] M.Z. Oskouei, M.A. Mirzaei, B. Mohammadi-Ivatloo, M. Shafiee, M. Marzband, A. Anvari-Moghaddam, A hybrid robust-stochastic approach to evaluate the profit of a multi-energy retailer in tri-layer energy markets, Energy. 214 (2021) 118948.

[24] A. Tavakoli, A. Karimi, M. Shafie-Khah, Linearized Stochastic Optimization Framework for Day-Ahead Scheduling of a Biogas-Based Energy Hub Under Uncertainty, IEEE Access. 9 (2021) 136045–136059.

[25] A. Tavakoli, A. Karimi, M. Shafie-khah, 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, J. Energy Storage. 51 (2022) 104344.

[26] Air pollution, (n.d.). https://www.who.int/news-room/air-pollution (accessed March 13, 2021).

[27] The Paris Agreement | UNFCCC, (n.d.). https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement (accessed March 13, 2021).

[28] E. Mboumboue, D. Njomo, Biomass resources assessment and bioenergy generation for a clean and sustainable development in Cameroon, Biomass and Bioenergy. 118 (2018) 16–23.

[29] P. McKendry, Energy production from biomass (part 1): overview of biomass, Bioresour. Technol. 83 (2002) 37–46.

[30] S. Moazeni, A.H. Miragha, B. Defourny, A risk-averse stochastic dynamic programming approach to energy hub optimal dispatch, IEEE Trans. Power Syst. 34 (2018) 2169–2178.

[31] G. Li, R. Zhang, T. Jiang, H. Chen, L. Bai, X. Li, Security-constrained bi-level economic dispatch model for integrated natural gas and electricity systems considering wind power and power-to-gas process, Appl. Energy. 194 (2017) 696–704.

[32] S. Clegg, P. Mancarella, Integrated modeling and assessment of the operational impact of power-to-gas (P2G) on electrical and gas transmission networks, IEEE Trans. Sustain. Energy. 6 (2015) 1234–1244.

[33] F. Salgado, P. Pedrero, Short-term operation planning on cogeneration systems: A survey, Electr. Power Syst. Res. 78 (2008) 835–848.

[34] G. Chicco, P. Mancarella, Matrix modelling of small-scale trigeneration systems and application to operational optimization, Energy. 34 (2009) 261–273.

[35] M.H. Barmayoon, M. Fotuhi-Firuzabad, A. Rajabi-Ghahnavieh, M. Moeini-Aghtaie, Energy storage in renewable-based residential energy hubs, IET Gener. Transm. Distrib. 10 (2016) 3127–3134.

[36] J.M. Arroyo, A.J. Conejo, Optimal response of a thermal unit to an electricity spot market, IEEE Trans. Power Syst. 15 (2000) 1098–1104.

[37] M. Majidi, S. Nojavan, K. Zare, A cost-emission framework for hub energy system under demand response program, Energy. 134 (2017) 157–166.

[38] R.K. Samal, M. Tripathy, Cost and emission additionality of wind energy in power systems, Sustain. Energy, Grids Networks. 17 (2019) 100179.

[39] A.-M. Hariri, M.A. Hejazi, H. Hashemi-Dezaki, Reliability optimization of smart grid based on optimal allocation of protective devices, distributed energy resources, and electric vehicle/plug-in hybrid electric vehicle charging stations, J. Power Sources. 436 (2019) 226824.

[40] H. Mehrjerdi, Optimal correlation of non-renewable and renewable generating systems for producing hydrogen and methane by power to gas process, Int. J. Hydrogen Energy. 44 (2019) 9210–9219.

[41] P. Zweifel, A. Praktiknjo, G. Erdmann, Energy economics: theory and applications, Springer, 2017.

[42] F. Safari, I. Dincer, Assessment and optimization of an integrated wind power system for hydrogen and methane production, Energy Convers. Manag. 177 (2018) 693–703.

[43] S. Nojavan, K. Zare, B. Mohammadi-Ivatloo, Application of fuel cell and electrolyzer as hydrogen energy storage system in energy management of electricity energy retailer in the presence of the renewable energy sources and plug-in electric vehicles, Energy Convers. Manag. 136 (2017) 404–417.

[44] S. Hochreiter, J. Schmidhuber, Long short-term memory, Neural Comput. 9 (1997) 1735–1780.

[45] A. Earnest, M.I. Chen, D. Ng, L.Y. Sin, Using autoregressive integrated moving average (ARIMA) models to predict and monitor the number of beds occupied during a SARS outbreak in a tertiary hospital in Singapore, BMC Health Serv. Res. 5 (2005) 36.

[46] B. Stappers, N.G. Paterakis, K. Kok, M. Gibescu, A class-driven approach based on long short-term memory networks for electricity price scenario generation and reduction, IEEE Trans. Power Syst. 35 (2020) 3040–3050.

[47] J. Yang, S. Zhang, Y. Xiang, J. Liu, J. Liu, X. Han, F. Teng, LSTM auto-encoder based representative scenario generation method for hybrid hydro-PV power system, IET Gener. Transm. Distrib. 14 (2020) 5935–5943.

[48] Welcome To Colaboratory - Colaboratory, (n.d.). https://colab.research.google.com/notebooks/intro.ipynb (accessed December 21, 2020).

[49] N. Growe-Kuska, H. Heitsch, W. Romisch, Scenario reduction and scenario tree construction for power

management problems, in: 2003 IEEE Bol. Power Tech Conf. Proceedings, IEEE, 2003: pp. 7-pp.

[50] Havaintojen lataus - Ilmatieteen laitos, (n.d.). https://www.ilmatieteenlaitos.fi/havaintojen-lataus (accessed December 21, 2020).

[51] JRC Photovoltaic Geographical Information System (PVGIS) - European Commission, (n.d.). https://re.jrc.ec.europa.eu/pvg_tools/en/#MR (accessed December 21, 2020).

[52] Market data | Nord Pool, (n.d.). https://www.nordpoolgroup.com/Market-data1#/nordic/table (accessed December 21, 2020).

[53] Statistics Finland -, (n.d.). https://www.tilastokeskus.fi/til/ehi/2020/02/ehi_2020_02_2020-09-10_kuv_003_en.html (accessed December 21, 2020).