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Linearized Stochastic Optimization Framework for Day-Ahead Scheduling of a Biogas-Based Energy Hub Under Uncertainty

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ABSTRACT Energy hubs (EHs), due to their multiple nature in the production, consumption, and storage of energy, as well as the ability to participate in different energy markets, have made their optimal and profitable scheduling important for operators. Considering the literature review, one of the main motivations of this paper is the use of biogas as a pivotal fuel and through production using biomass in the structure of EHs. Therefore, this paper proposes a linearized optimization framework for optimal scheduling of a biogas-based EH for participation in day-ahead (DA) electricity and thermal energy markets. The proposed EH directly converts local biomass into biogas, thereby providing the fuel to generate electricity and thermal. This EH comprises digester, biogas storage, electric heat pump (EHP), biogas burner CHP and boiler, solar farm, electrical storage, and internal electrical and thermal loads. In this framework, the uncertainties related to solar radiation and the DA price are modeled to generate random scenarios using the Monte-Carlo method. The proposed EH is simulated for numerical studies based on data from Finland's two selected spring and autumn days. The results show the optimal performance of the EH because it can participate in the electricity and thermal markets by using the biogas produced inside it and providing complete internal loads, and earns a decent income. In the autumn, operating the EH is more economical than in the spring. Moreover, comparative results have shown that eliminating the biogas unit and using natural gas significantly increases the expected costs of EH.

INDEX TERMS Optimal scheduling, energy conversion, renewable energy sources, biomass, biogas, uncertainty.

NOMENUCLATURE

A. PARAMETERS

π_s	Probability of scenarios.
C_{th}	Thermal price (€/MWh).
$P_{e,\min}^{in/\text{out}}$	Min value of electricity input/output to/from the EH (MW).
$P_{e,\max}^{in/\text{out}}$	Max value of electricity input/output to/from the EH (MW).
$P_{th,\min/\max}^{\text{out}}$	Min/max thermal output from the EH (MW).
HV_{Biogas}	The heating value of biogas (kWh/m^3).
M	A large number.
η_e^{CHP}	Biogas to electricity efficiency of CHP (%).
η_{th}^{CHP}	Biogas to thermal efficiency of CHP (%).
$P_{e,min}^{CHP}$	Min amount of electricity generation by CHP (MW).
$P_{e,max}^{CHP}$	Max amount of electricity generation by CHP (MW).
$P_{th,min}^{CHP}$	Min amount of thermal generation by CHP (MW).
$P_{th,max}^{CHP}$	Max amount of thermal generation by CHP (MW).
$CCSU$	Cost coefficient of CHP unit start-up (€).
$CCSD$	Cost coefficient of CHP unit shut-down (€).
L, F	Number of hours unit CHP must be on & off.
$U(0)$	Periods unit has been on at the beginning of the j unit planning horizon (hour).

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S	Periods that CHP unit has been shut-down at the hour (hour).
η_{th}^{Boiler}	Biogas to the thermal efficiency of the boiler (%).
$P_{th,\min}^{Boiler}$	Min value of boiler thermal generation (MW).
$P_{th,\max}^{Boiler}$	Max value of boiler thermal generation (MW).
$\eta_e^{EHP-Dig}$	EHP Electrical efficiency of digester unit.
$P_{th,\min}^{EHP-Dig}$	Min value of thermal power generated by EHP (MW).
$P_{th,\max}^{EHP-Dig}$	Max value of thermal power generated by EHP (MW).
R_{in}	Thermal resistance inside the digester (°C/kW).
R_{W1}	The thermal resistance of the digester first wall (°C/kW).
R_{W2}	The thermal resistance of the digester second wall (°C/kW).
R_{out}	Thermal resistance outside the digester (°C/kW).
a, b	Coefficients related to biogas production rate.
$T_{optimal}$	The optimum temperature for most mesophilic organisms (°C).
α_{Biogas}^{min}	Min coefficient for biogas storage.
α_{Biogas}^{max}	Max coefficient for biogas storage.
P_{Capa}^{BES}	Biogas storage capacity (m^3).
α_e^{loss}	Loss factor for electrical storage.
α_e^{min}	Min coefficient for electricity storage.
α_e^{max}	Max coefficient for electricity storage.
P_{Capa}^{ES}	Electrical storage capacity (MW).
η_e^{ch}	Charging efficiency of electric storage.
η_e^{dis}	Dis-charging efficiency of electric storage.
COP	Coefficient of performance for EHP.
$P_{th,min}^{EHP}$	Min thermal generated by EHP (MW).
$P_{th,max}^{EHP}$	Max thermal generated by EHP (MW).
G_0	Standard solar irradiance (W/m^2).
N_{OT}	Nominal operating temperature (°C).
T_c	Solar cell temperature (°C).
T_a	Ambient temperature (°C).
I	Max power point current (A).
V_{MPP}	Max power point voltage (V).
K_I	Current temperature coefficient (A/°C).
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 (%).
P_e^{load}	The amount of electrical load inside the EH (MW).
P_{th}^{load}	The amount of thermal load inside the EH (MW).

B. VARIABLES

$P_e^{in/out}$	Total electricity purchased/sold from/to the energy market (MW).
P_{th}^{out}	Thermal power sold to the energy market (MW).
C_{DA}	Day-ahead electricity market price (€/MWh).
$Biogas_{Gen}$	Generated biogas (m^3).
$Fuel_{Biogas}^{CHP}$	Biogas consumed by CHP (m^3).
$Fuel_{Biogas}^{Boiler}$	Biogas consumed by a boiler (m^3).
F_{th}	Total thermal power input to digester (kW).
$P_{th}^{Net2Dig}$	Thermal power input to the digester of the thermal network (kW).
$P_{th}^{EHP-Dig}$	Thermal generated by EHP of digester unit (kW).
$P_e^{EHP-Dig}$	Electricity consumed by EHP of digester unit (kW).
T_d	The temperature inside the digester (°C).
T_{W1}	The temperature of the first wall of the digester (°C).
T_{W2}	The temperature of the second wall of the digester (°C).
T_{out}	The temperature outside the digester (°C).
P_{Biogas}^{SOC}	Biogas level stored in biogas storage (m^3).
P_{Biogas}^{ch}	Charging power of biogas storage (m^3).
P_{Biogas}^{dis}	Dis-charging power of biogas storage (m^3).
P_e^{CHP}	Electricity generated by CHP biogas burner (MW).
P_{th}^{CHP}	Thermal generated by CHP biogas burner (MW).
U	Binary variable to on/off unit of CHP.
v	Binary variable for the commitment of CHP unit.
UT, DT	MUT/MDT of CHP unit (hour).
y, z	Binary variable to startup/shutdown the CHP unit.
P_{th}^{Boiler}	The thermal generated by the boiler biogas burner (MW).
P_e^{ch}	Electric charging power of electric storage (MW).
P_e^{dis}	Electric charging power of electric storage (MW).
P_e^{loss}	Loss power of electric storage (MW).
P_e^{SOC}	Electrical storage level (MW).
I_e^{ch}	Binary variable for electric storage charging status.
I_e^{dis}	Binary variable for electric storage dis-charging status.
P_e^{EHP}	Electrical power consumed by EHP (MW).
P_{th}^{EHP}	Thermal power generated by EHP (MW).
P_{SF}	Electric power generated by the solar farm (MW).

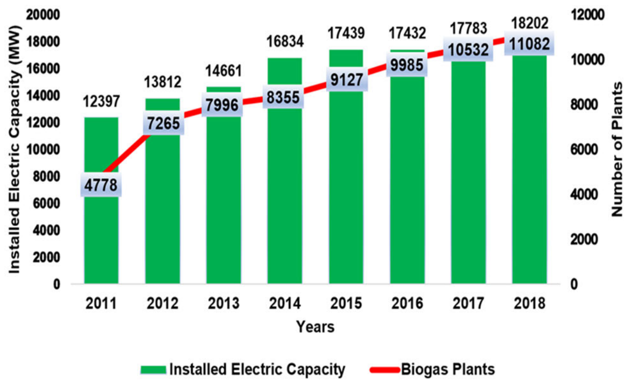

FIGURE 1. Installed capacity and number of biogas units in Europe.

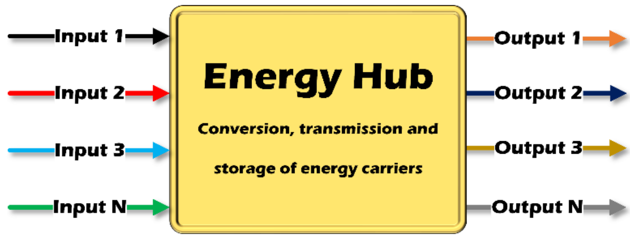

FIGURE 2. The overall structure of an EH.

G Solar irradiance (m/s,W/m^2).
K_t Clearness index.
I, V Output current/voltage of PV (A, V).

C. INDICES
s Scenario index.
T, t Set and index of hours in the time horizon.

I. INTRODUCTION
Today, energy as the main element has become so important that it has made things like economic growth and social welfare dependent on itself. According to the world bank, energy and four other factors, namely water, food, information technology, and waste, form the Achilles heel of each city. Accordingly, the focus and priority of cities are focused on the current sustainable development. The increasing growth of electrical energy demand as a mother and main energy has led to challenges such as security and increased competition in energy supply, adaptation and observance of environmental issues, retirement, and depreciation of energy transfer equipment are among the most important study priorities of the beneficiaries of these systems.

With studies conducted by researchers, solutions have been proposed to meet these challenges. The most important of these options are smart grids (establishing relationships between producers and consumers using automation system) and energy platforms, changing the approach and applying policies for the use of renewable energy sources (RESs), as well as creating and applying cooperation and exchange between energy carriers. Cooperation between energy carriers means minimizing losses and increasing efficiency in conversion between energy by converters. For example, when electricity is generated by a prime mover such as an internal combustion engine, surplus thermal can be used to supply thermal loads in the electrical energy production process. The combined heat and power units, which are briefly called CHP, can be a great example of this.

The use of water potential, wind speed, sunlight, and biomass are among the most important RESs that operators and politicians of organizations and governments have shown more willingness to use [1]. Considering the importance of municipal waste and wastewater management, air pollution control, and cost reduction for energy production, biomass resources in urban energy converters are important fuels. Fig. 1 shows the amount of installed capacity and the number of energy generation units fed with biogas fuel in Europe between 2011 and 2018 [2]. Multi-energy systems (MESs) are very suitable infrastructures for covering the mentioned items. These systems are more receptive to one type of energy carrier. Their advantages include increasing energy efficiency, being the most suitable platform for RESs and waste management, increasing actors and reducing the monopoly of energy markets, as well as increasing flexibility in the operation of energy systems [3].

One of the most common smart elements in MES is the energy hub (EH). EHs resemble a black box such as Fig. 2, which usually have one or more energy carriers as input, and one or more energy carriers as output [4], [5]. These elements depend on the application and geographical location in which they are located and can receive different energies and implement various operations such as energy transfer, storage, and conversion to provide the desired output carriers. EHs include electricity, thermal, cooling, hydrogen, biogas, etc., that can be best used for cooperation and exchanges among them. Accordingly, it is natural for different energy converters to be used in the body of an EH. The most common energy converters include CHP units, electric and thermal boilers, electric heat pumps (EHPs), wind and solar farms, as well as electrical and thermal storages.

Considering the connection of EHs to the incoming and outgoing energy carriers and the energy converters that are placed in their structure, the dimensions of EHs can vary from home, regional, and area to smart grids. Of course, it should be noted that the dimensions of these MESs can vary smaller, such as cars, or much larger ones, such as a country. One of the most important divisions that can be implemented on EHs is the division based on the participation of these elements with energy markets. With researches conducted and paying attention to the nature and structure of EHs, it can be concluded that the exchanges of these MESs for the purchase and sale of energy carriers are divided into four types in the following form. The first type is the EH, which buys a series of energy carriers from energy networks to generate energy and does not intend to sell its converted energy to any market.

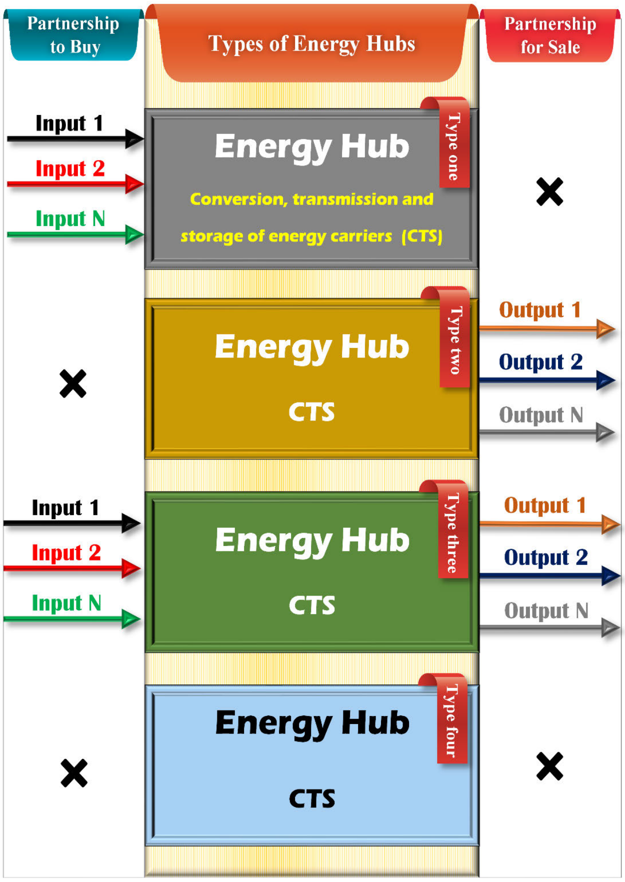

FIGURE 3. Types of EHs based on participation in energy markets.

The second type is the opposite of the first type of EH, and using its domestic energy resources, it intends to participate and sell its produced energies to the energy markets.

The third type of EH, which is the most common type in smart grids, is a combination of the first and second types. In addition to contributing to the provision of incoming energies, this type of EHs also sell its produced energies. The fourth type of EH, which is the most independent type relative to participation in energy markets, uses its domestic resources to convert energy and merely supplies its domestic loads. A summary of this division of EHs from participation in energy markets is shown in Fig. 3.

In [6], the authors presented an MINLP model to minimize the cost for the probabilistic scheduling of the sample EH, which is composed of natural gas-fueled boilers and CHP, and electrical and thermal storages. This study considers demand response (DR) and uncertainties related to loads and prices of incoming energy carriers. In [7], optimal operation of an EH for power generation, thermal and cold is presented in the form of a robust chance-constrained optimization framework. This reference has modeled the uncertainties related to sunlight and loads by a robust chance-constrained model. The framework for the stochastic operation of electricity, thermal, natural gas, and hydrogen for a sample EH is presented in [8]. The authors have only considered the uncertainty associated with electricity prices alongside constraints such as MUT and MDT to minimize operational risks. Mansouri *et al.* in [9] have presented a stochastic framework for optimal operation and planning of an EH to supply electrical, thermal, and cold loads. For modeling the uncertainties of wind speed and loads, the Monte Carlo (MC) method has been used to generate scenarios, and the K-means algorithm is used to reduce them. Also, benders decomposition is used to reduce the complexity of the problem. The results of this modeling show its appropriate efficiency.

The researchers of [10] have considered an EH by linking the energy conversions made from CHP, boiler, chiller, and electrical storage units. The operation of this EH has been optimized in the form of a stochastic problem due to uncertainties related to loads and prices, as well as compliance with pollution and risk production constraints. Moreover, the MC method has been used to model uncertainties. In [11], the optimal operation of an EH, including wind farm, electrical and thermal storages, electricity, and thermal demand response programs to participate in the electricity and thermal markets, is presented. In this reference, the MC method is also used to cover the uncertainty aspects of loads, market prices, and wind speed. One of the things that can be implemented well in the EH platform is converting cheap and alternating energy such as wind to another valuable energy such as natural gas. By presenting an EH including electricity, heat, and natural gas, authors in [12] have proposed an optimal probabilistic framework, the results of which indicate a 7% reduction in operating costs. In [13], a planning framework for an EH in the structure of a distribution network has been considered considering energies such as hydrogen and water. The results of this study show that operating costs are reduced, and the consumption pattern is smoother. One of the modeling methods used in optimal operation EH concerning uncertainty is robust optimization. Reference [14] introduced an energy management framework for a typical EH in terms of electricity and heat carriers, as well as parking for electric vehicles using robust scenario-based optimization. In this reference, it was shown that there is a direct relationship between the number of electric vehicles and the operating profit. Zhang et al in [15] have tried to provide the electrical, thermal and cooling energy needed by the residents of a remote village in China using biogas fuel. Biogas production in this structure is done using biomass fuel in the digester. References [16]–[18] have tried to introduce the operating frameworks of an EH to convert wind or solar energy to other energies such as electricity and heat using biogas. In the presented frameworks, only uncertainties related to the production of renewable energy sources have been taken into account, and the aim has been to minimize operating costs.

Table 1 summarizes the literature review for structural comparison. Also, the proposed framework of this paper is clarified by comparing previous studies in this table. One of the main motivations of this paper is the use of biogas fuel as a pivotal fuel in the structure of EHs. Moreover, the lack of an optimal scheduling framework for the supply of electrical and thermal loads inside a biogas-based EH and participation in day-ahead (DA) energy markets, as well as considering the uncertainties of electricity prices and solar radiation, is fully felt.

According to the importance and growth of biogas fuel application as a clean and valuable energy carrier as well as the gaps shown in Table 1, this paper proposes a stochastic optimization framework for optimal scheduling of a biogas-based EH for DA power and thermal markets. This EH is the third type of EHs (in terms of participation in energy markets) and is composed of digester units for generating biogas, biogas burner CHP and boiler, EHP, electrical and thermal loads, solar farm, as well as electrical and biogas storages. According to the comparison of previous researches, the contributions of this article are in two parts. The first contribution is the suggestion of a new biogas-based EH structure with biomass fuel, in which all the electrical and thermal energy generated by this system is taken through the biogas production unit and a solar farm. Therefore, it is environmentally friendly. The second contribution is proposing a stochastic optimization framework for optimal scheduling of the suggested EH to supply internal electrical and thermal loads and participation in DA energy markets. This framework considers the uncertainties of sunlight and the price of the DA electricity market. In addition to having the proper environmental conditions, the proposed EH is also cost-effective to operate, so that eliminating the biogas production unit and replacing it with conventional energy carriers will greatly increase its operation cost. For numerical studies, actual data in Finland is used. Finland is considered as a case study due to geographical conditions such as the widespread presence of biomass fuel as the input of digester, temperature changes, and sunlight in different seasons.

In Section II, the proposed biogas-based EH and stochastic optimization framework are expressed. This section is divided into two subsections to describe the modeling of the structure and elements located in the EH and to model the uncertainties related to DA electricity prices and solar radiation. Section III presents the simulation results performed in MATLAB and GAMS in the spring and autumn seasons. Finally, Section IV expresses the conclusions of this research.

II. PROPOSED SCHEDULING FRAMEWORK

When the owner or operator of an energy system wants to operate its system in terms of modeling its elements, along with cost minimization or maximizing profits, the topics related to optimization are discussed with a mathematical approach. In this case, various optimization methods such as classic, modern and hybrid methods can help him. However, if the operator wants to consider the aspects of uncertainties, well-known methods, such as stochastic optimization, robust optimization, information gap decision theory (IGDT), come before him, which other researchers use more.

Among these methods and according to the research history of energy systems planning, the stochastic optimization method has been used more widely. Fig. 4 shows an overview of scheduling using optimization and considering scenarios. In this figure, after determining the uncertainty parameters, the operator models their behavior in each time interval related to the future and uses scenario generation. This modeling causes uncertain parameters to be associated with each other at any time and with a certain probability similar to chains. In the modeling subsection, the uncertainty and optimization framework will be discussed in more detail.

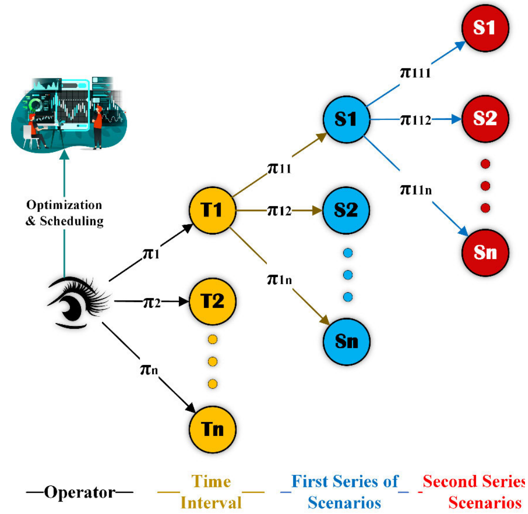

FIGURE 4. Operators' overview of uncertainty modeling in stochastic optimization problems.

A. BIOGAS-BASED EH MODELING

The proposed EH under study in this paper, connected to power and thermal networks, is shown in Fig. 5. This EH comprises biogas burner CHP unit, section related to biogas production and transmission (including digester, biomass fuel, separate EHP, and biogas storage), biogas-fueled boiler, solar farm, electrical storage, EHP, electrical and thermal loads. This framework provides optimal scheduling for supplying domestic electrical and thermal loads and profitable participation in the DA electricity and thermal markets to sell surplus energies. As mentioned earlier, stochastic optimization will be used as a suitable framework for the optimal scheduling of the desired EH.

This framework consists of two main parts: objective function and constraints modeling.

1) OBJECTIVE FUNCTION OF FRAMEWORK OPTIMIZATION

The main objective in the DA operation of the proposed EH is to minimize the total cost, according to (1).

$$OF = \pi_s \sum_{s=1}^{N_s} \sum_{t=1}^{24} \begin{bmatrix} P_e^{in/out}(t,s).C_{DA}(t,s) + y(t,s).CCSU \\ +z(t,s).CCSD - P_{th}^{out}(t,s).C_{th} \end{bmatrix} \tag{1}$$

TABLE 1. The structure of the proposed EH in comparison to the literature review.

Ref	Biomass	Biogas	Biogas based EH	Internal loads	Sales to energy markets	Biogas storage	Electrical storage	Optimization		Linear model	Linearization	MUT & MDT of CHP	Uncertainty Modeling	
								Stochastic	Robust				DA price	RES
[6]	-	-	-	✓	-	-	✓	✓	-	-	-	-	✓	-
[7]	-	-	-	✓	-	-	✓	✓	-	✓	-	-	-	✓
[8]	-	-	-	✓	✓	-	✓	✓	-	✓	-	✓	✓	-
[9]	-	-	-	✓	-	-	✓	✓	-	✓	-	-	-	✓
[10]	-	-	-	✓	-	-	✓	✓	-	✓	-	✓	-	-
[11]	-	-	-	✓	-	-	✓	✓	-	✓	-	-	✓	✓
[12]	-	-	-	✓	-	-	✓	✓	-	✓	-	-	✓	✓
[13]	-	-	-	✓	-	-	-	✓	-	✓	-	-	-	-
[14]	-	-	-	✓	-	-	-	-	✓	✓	-	-	✓	✓
[15]	✓	✓	-	✓	-	✓	✓	✓	-	✓	✓	-	-	✓
[16]	✓	✓	-	-	✓	✓	✓	✓	-	✓	✓	-	-	✓
[17]	✓	✓	-	✓	-	✓	✓	✓	-	✓	✓	-	-	✓
[18]	✓	✓	-	✓	-	✓	✓	✓	-	✓	✓	-	-	✓
This paper	✓	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✓	✓	✓

The items considered in this objective function include the costs associated with the purchase of electricity from the DA market (taking into account its price uncertainties) along with the costs of start-up and shut-down of the CHP unit. Note that $P_e^{in/out}$ variable, if negative, means selling electricity to the grid, and if it is positive, it means buying electricity from the network.

2) CONSTRAINTS OF FRAMEWORK OPTIMIZATION

a: BIOGAS PRODUCTION

Biogas is a renewable and environmentally friendly fuel that can be produced in a variety of ways. The primary input element in biogas production is biomass fuel such as municipal wastewater, animal manures, and agricultural waste. In general, the biogas production process is such that microorganisms start to decompose and break down biomass fuel in the absence of oxygen, and the result of this chemical process produces biogas fuel. The process is usually performed on devices called digesters. These devices provide the conditions for the activity of microorganisms and form the main infrastructure for biogas production. Fig. 6 shows a sample of the digester that, after entering the biomass fuel into it and establishing the appropriate conditions, with the chemical process created, produces biogas and finally, by collecting the produced gas and transferring it to the desired location, is used as a valuable fuel [19]–[21].

Digesters are usually composed of two walls, and the biogas process produced in them depends on four temperatures, including digester internal temperature, first wall temperature, second wall temperature, and ambient temperature. By analyzing thermodynamics, these temperature changes and their dependence can be considered as an electrical circuit such as Fig. 7 [18].

In the modeled circuit, F_{th} is the incoming thermal into the circuit. This thermal can be obtained in two ways, i.e., direct reception of the total thermal generated by the EH or from its own EHP digester. This thermal similar to electrical current can cause voltage drops if it passes through a resistance. The drop in voltages modeled in this circuit is the same temperature drop as T_d (temperature inside the digester), T_{w1} (first wall temperature), T_{w2} (second wall temperature), and T_{out} (temperature outside digester). In this circuit, given that all elements are series to each other, so the current passing through all of them is the same. The equations of (2) to (12) have done this modeling.

Equation (8) is nonlinear, and if used in the framework of EH optimal scheduling based on biogas presented in this paper, it makes the desired optimization framework nonlinear. The Nonlinearization of this scheduling framework can harm operational decision-making, computation time, and the burden of the problem. Therefore, (8) shown in Fig. 8 as nonlinear (the blue curve) is estimated using four lines (the red curve), and its equations are estimated by (13)-(14).

$$F_{th}(t,s) = P_{th}^{Net2Dig}(t,s) + P_{th}^{EHP-Dig}(t,s) \tag{2}$$

$$P_{th}^{EHP-Dig}(t,s) = \eta_e^{EHP-Dig} \times P_e^{EHP-Dig}(t,s) \tag{3}$$

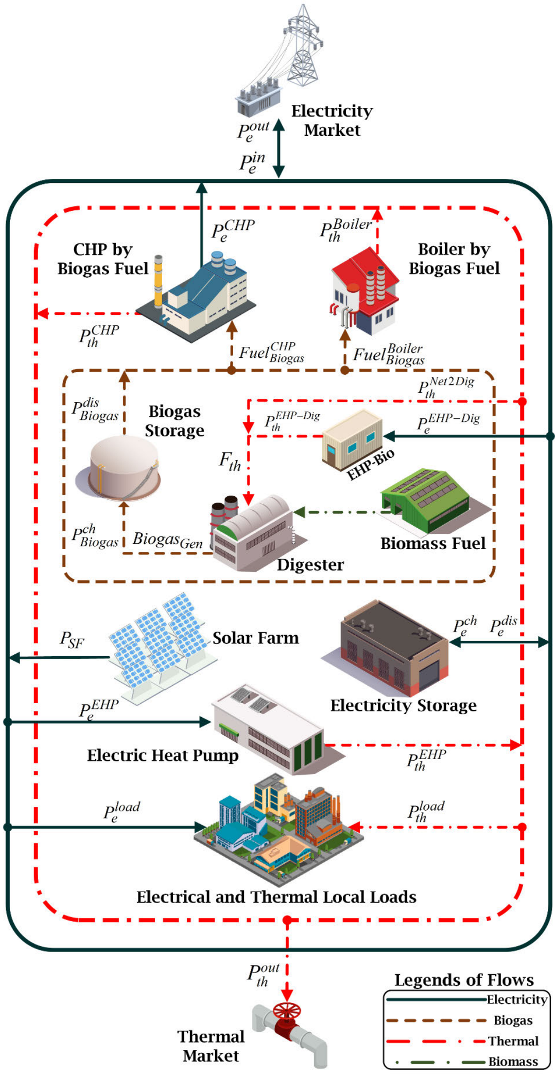

FIGURE 5. Proposed biogas-based EH structure.

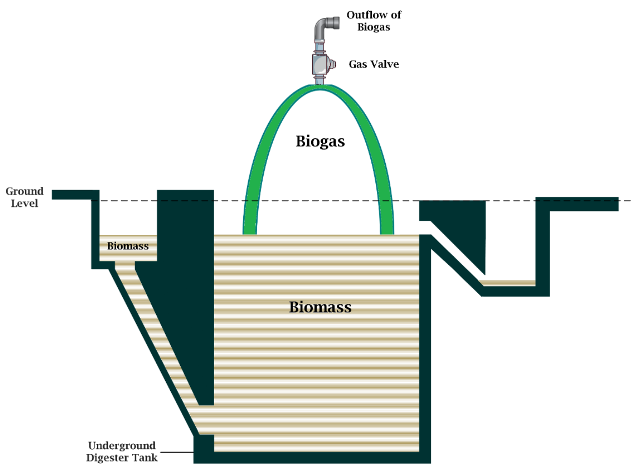

FIGURE 6. The general structure of a digester.

$$P_{th,min}^{EHP-Dig} \leq P_{th}^{EHP-Dig}(t,s) \leq P_{th,max}^{EHP-Dig} \tag{4}$$

$$F_{th}(t,s) = \frac{T_d(t,s) - T_{W1}(t,s)}{Rin + {}^{R}{}_{W1}/2} \tag{5}$$

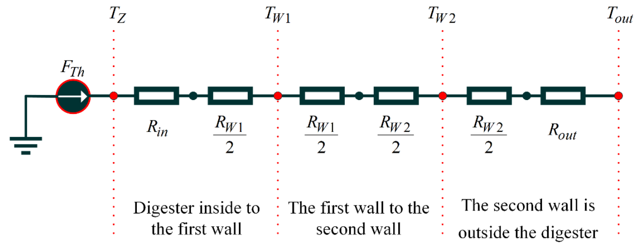

FIGURE 7. Modeling a digester into an electrical circuit.

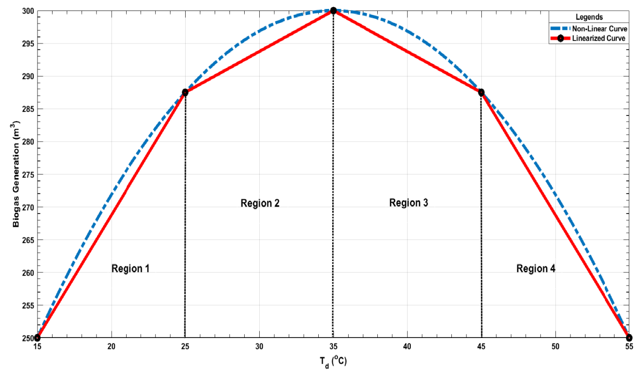

FIGURE 8. Nonlinear and linear curves in this paper for modeling biogas production rate.

$$F_{th}(t,s) = \frac{T_{W1}(t,s) - T_{W2}(t,s)}{{}^{R}{}_{W1}/2 + {}^{R}{}_{W2}/2} \tag{6}$$

$$F_{th}(t,s) = \frac{T_{W2}(t,s) - T_{out}(t,s)}{R_{W2}/2 + R_{out}} \tag{7}$$

$$Biogas_{Gen}(t,s) = a \times (T_d(t,s) - T_{optimal})^2 + b \tag{8}$$

$$P_{Biogas}^{SOC}(t,s) = P_{Biogas}^{SOC}(t-1,s) + P_{Biogas}^{ch}(t,s) - P_{Biogas}^{dis}(t,s) \tag{9}$$

$$P_{Biogas,min}^{SOC} \leq P_{Biogas}^{SOC}(t,s) \leq P_{Biogas,max}^{SOC} \tag{10}$$

$$\alpha_{Biogas}^{\min}.P_{Capa}^{BES} \leq P_{Biogas}^{ch}(t,s) \leq \alpha_{Biogas}^{\max}.P_{Capa}^{BES} \tag{11}$$

$$\alpha_{Biogas}^{\min}.P_{Capa}^{BES} \leq P_{Biogas}^{dis}(t,s) \leq \alpha_{Biogas}^{\max}.P_{Capa}^{BES} \tag{12}$$

$$\begin{aligned} Biogas_{Gen}(t,s) = {} & [3.75 \times T_d(t,s) + 193.75]\,.I_{Bio}^{Region1}(t,s) \\ & + [1.25 \times T_d(t,s) + 256.25] \\ & .I_{Bio}^{Region2}(t,s) \\ & + [-1.25 \times T_d(t,s) + 343.75] \\ & .I_{Bio}^{Region3}(t,s) \\ & + [-3.75 \times T_d(t,s) + 456.25] \\ & .I_{Bio}^{Region4}(t,s) \end{aligned} \tag{13}$$

$$I_{Bio}^{Region1} + I_{Bio}^{Region2} + I_{Bio}^{Region3} + I_{Bio}^{Region4} \leq 1 \tag{14}$$

To investigate four linear equations in the optimization framework, (13), with the help of four binary variables, has been used. To linearize the binary variable multiplication in the continuous variable, (15)-(17) are used as follows [22].

$$W_{1,2,3,4}(t,s) \leq Td(t,s) \tag{15}$$

$$W_{1,2,3,4}(t,s) \leq M \times I_{Bio}^{Region1,2,3,4}(t,s) \tag{16}$$

$$W_{1,2,3,4}(t,s) \geq Td(t,s) - M(1 - I_{Bio}^{Region1,2,3,4}(t,s)) \tag{17}$$

The order of $W_{1,2,3,4}$ is the result of multiplying binary variables $I_{Bio}^{Region1,2,3,4}$ in the T_d continuous variable.

b: BIOGAS-BURNER CHP WITH CONSIDERING MUT & MDT

CHP units are commonly known as the main energy generation sector in EHs due to their high efficiency and cogeneration of electricity and thermal. In this paper, the internal combustion engine with biogas fuel forms the prime mover of the CHP unit [18].

Equations (18)-(21) show biogas-fueled electricity and thermal generation, while for modeling MUT and MDT constraints, this unit is used from (22)-(29) [23].

$$P_e^{CHP}(t,s) = \eta_e^{CHP}.Fuel_{Biogas}^{CHP}(t,s).HV_{Biogas} \tag{18}$$

$$P_{th}^{CHP}(t,s) = \eta_{th}^{CHP} \Big/ \eta_e^{CHP}.P_e^{CHP}(t,s) \tag{19}$$

$$P_{e,\min}^{CHP} \times U(t,s) \leq P_e^{CHP}(t,s) \leq P_{e,\max}^{CHP} \times U(t,s) \tag{20}$$

$$P_{th,\min}^{CHP} \times U(t,s) \leq P_{th}^{CHP}(t,s) \leq P_{th,\max}^{CHP} \times U(t,s) \tag{21}$$

$$\sum_{t=1}^{L} [1 - v(t,s)] = 0, \quad \forall s \tag{22}$$

$$\sum_{t=k}^{k+UT-1} v(t,s) \geq UTy(t,s), \quad \forall s, \forall k = L+1 \ldots T - UT + 1 \tag{23}$$

$$\sum_{t=k}^{T} [v(t,s) - z(t,s)] \geq 0, \quad \forall s, \forall t = T - UT + 2 \ldots T \tag{24}$$

$$L = Min\,[T, (UT - U(0)v(0)] \tag{25}$$

$$\sum_{t=1}^{F} v(t,s) = 0, \quad \forall s \tag{26}$$

$$\sum_{i=k}^{k+DT-1} [1 - v(t,s)] \geq DT.z(t,s), \quad \forall s,\ \forall k = F+1 \ldots T - DT + 1 \tag{27}$$

$$\sum_{t=k}^{T} [1 - v(t,s) - z(t,s)] \geq 0, \quad \forall s,\ \forall t = T - DT + 2 \ldots T \tag{28}$$

$$F = Min\,\{T, [DT - s(0)]\,[1 - v(0)]\} \tag{29}$$

c: BIOGAS-BURNER BOILER

The boiler unit considered in this paper consumes part of the biogas produced in this EH. By consuming biogas, it produces thermal based on (30) that the permissible limit of this production is based on (31) [18].

$$P_{th}^{Boiler}(t,s) = \eta_{th}^{Boiler}.Fuel_{Biogas}^{Boiler}(t,s).HV_{Biogas} \tag{30}$$

$$P_{th,\min}^{Boiler} \leq P_{th}^{Boiler}(t,s) \leq P_{th,\max}^{Boiler} \tag{31}$$

d: SOLAR FARM

Electricity generated from the solar farm is usually accompanied by uncertainty due to its dependence on the weather. This issue is considered in this paper in the uncertainty modeling section. The conversion equations of solar radiation energy into electricity are (32)-(36) [24].

$$k_t(t,s) = G(t,s)/G_0 \tag{32}$$

$$T_c(t,s) = T_a(t,s) + (G(t,s) \times ((N_{OT} - 20)/800) \tag{33}$$

$$I(t,s) = k_t(t,s) \times (I_{MPP} + (T_c(t,s) - T_a(t,s)) \times K_I) \tag{34}$$

$$V(t,s) = V_{MPP} - T_c(t,s) \times K_v \tag{35}$$

$$P_{SF}(t,s) = I(t,s) \times V(t,s) \times N_{PV} \times \eta_{Inv} \tag{36}$$

e: ELECTRIC HEAT PUMP

Because of the type of electricity conversion to the thermal they have, EHP converters can help the EH in profitable opportunities. In fact, when thermal prices exceed electricity, they can convert cheaper energy, i.e., electricity, into thermal if they make an optimal decision. Of course, this also applies to providing a portion of the thermal required for the internal loads of the EH. The amount of thermal generated of EHP is shown in (37), and (38) displays its acceptable range [25].

$$P_{th}^{EHP}(t,s) = COP.P_e^{EHP}(t,s) \tag{37}$$

$$P_{th,\min}^{EHP} \leq P_{th}^{EHP}(t,s) \leq P_{th,\max}^{EHP} \tag{38}$$

f: ELECTRICAl ENERGY STORAGE

Uncertainties in the EH can create challenges for optimal scheduling. Hence, the electrical energy storage system can reduce scheduling challenges in the EH. Constraints related to this element in the scheduling problem are presented in (39) to (44). It should be noted that constraint (44), which has binary variables, has been used to prevent simultaneous charging and discharging of the storage [11].

$$P_e^{SOC}(t,s) = P_e^{SOC}(t-1,s) + P_e^{ch}(t,s) - P_e^{dis}(t,s) - P_e^{loss}(t,s) \tag{39}$$

$$P_e^{loss}(t,s) = \alpha_e^{loss}.P_e^{SOC}(t,s) \tag{40}$$

$$\alpha_e^{\min}.P_{Capa}^{ES} \leq P_e^{SOC}(t,s) \leq \alpha_e^{\max}.P_{Capa}^{ES} \tag{41}$$

$$\alpha_e^{\min}.\left(1\Big/\eta_e^{ch}\right).P_{Capa}^{ES}.I_e^{ch}(t,s) \leq P_e^{ch}(t,s) \leq \alpha_e^{\max}.\left(1\Big/\eta_e^{ch}\right).P_{Capa}^{ES}.I_e^{ch}(t,s) \tag{42}$$

$$\alpha_e^{\min}.\eta_e^{dis}.P_{Capa}^{ES}.I_e^{dis}(t,s) \leq P_e^{dis}(t,s) \leq \alpha_e^{\max}.\eta_e^{dis}.P_{Capa}^{ES}.I_e^{dis}(t,s) \tag{43}$$

$$0 \leq I_e^{ch}(t,s) + I_e^{dis}(t,s) \leq 1 \tag{44}$$

g: ELECTRICITY & THERMAL NETWORK

The electricity and thermal EH exchanges proposed in this paper are carried out with their outside environment by electricity and thermal distribution networks. Due to the physical limitations, these networks have with the elements attached to them, (45) and (46), respectively, consider the limits of the electricity purchased, the electricity sold, and the thermal sold.

$$P_{e,min}^{in/out} \leq P_{e}^{in/out}(t,s) \leq P_{e,max}^{in/out} \tag{45}$$

$$P_{th,\min}^{out} \leq P_{th}^{out}(t,s) \leq P_{th,\max}^{out} \tag{46}$$

h: BALANCING OF BIOGAS, ELECTRICITY & THERMAL

According to the proposed structure of EH in this paper, (47) to (49) constraints express the balance of generation and consumption of biogas, electricity, and thermal energy carriers, respectively.

$$Biogas_{Gen}(t,s) = Fuel_{Biogas}^{CHP}(t,s) + Fuel_{Biogas}^{Boiler}(t,s) \tag{47}$$

$$\begin{aligned} P_{e}^{in}(t,s).\eta_{e}^{Tra} + P_{e}^{CHP}(t,s) + P_{SF}(t,s) + P_{e}^{dis}(t,s) \\ = P_{e}^{out}(t,s) \\ + P_{e}^{load}(t,s) + P_{e}^{ch}(t,s) + P_{e}^{EHP}(t,s) + P_{e}^{EHP-Dig}(t,s) \end{aligned} \tag{48}$$

$$\begin{aligned} P_{th}^{CHP}(t,s) + P_{th}^{Boiler}(t,s) + P_{th}^{EHP}(t,s) = P_{th}^{out}(t,s) \\ + P_{th}^{load}(t,s) + P_{th}^{Net2Dig}(t,s) \end{aligned} \tag{49}$$

B. UNCERTAINTY MODELING

As mentioned, the first step of stochastic optimization is to model uncertain parameters using a set of scenarios with a specific probability of occurrence. The common method for modeling uncertainty is the MC approach. In this approach, first, the historical data are separated from each uncertain parameter in the form of a vector every hour, and then the missing data is investigated in it. Then, on each of them, a specific probability distribution function (PDF) is fitted. After the fitting operation, the parameters of each PDF are extracted, based on the same parameters, several random numbers are generated. It should be noted that PDFs that are common for modeling the behavior of sunlight parameters and DA market price include the Beta and Normal, according to (50) and (51), respectively [26].

$$PDF(SL) = \begin{cases} \dfrac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)+\Gamma(\beta)} \times S_i^{\alpha-1} \times (1-S_i)^{\beta-1}, \\ \qquad for 0 \leq S_i \leq 1, \alpha, \beta \geq 0 \\ 0, \qquad else \end{cases} \tag{50}$$

$$PDF(Price) = \frac{1}{\sqrt{2\pi\sigma_{Price}^2}} e^{-\frac{(Price-\mu_{Price})^2}{2\sigma_{Price}^2}} \tag{51}$$

Solving optimization problems with many scenarios and at intervals can be very time-consuming or even beyond the capabilities of computers. Therefore, researchers reduce the generated set of scenarios considering similarity or very low probability. This reduction is possible using different methods. In this paper, the K-means, which is a well-known algorithm in clustering, is used. In general, the K-means clustering algorithm can be introduced as a way to determine the representations among the scenarios that have been produced.

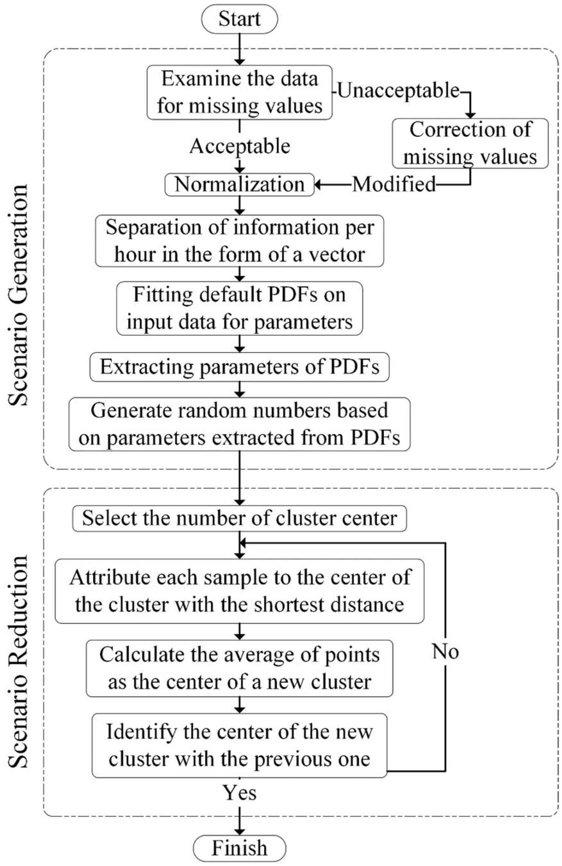

FIGURE 9. Uncertainty modeling process.

The initial set of cluster centers is randomly generated after determining the number of cluster centers in this algorithm. After this, the scenarios are initially placed in clusters. This placement is updated by recalculating the cluster center and forming the closest scenarios together in the cluster center [27]. Fig. 9 shows the flowchart of the uncertainty modeling process. The results of generation and reduction scenarios based on the description of this subsection are discussed and shown in the simulation section.

III. SIMULATION RESULTS

The simulation results of the proposed framework for optimal scheduling of biogas-based EH include two categories of input and output data. This simulation uses actual data on energy markets price and weather conditions in Finland [28]–[31], the parameters listed in Table 2, and the electrical and thermal loads shown in Fig. 10. These loads follow the demand pattern of an actual commercial complex in Finland. The historical data of the Varsinais_Suomi region in Finland from 2010 to 2016, due to the existence of renewable energy sources and access to electricity and heating networks, has been used to model the uncertain parameters.

In this section, to evaluate the proper performance of the proposed framework despite the weather conditions and various prices of energy markets, the simulation is performed

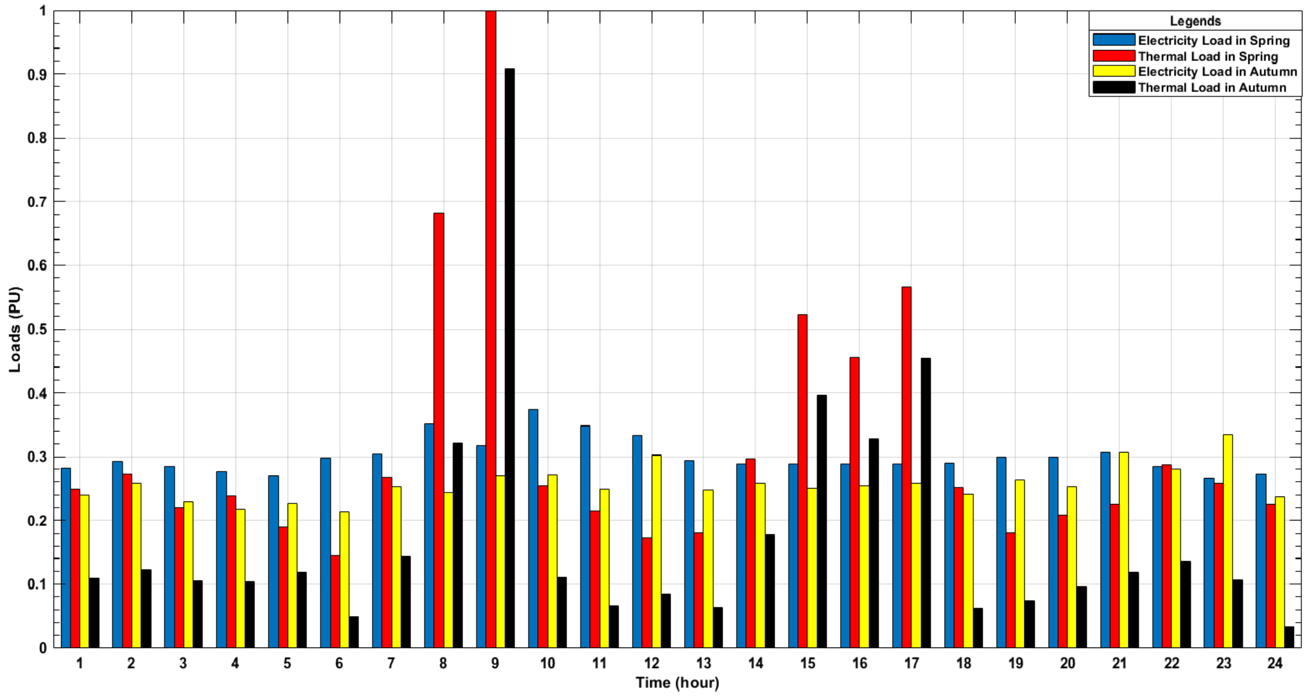

FIGURE 10. The amount of internal electrical and thermal loads in the EH for selected days of spring and autumn.

on two selected days of spring and autumn. These days are April 14 and October 14, respectively. Input data means modeling for behavior with solar radiation uncertainty and DA prices. Also, the output data consisted of the result of optimal decision-making for the use of elements and EH exchanges.

A. INPUT DATA TO THE SCHEDULING FRAMEWORK

As mentioned earlier, input data to the optimal scheduling structure included generated scenarios and reduced by MC methods and K-means clustering algorithm for solar power and DA price. These scenarios have been generated and reduced in MATLAB, as Fig. 11 and Fig. 12 for selected days in spring and autumn, respectively. For covering the broader aspects of uncertain parameters and based on the analysis, it has been appropriately determined that 500 scenarios for each parameter be generated, and finally, their number has been reduced to 10.

As it is known and also based on the studies of the behavior of historical data of sunlight parameters and DA price, the generated scenarios are of good quality and consider different aspects of parameters. However, with its good performance, the K-means algorithm summarizes this number of scenarios into 10 numbers. This summarization, in other words, the reduction of the scenario, has been able to transfer the different behaviors of the generated scenarios and the input to it in smaller numbers.

B. OUTPUT DATA FROM THE SCHEDULING FRAMEWORK

After applying the reduced scenarios by the K-means algorithm to the optimal scheduling framework, this optimization problem is solved by GAMS with CPLEX salvor. The simulation has been performed in a system with 6 GB of RAM and CPU-Core i5-7200. According to the linearization of the proposed problem, the computation time equals 10 seconds for the spring day and 7 seconds for the autumn day. These computation times are desirable for such problems. Also, the expected cost of EH scheduling on the spring day is 112.74 euros, and on the autumn day is -317.73 euros.

As for these costs, it can be said that the EH proposed in this paper has been able to supply its internal electrical and thermal loads well and sell them to energy networks if it has additional thermal and electricity. In spring, the number of hours that the solar farm has been able to generate electricity has been higher, but in this season, the amount of electrical and thermal loads in the interior has been higher than in the autumn.

Consequently, due to this issue, as well as the lower price of thermal in the spring, it has caused, firstly, there is less surplus energy for sale, and secondly, the revenue from this sale is lower than in the autumn. For this reason, the cost of scheduling in autumn has turned negative due to the EH's higher income than its costs. The following summarizes the behavior and expected reactions of the EH to scheduling and optimal decision-making on the selected days of spring and autumn.

The expected behavior in the generation, consumption, and storage of biogas is shown in Fig. 13 for the spring day. As was evident from the modeling section and the shape of the EH proposed in this paper, the generated biogas is divided between two elements: CHP and boiler. This division, which

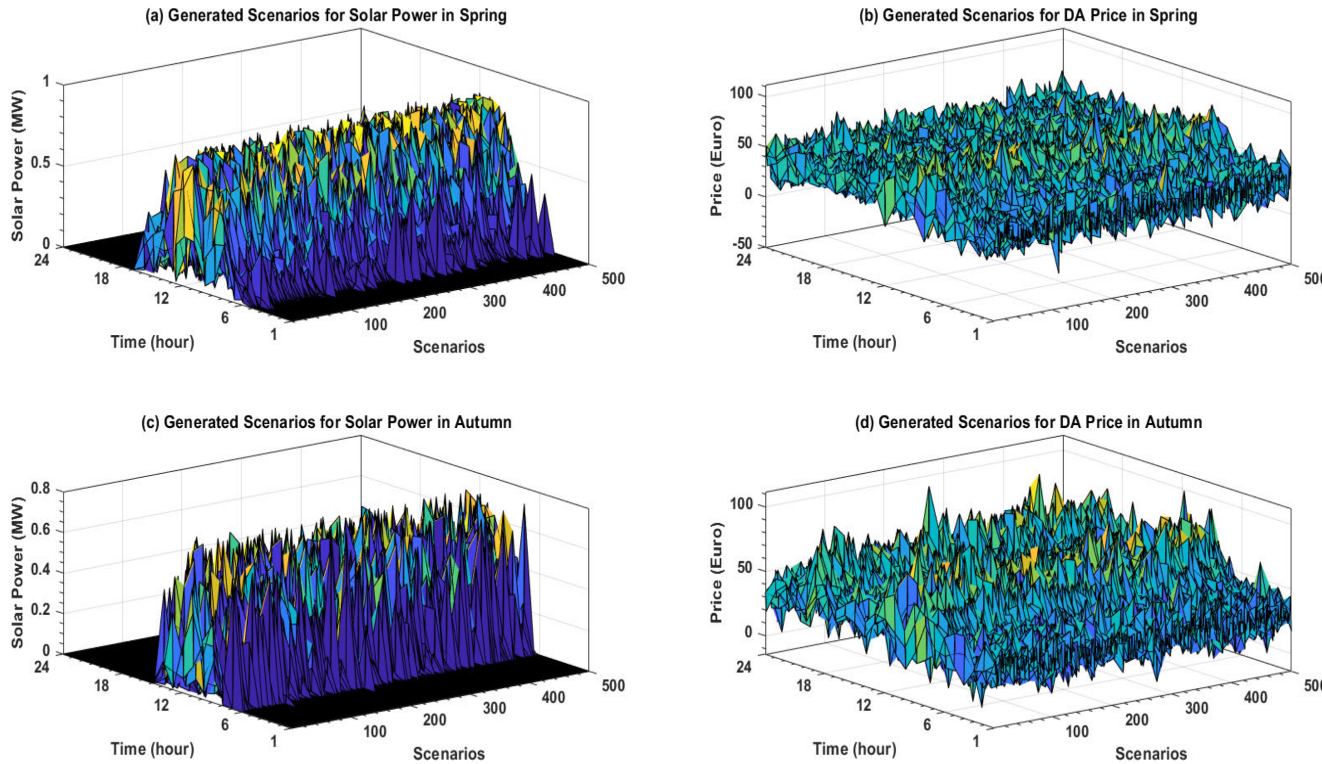

FIGURE 11. Scenarios generated for modeling solar power and DA price on selected days of spring and autumn.

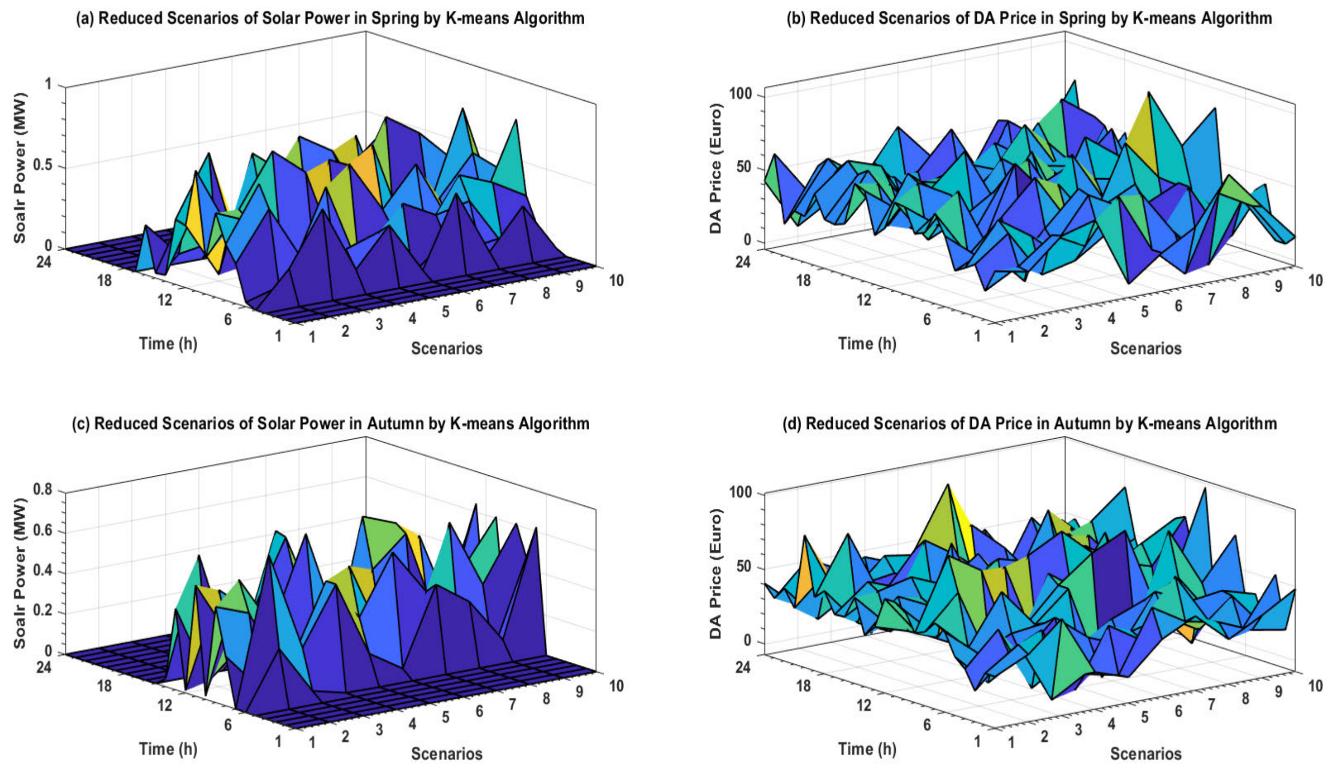

FIGURE 12. Reduced scenarios for modeling solar power and DA prices on selected days of spring and autumn.

is based on the scheduling problem, shows that their expected behavior toward each other has been the opposite. When CHP unit generation has been declining, boiler unit consumption has been on the rise and vice versa. Given that the level of biogas generated can be uncertain, it is therefore transferred to the storage after biogas generation and collection. For this

TABLE 2. Parameters of biogas-based EH.

Parameter	Value	Parameter	Value	Parameter	Value
R_{in}	155.78×10^{-4} °C/kW	$P_{th,min}^{CHP}$	0.005 MW	$P_{th,max}^{Boiler}$	1.05 MW
R_{W1}	10.99×10^{-4} °C/kW	$P_{th,max}^{CHP}$	0.55 MW	N_{PV}	4000
R_{W2}	85.78×10^{-4} °C/kW	$CCSU$	8 €	G_0	1000
R_{out}	50.71×10^{-4} °C/kW	$CCSD$	8 €	N_{OT}	25 °C
$T_{Optimal}$	35 °C	UT, DT, U^0	1	I_{MPP}	7.35
HV_{Biogas}	6.11 kWh/m^3	η_e^{ch}	0.9	V_{MPP}	30.5
a	-0.125	η_e^{dis}	0.9	K_I	0.0003
b	300	$P_{e,0}^{SOC}$	0.05 MW	K_v	0.0027
$\eta_e^{EHP-Dig}$	0.7	P_{Capa}^{EES}	0.7 MW	η_{Inv}	0.88
a_{Biogas}^{min}	0.35	α_e^{loss}	0.05	$C_{th,\text{ Spring}}$	36 €
a_{Biogas}^{max}	0.35	a_e^{min}	0.05	$C_{th,\text{ Autumn}}$	40 €
P_{Capa}^{BES}	1000 m^3	a_e^{max}	0.9	η_e^{Tra}	0.98
$P_{Biogas,min}^{SOC}$	100 m^3	COP	2	$P_{e,min}^{in,out}$	0 MW
$P_{Biogas,max}^{SOC}$	1000 m^3	$P_{th,min}^{EHP}$	0.003 MW	$P_{e,max}^{in,out}$	4 MW
$\eta_{e,th}^{CHP}$	0.4, 0.45	$P_{th,max}^{EHP}$	0.7 MW	$P_{th,min}^{out}$	0 MW
$P_{e,min}^{CHP}$	0.005 MW	η_{th}^{Boiler}	0.7	$P_{th,max}^{out}$	4 MW
$P_{e,max}^{CHP}$	0.45 MW	$P_{th,min}^{Boiler}$	0 MW		

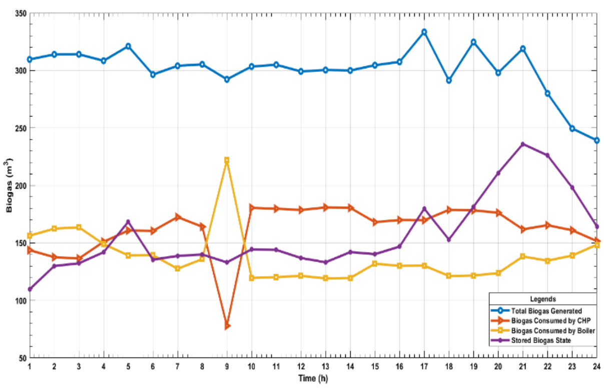

FIGURE 13. Biogas generated, consumed, and stored EH elements on the spring day.

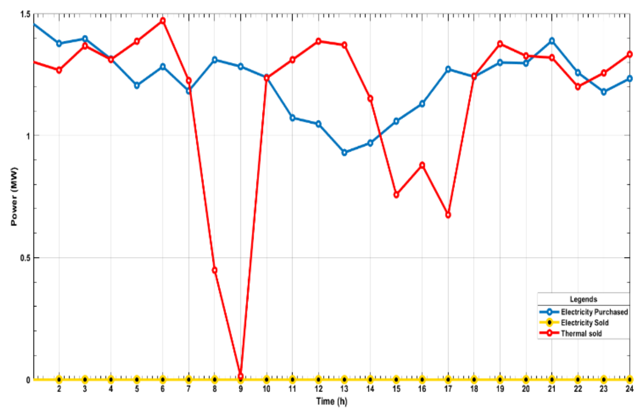

FIGURE 14. Electricity and thermal exchanged EH with energy networks on the spring day.

reason, the biogas level has been relatively directly related during the periods of the produced biogas ratio, and the storage state values are located in the specified constraints.

Fig. 14 shows the thermal and electricity exchanges taken by the EH with the energy market on the spring day. Although the EH has been able to sell electricity to a certain extent, it has been more priority because it has large electrical loads, and its full supply has been a priority, so it has not been able to sell surplus electricity to the energy market. In addition to domestic electricity generation, the EH has also purchased electricity from the energy market. In contrast, the EH has not only supplied its domestic thermal loads but also sold its surplus to the energy market, thereby earning money for itself.

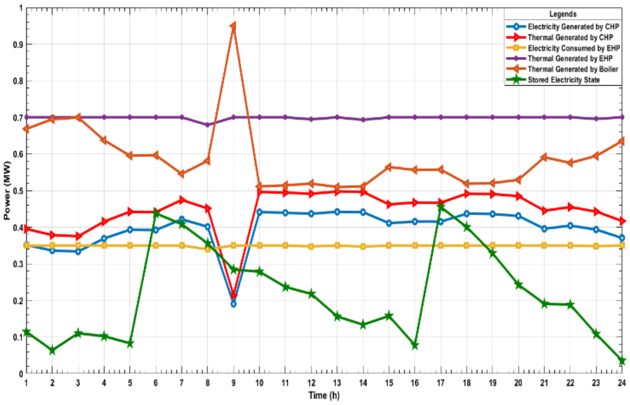

FIGURE 15. Electricity and thermal generated, consumed, and stored by CHP, boiler, EHP, and electricity storage on the spring day.

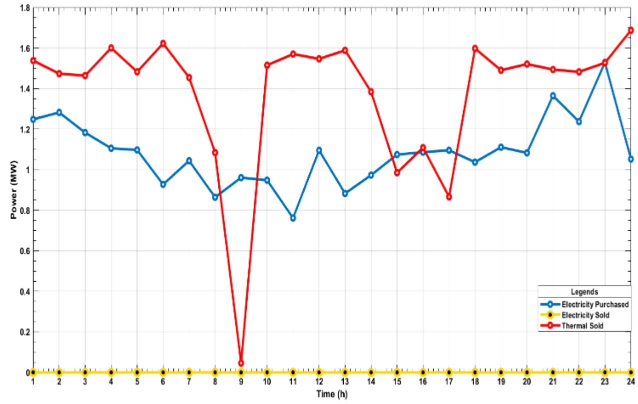

FIGURE 17. Electricity and thermal exchanged EH with energy networks on the autumn day.

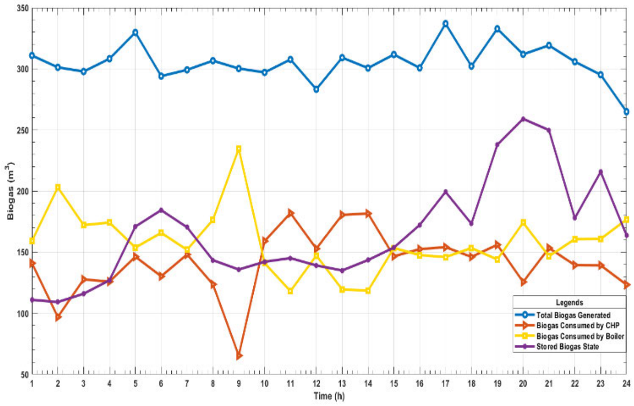

FIGURE 16. Biogas generated, consumed, and stored EH elements on the autumn day.

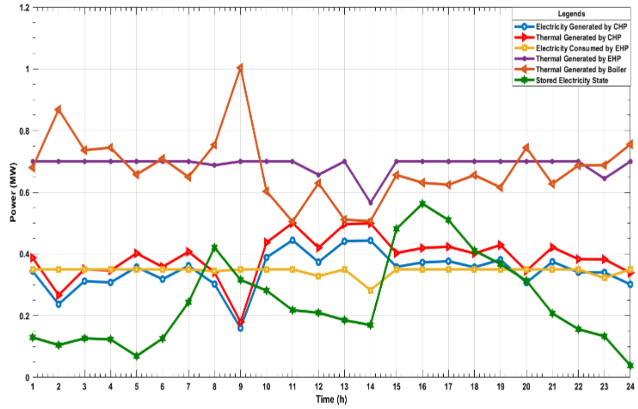

FIGURE 18. Electricity and thermal generated, consumed and stored by CHP, boiler, EHP, and electricity storage on the autumn day.

Fig. 15 shows the expected behavior of CHP, boiler, EHP, electrical storage for the generation, consumption, and storage of electricity and thermal on the spring day. Also, due to the constraints and modeling, the dependence of electricity and thermal generation behavior of EHP and CHP units between electricity and thermal can be seen with a certain coefficient. Another result expressed in Fig. 16 is the appropriate and almost continuous behavior of electrical storage in charging and charging situations. When the discharge has occurred after the charge, there has been no drastic change again, and in the scheduling, the behavior of the discharge has been continued until the need for electrical storage charging arises. This increases battery or electrical storage life in EH operation.

Fig. 16, Fig. 17, and Fig. 18 have been used to investigate the expected behavior of parameters such as Fig. 13, Fig. 14, and Fig. 15, respectively, but on the autumn day. In autumn, due to changes in the behavior of electrical and thermal loads and, on the other hand, higher thermal prices in this season, the EH has focused on selling more thermal and buying less electricity. Boiler and CHP behaviors have been the opposite due to their relationship in biogas feeding, such as spring. Also, in this season, the behavior of the electrical storage has been such that the change in the status between the charge and its discharge is low, and as a result, this issue, like spring, increases its lifespan.

C. COMPARATIVE TEST RESULTS

This section evaluates and compares the biogas production unit's performance in the proposed EH's optimal scheduling. By removing the biogas production unit, the EH loses a cheap and clean energy carrier. In this case, to supply energy to the CHP and Boiler units located in the proposed structure, alternative fuel (natural gas) is used, as shown in Fig. 19. In this figure, P_{NG}^{in}, NG_{ICE} and NG_{Boiler} are inlet gases to the EH, CHP unit, and ICE unit, respectively.

The DA scheduling for the EH shown in Fig. 19 is such that it must also participate in the natural gas distribution market to supply the amount of natural gas it needs. The simulation of this section uses Finnish natural gas price information on the selected days of spring and autumn. The results of this comparative test are shown in Table 3. According to the results of this table, eliminating the biogas production unit significantly increases the expected costs of EH's scheduling. In fact,

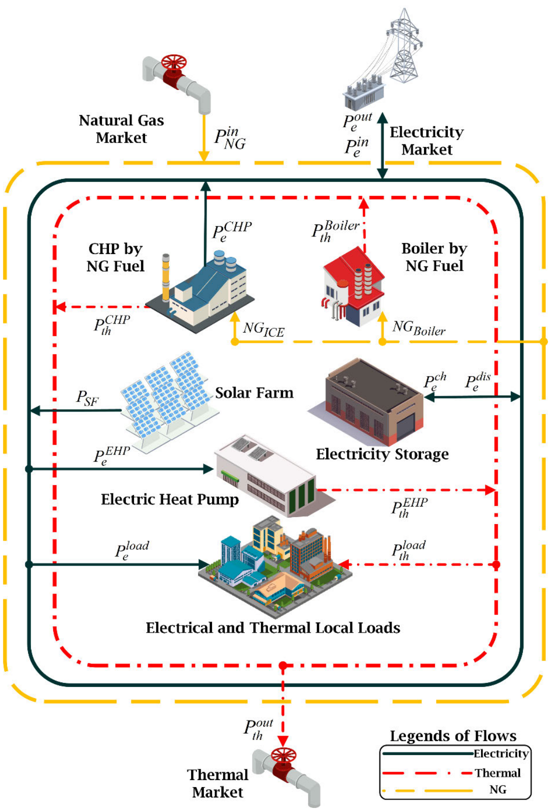

FIGURE 19. The EH structure without biogas unit.

TABLE 3. Comparative test results.

Selected day	Daily expected cost (€)	
	Biogas-based	Without biogas unit
Spring	112.74	1439.49
Autumn	-317.73	1126.11

the high purchase price of natural gas has increased the cost of operating the EH. In addition, this type of operation also leads to environmental pollution. Therefore, the proposed biogas-based structure of the EH, in addition to reducing pollution, makes system scheduling more economical.

IV. CONCLUSION

This paper proposed a linearized stochastic optimization framework for DA optimal scheduling of a biogas-based EH under the uncertainties of electricity price and solar radiation. The EH had a digester unit as a converter for converting biomass fuel into biogas, biogas storage unit, biogas-burning CHP unit, biogas burner boiler, solar farm, electrical storage, electrical and thermal loads, as well as EHP. Uncertainties related to solar radiation and DA price were scenarioized by the Monte Carlo method and default PDFs, and then their number was reduced by K-means clustering. After modeling the uncertainty parameters, the reduced scenarios were entered into the optimization problem framework.

The results of output from the proposed framework in this paper show that the EH has been able to achieve the optimal cost for scheduling in the DA market and supply its electrical and thermal loads in both spring and autumn. The optimal scheduling costs for the spring and autumn seasons were 112.7363 and -317.73 euros, respectively. The reason for the negative scheduling cost in the autumn is that the EH's income from participation in energy markets has been much higher than its scheduling costs.

Biogas production in the proposed EH has resulted in a valuable, inexpensive, and clean fuel available to the multi-energy system's operator. The production and use of this fuel have brought advantages. The most important advantages include minimizing the cost of scheduling, minimizing dependence on primary energy carriers for supplying internal loads, participation in DA energy markets, minimizing pollution production, and making the DA scheduling problem lighter. Comparative test results show that eliminating the biogas production unit in the EH can increase the scheduling costs and dependency for supplying energy carriers. The existence of dependent relationships between biogas fuels generated and consumed by CHP and boilers shows that the relationships of electricity and thermal generation in these units have been opposed to each other. On the other hand, the continuous behavior in the use of electrical storage has shown that this scheduling framework has been able to increase the life and health of this unit.

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