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Optimization of Micro Multi-Carrier Energy Hub Operation Under Uncertain Predictions

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Abstract—Finding an optimal schedule(s) for the buildings' energy equipment cluster is vital to realize sustainable development and energy-saving goals. However, high-impact uncertainties pose critical challenges in this regard. To relax these challenges, this paper develops an optimization model for operating the buildings' energy equipment cluster under uncertain predictions whose principal elements are the energy hub (EH) concept and the two-point estimate (TPE) method. The EH concept is used to find levels of the degree of freedom for optimization by modeling efficiently how multi-carrier energy resources and demands can be connected through this cluster of converters, conditioners, storage, and others. The TPE method is, however, used to improve the reliability and robustness of the model's predictions, leading to better decision-making under uncertainty. The TPE method integrates high-impact uncertainties related to multi-carrier energy prices and demands and the production capacity of renewable energy resources in optimization. The proposed optimization model has been applied to an industrial building, and its sufficiency and profitability are examined in different scenarios.

Keywords—Buildings, energy hub, integrated energy systems, two-point estimate method, uncertainty.

NOMENCLATURE

- Index and set:
 - t, T Index and set for the operation horizon
- Parameters:
 - H_{hp}^{min} Minimum output heat of the HP
 - H_{hp}^{max} Maximum output heat of the HP
 - S_{pv} The PV array area
 - ψ_{hp} Coefficient of performance for the HP
 - $\eta_{chp,gte}$ The CHP efficiency for gas to electricity
 - $\eta_{chp,gth}$ The CHP efficiency for gas to heat
 - $\eta_{ch,es}$ The charging efficiency of the BS
 - $\eta_{di,es}$ The discharging efficiency of the BS
 - χ_{es} The self-discharge rate of the ES
 - φ_e The emission factor of the natural gas
 - φ_g The emission factor of the purchased electricity
 - ϖ_{CO_2} The cost factor of the CO₂ emission
- Variables:
 - $b_{h,hp}$ Binary variable to define the heating and cooling modes of the HP
 - $b_{c,hp}$ Binary variable to define the heating and cooling modes of the HP
 - $b_{ch,es}$ Binary variable to define the charging and discharging modes of the BS
 - $b_{di,es}$ Binary variable to define the charging and discharging modes of the BS
 - $D_{c(t)}$ Predicted cooling demand
 - $D_{e(t)}$ Predicted Electricity demand
 - $D_{h(t)}$ Predicted heating demand
 - $E_{ch,es}$ Charged electricity in the BS
 - $E_{di,es}$ Discharged electricity from the BS
 - H_{hp} The heat generated by the heat pump

I_{pv}	Solar radiation intensity
$P_{tr,in}$	Input power to the TR
$P_{e,n}$	Purchased electricity from the network
$V_{gas,chp}$	Consumed gas by the CHP
$V_{g,n}$	Purchased gas from the network
π_e	Predicted price for purchasing electricity
π_g	Predicted price for purchasing natural gas

Note:

The corresponding variables are expanded for the operation horizon index t .

The corresponding parameters and variables are considered for the cooling, power, and energy by changing the capital letter H to C , P , and E , respectively. For example, $H_{hp(t)}$ changes to $C_{hp(t)}$ (the cooling generated by the heat pump) by changing H to C .

The corresponding parameters and variables are considered for the photovoltaic, combined heat and power, auxiliary boiler, absorption chiller, transformer, electrical storage, and heating storage by replacing the subtitle hp with the pv , chp , ab , ach , tr , es , and hs , respectively. For example, H_{hp}^{min} changes to the minimum level of stored energy in the electrical storage by replacing H with E and hp with es).

I. INTRODUCTION

A. Background and Motivation

Urban area customers consume around 67% of global energy consumption; consequently, they are the main culprit in producing greenhouse gas emissions (GGEs), a share of about 70% [1]. Around 60% of the energy consumed in these regions can be attributed to various residential, commercial, industrial, or office buildings [2]. Conventionally, buildings met all their needs for different energy carriers by connecting to the relevant supply infrastructure (e.g., electricity, gas, and district heating networks). Precisely, they were passive end-users (consumers) that only consumed different energy carriers. This structure had a low level of degree of freedom for optimization. There are currently notable changes taking place as a result of the restructuring of the power system, techno-economic revolutions in scaled-down renewable energy resources (RERs), new advancements in multi-carrier energy conversion and storage technologies, updated environmental monitoring roadmaps, and other factors. These changes challenge our conventional notions of multi-carrier energy supply infrastructures and integrated energy systems (IESs) [3], [4]. Buildings serve as a vital part of this new environment, transitioning from a consumer to a prosumer (active end-users that can consume, produce, store, and supply different energy carriers) [5], [6]. This role change brings a higher degree of freedom for optimization in buildings, especially in the process of their operation in the form of IESs.

TABLE I. A COMPREHENSIVE AUDIT OF THE LITERATURE

Ref.	Energy carriers		Energy equipment cluster		Uncertainty		Optimization process	
	Input energy resource	Output energy demand	Energy converter and conditioner	Energy storage	Uncertainty consideration	Non-deterministic model	Objective functions	Solution method
[7]	EL, G, and SO	EL, HE, and CO	GB, GT, ECH, ACH, and PV	ES	---	---	OC	TAS
[8]	EL, G, and HE	EL, HE, and CO	HP, CHP, GB, ECH, and ACH	HS and ES	---	---	OC	ABCA
[9], [10]	EL, G, and SO	EL and HE	[9], [10]: PV and CHP [10]: GB and HP	ES	---	---	[9]: PS [10]: OC	[9]: Heuristic [10]: PSO
[11]	EL, G, SO, WI, and HE	EL, HE, CO, and HY	GB, CHP, PV, WT, ACH, ECH, EB, FC, TR, and ELC	HS, ES, and GS	---	---	OC	Gurobi
[12]	EL, G, and SO	EL, HE, and CO	GB, CHP, PV, and ACH	HS	---	---	OC	LP, GA, and PSO
[13], [14]	EL, G, SO, and WI	EL, HE, and CO	[13], [14]: PV, WT, GT, ECH, GB, and HEX [13]: ACH	HS, ES, and CS	---	---	OC	GAMS: MILP
[15]	EL and SO	EL, HE, and CO	HP, PV, and ECH	HS and CS	---	---	OC	---
[16]	G	EL and HE	CHP	HS	EL, G, and HE prices	MCS	PR	---
[17]	EL and G	EL, HE, and CO	AB, ACH, TR, and CCHP	ES	EL and G prices, ED	MCS and CVaR	OC and EC	GAMS: MILP
[18]	EL and G	EL, HE, and G	EB and CHP	HS and ES	PV and WT output, ED and HD, EL and G prices	SDMM	OC	NC&CG
[19]	EL, G, and SO	EL, HE, and CO	PV, CCHP, and TR	---	PV output and ED	SDMM	OC	MILP
[20]	EL, G, SO, and WI	EL and HE	PV, WT, GB, and CHP	HS and ES	EL price and charging load of the EV	MCS and RO	OC	MILP
[21]	EL, G, SO, and HE	EL, HE, and CO	PV, GV, HP, and CHP	HS and ES	PV output, ED, and HD	MCS	OC and EC	MILP
This work	EL, G, and SO	EL, HE, and CO	PV, AB, ACH, HP, CHP, and TR	HS and ES	EL, and G prices, ED, HD, CD, and PV output	TPE method	OC and EC	GAMS: MILP

In this Table: AB, auxiliary boiler; ABCA, artificial bee colony algorithm; ACH, absorption chiller; CCHP, combined cooling, heat, and power; CD, cooling demand; CHP, combined heat and power; CO, cooling; CS, cooling storage; CVaR; conditional value-at-risk; EB, electric boiler; EC, emission cost; ELC, electrolytic cell; ECH, electric chiller; ED, electrical demand; EL, electricity; ES, electrical storage; EV, electric vehicle; FC, fuel cell; G, gas; GA, genetic algorithm; GB, gas boiler; GS, gas storage; GT, gas turbine; HD, heating demand; HE, heating; HEX, heat exchanger; HP, heat pump; HS, heat storage; HY, hydrogen; LP, linear programming; MCS, Monte Carlo simulation; NC&CG, nested column-and-constraint generation; OC, operational cost; PR, profit; PS, peak shaving; PSO, particle swarm optimization; PV, photovoltaic; RO, robust optimization; SDMM, scenario-based decision-making method; SO, solar; TAS, tabu search; TPE, two-point estimate; TR, transformer; WI, wind; WT, wind turbine.

The operation process is to obtain an optimum schedule(s) for the buildings' energy equipment cluster that is involved in generating, converting, transferring, and distributing different energy carriers to minimize or maximize a set of techno-economic and environmental objective functions under predefined constraints. Therefore, a potential capacity for saving different energy carriers, reducing GGEs, increasing reliability, and others can be envisioned in this process.

B. Literature Review and Contribution

There are different concepts in the literature to model buildings as IESs, such as the energy-service supply system, basic unit, microgrid, virtual power plant, and energy hub (EH) [22]. The EH is a highly effective tool that accurately models buildings as an IES by creating links between multi-carrier energy resources and demands through conversion, storage, condition, and distribution processes [22]. Here, the authors concentrate on the literature scrutinizing buildings as an IES using the EH tool—micro multi-carrier EH (μ MEH). In the literature, the mathematical models for operating μ MEHs can fall into two policies for dealing with uncertainties: deterministic and non-deterministic [23]. In the former, the μ MEH is designed to simulate the most severe scenario (highest possible values) for all parameters, including multi-carrier energy prices and demands, component outage rate, and the output power of RERs, regardless of how likely they are to happen [7]–[15]. These studies indicate that employing the μ MEH with this policy offers the advantage of

simplicity. However, it fails to accurately represent the behavior associated with various parameters in practical cases, resulting in impractical outcomes that lack real-world implementation capability. Hence, the logical choice to omit this substantial limitation present in deterministic policy is to construct the μ MEH's model under a non-deterministic policy. Under this policy, the μ MEH is simulated to encompass all potential scenarios that could arise in the future for parameters with stochastic characteristics, taking into account their respective probabilities of occurrence. These studies show that considering different uncertainties brings a much more adaptable operation process than the deterministic policy and provides more feasible outcomes in the μ MEH's operation studies. Detailed examinations represent that the buildings under investigation in these studies, depending on the geographical location, usage, available energy resources, required energy carriers, and others, have used various clusters of converters, storages, and conditioners to match their resources with demands optimally. In addition, each study has used different objective functions, constraints, and assumptions in optimization depending on the operator's needs. Table I presents a comprehensive audit of all these features in μ MEH studies. Abbreviations mentioned in Table I may be used in the rest of the paper. Table I shows that these studies have some weaknesses. First, they have an excessive dependence on electricity and gas networks and a lack of attention to RERs. Next, in some studies, important output energy carriers (e.g., cooling) are ignored. Then, they have

excessive use of low-efficiency converters (e.g., single-input single-output and multiple-input single-output) in the energy equipment cluster. In addition, in some cases, they rely on unrealistic assumptions. Furthermore, they consider a limited number of uncertain parameters and use traditional methods for their handling.

In this paper, the authors develop an optimization model for operating a μ MEH (an industrial building) under uncertain predictions considering realistic assumptions to relax these shortcomings. The EH concept and the TPE method form the foundation of the proposed model. The former perfectly models the buildings' energy equipment cluster and their connections. The latter integrates uncertainties related to electricity and gas prices, electrical, heating, and cooling demands, as well as the production capacity of the PV system in the optimization model. The OC of the buildings' energy equipment cluster and the EC are added together using weighting coefficients and considered the objective function (OF). Concurrently, technical and logical limitations are considered two classes of problem restrictions. Finally, this optimization model is formulated as a MILP optimization problem to use powerful commercial solvers of the GAMS platform to find the optimal solution.

C. Paper Outline

The structure of the article continues as follows. Section two presents the mathematical model of the μ MEH's energy equipment cluster in detail. Besides, section three describes the optimization model of the μ MEH's operation. Moreover, section four represents how the TPE method integrates high-impact uncertainties in optimization. Next, section five implements case studies and discusses simulation results. Finally, section six ends the paper with a summary.

II. MATHEMATICAL MODEL OF THE OFFERED μ MEH

Fig. 1 demonstrates the configuration of the offered μ MEH. The μ MEH's energy equipment cluster consists of converters (HP, CHP, AB, ACH, and PV), conditioners (TR), storages (ES and HS), and transmission lines (electrical cables, gas pipelines, and heat pipes). The μ MEH is fed by electricity and natural gas from the upstream networks and solar radiation as input carriers and must feed electrical, heating, and cooling demands.

A. Converters

Converters convert input energy carriers into other carriers according to the type, nature, quantity, and quality required.

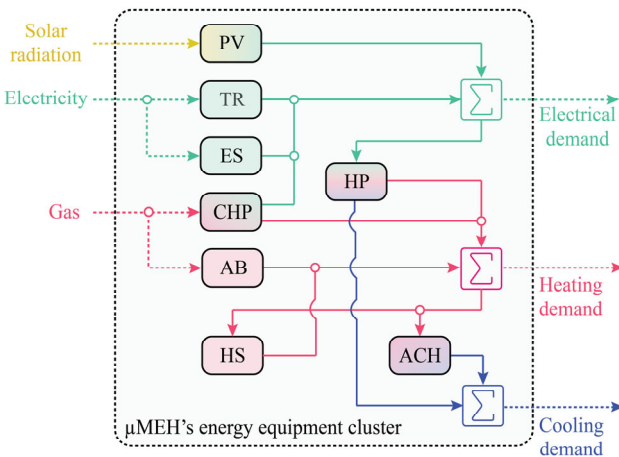


Fig. 1. The structure of the proposed μ MEH

• Electric heat pump

Electric HP is a heating and cooling system, based on the operating mode, that transfers heat from one location to another using electricity, making it an efficient and eco-friendly alternative to traditional heating and cooling systems (see (1)-(4)) [8].

$$H_{hp(t)} + C_{hp(t)} = P_{hp(t)} \cdot \psi_{hp(t)}; \forall t \in \Omega_T \quad (1)$$

$$H_{hp}^{\min} \cdot b_{h, hp(t)} \leq H_{hp(t)} \leq H_{hp}^{\max} \cdot b_{h, hp(t)}; \forall t \in \Omega_T \quad (2)$$

$$C_{hp}^{\min} \cdot b_{c, hp(t)} \leq C_{hp(t)} \leq C_{hp}^{\max} \cdot b_{c, hp(t)}; \forall t \in \Omega_T \quad (3)$$

$$b_{h, hp(t)}, b_{c, hp(t)} \in \{0, 1\}, b_{h, hp(t)} + b_{c, hp(t)} \leq 1; \forall t \in \Omega_T \quad (4)$$

• Combined heat and power

The CHP system is the most well-known single-input and multiple-output converter, which uses natural gas as input and generates electricity and heat as outputs (see (5)-(8)) [8], [16].

$$P_{chp(t)} = V_{gas, chp(t)} \cdot \eta_{chp, gte(t)}; \forall t \in \Omega_T \quad (5)$$

$$H_{chp(t)} = V_{gas, chp(t)} \cdot \eta_{chp, gth(t)}; \forall t \in \Omega_T \quad (6)$$

$$P_{chp}^{\min} \leq P_{chp(t)} \leq P_{chp}^{\max}; \forall t \in \Omega_T \quad (7)$$

$$H_{chp}^{\min} \leq H_{chp(t)} \leq H_{chp}^{\max}; \forall t \in \Omega_T \quad (8)$$

• Auxiliary boiler

The AB is used as a backup to provide heat in case the CHP and electric HP in heat generation mode fail to meet the HD of the μ MEH completely. The AB uses natural gas as input and provides heating as output (see (9) and (10)) [17].

$$H_{ab(t)} = V_{gas, ab(t)} \cdot \eta_{ab(t)}; \forall t \in \Omega_T \quad (9)$$

$$H_{ab}^{\min} \leq H_{ab(t)} \leq H_{ab}^{\max}; \forall t \in \Omega_T \quad (10)$$

• Absorption chiller

The ACH is a refrigeration system that uses heat to drive the cooling cycle through the absorption and desorption of a refrigerant by a liquid absorbent (see (11) and (12)) [7], [11].

$$C_{ach(t)} = H_{ach(t)} \cdot \eta_{ach(t)}; \forall t \in \Omega_T \quad (11)$$

$$C_{ach}^{\min} \leq C_{ach(t)} \leq C_{ach}^{\max}; \forall t \in \Omega_T \quad (12)$$

• Photovoltaic system

Due to the negligible emission of GGEs, the PV system is the most environmentally friendly way of producing electricity. This system converts sunlight into electricity using solar cells (see (13) and (14)) [19]–[21].

$$P_{pv(t)} = S_{pv(t)} \cdot I_{pv(t)} \cdot \eta_{pv(t)}; \forall t \in \Omega_T \quad (13)$$

$$P_{pv}^{\min} \leq P_{pv(t)} \leq P_{pv}^{\max}; \forall t \in \Omega_T \quad (14)$$

B. Conditioners

In the conditioning process, the type and nature of input energy carriers remain unchanged in the output, and only their quantity/quality change.

• Transformer

The TR is used to transfer electrical energy from one circuit to another one using an electromagnetic induction process, typically by changing (increasing or decreasing) the voltage level of the power supply (see (15) and (16)) [19].

$$P_{tr(t)} = P_{tr,in(t)} \cdot \eta_{tr(t)}; \forall t \in \Omega_T \quad (15)$$

$$P_{tr}^{\min} \leq P_{tr(t)} \leq P_{tr}^{\max}; \forall t \in \Omega_T \quad (16)$$

C. Storages

In the μ MEH's operation, using suitable storage that helps maintain and increase flexibility and reliability is critical. Here, electrical and heating storages are desirable for energy backup due to their installation and operational benefits. They compensate or save the energy deficit or surplus due to the non-deterministic features of electrical, heating, and cooling demands, electricity and gas prices, the production capacity of the PV system, and others. For electrical storage, please see (17)-(22) [7]–[11].

$$E_{es(t)} = E_{es(t-1)} + \eta_{ch,es} \cdot E_{ch,es(t)} - (E_{di,es(t)}/\eta_{di,es}) - \lambda_{es} \cdot E_{es(t-1)}; \forall t \in \Omega_T \quad (17)$$

$$E_{ch,es}^{\min} \cdot b_{ch,es(t)} \leq E_{ch,es(t)} \leq E_{ch,es}^{\max} \cdot b_{ch,es(t)}; \forall t \in \Omega_T \quad (18)$$

$$E_{di,es}^{\min} \cdot b_{di,es(t)} \leq E_{di,es(t)} \leq E_{di,es}^{\max} \cdot b_{di,es(t)}; \forall t \in \Omega_T \quad (19)$$

$$E_{es}^{\min} \leq E_{es(t)} \leq E_{es}^{\max}; \forall t \in \Omega_T \quad (20)$$

$$E_{es(t=24)} \geq E_{es(t=0)}; \forall t \in \Omega_T \quad (21)$$

$$b_{ch,es(t)}, b_{di,es(t)} \in \{0,1\}, b_{ch,es(t)} + b_{di,es(t)} \leq 0; \forall t \in \Omega_T \quad (22)$$

In this study, the HS is modeled with a similar formulation of the ES (by replacing the capital letter E with H and the subtitle *es* with *hs* in (17)-(22)).

III. OPTIMIZATION MODEL

The operator's main target is to provide a cost-effective and eco-friendly operation plan for the μ MEH's energy cluster equipment over the desired horizon (here, 24 hours). Hence, the operator considers the sum of OC (purchased energy cost from the upstream electricity and gas networks) and EC (the price of CO₂ emission) as the OF in the optimization according to (23). The OF is subjected to technical and logical limitations, according to (24)-(30):

$$P_{pv(t)} + P_{tr(t)} + P_{chp(t)} + E_{di,es(t)} = P_{hp(t)} + D_e(t); \forall t \in \Omega_T \quad (24)$$

$$P_{tr,in(t)} + E_{ch,es(t)} = P_{e,n(t)}; \forall t \in \Omega_T \quad (25)$$

$$V_{gas,chp(t)} + V_{gas,ab(t)} = V_{g,n(t)}; \forall t \in \Omega_T \quad (26)$$

$$H_{chp(t)} + H_{ab(t)} + H_{hp(t)} + H_{di,ts(t)} - H_{ch,ts(t)} = D_h(t); \forall t \in \Omega_T \quad (27)$$

$$C_{ach(t)} + C_{hp(t)} = D_c(t); \forall t \in \Omega_T \quad (28)$$

Equations (1) –

$$(4), (7), (8), (10), (12), (14), (16), (17) - (22) \quad (29)$$

Equations (17) –

$$(22); \text{ with replacing E with H and es with hs} \quad (30)$$

IV. UNCERTAINTY CONSIDERATION

Here, the efficient TPE method is used to handle uncertainties in optimization. Unlike its original version, which requires 2^N probability concentrations located at 2^N distinct positions to replace the original joint PDF of N uncertainty input parameters (UIPs) by matching the second-order and third-order non-crossed moments; the TPE method needs only 2N probability concentration places, resulting in a significant decline in the computational complexity [23], [24]. Here, the electricity and gas prices, electrical, heating, and cooling demands, as well as the production capacity of the PV system, are considered as UIPs, as given by (31):

$$x = [\pi_e(t), \pi_g(t), D_e(t), D_h(t), D_c(t), P_{pv(t)}]; \forall \{t \in \Omega_T\} \quad (31)$$

Thus, the proposed model is a multivariate function of UIPs, as given by (32):

$$y = f(x) \quad (32)$$

A sequential process to implement the TPE method in the μ MEH's operation process is developed as follows [23]:

- Stage 1: Set the number of UIPs equal to N.
- Stage 2: Set the first and second moments of the output variable y , using (33):

$$E(y) = E(y^2) = 0 \quad (33)$$

- Stage 3: Set the counter of UIPs: $n = 1$.
- Stage 4: Compute the skewness coefficient related to the UIP n , using (34):

$$\lambda_{x_{n,3}} = E[(x_n - \mu_{x_n})^3] / (\sigma_{x_n})^3 \quad (34)$$

In (34), μ_{x_n} and σ_{x_n} are the mean and variance of the UIP n , respectively. Also, $E[(x_n - \mu_{x_n})^3]$ is defined using (35):

$$E[(x_n - \mu_{x_n})^3] = \sum_m^M (x_{n,m} - \mu_{x_{n,m}})^3 \cdot p(x_{n,m}) \quad (35)$$

In (35), M and $p(x_{n,m})$ are the number of observations of the UIP n and the probability of observation m associated with the UIP n , respectively.

- Stage 5: Compute the position and probability (weighting) of two concentration points associated with the UIP n , according to (36) and (37), respectively:

$$v_{x_{n,i}} = \frac{\lambda_{x_{n,3}}}{2} + (-1)^{3-i} \cdot \sqrt{N + (\lambda_{x_{n,3}}/2)^2}; \forall i \in \{1,2\} \quad (36)$$

$$p_{x_{n,i}} = \frac{(-1)^i \cdot \lambda_{x_{n,3}}}{2N \cdot \sqrt{N + (\lambda_{x_{n,3}}/2)^2}}; \forall i \in \{1,2\} \quad (37)$$

In (37), each probability's value, $p_{x_{n,i}}; \forall i \in \{1,2\}$, can range from 0 to 1, but their total is always 1.

- Stage 6: Compute two concentration points using (38):
- $$u_{x_{n,i}} = \mu_{x_n} + \zeta_{x_{n,i}} \cdot \sigma_{x_n}; \forall i \in \{1,2\} \quad (38)$$
- Stage 7: Compute the output variable y based on the UIPs' vector, using (39):
- $$y = f(x); \forall x = \{\mu_{x_1}, \mu_{x_2}, \dots, u_{x_{n,i}}, \dots, \mu_{x_N}\}; \forall i \in \{1,2\} \quad (39)$$
- Stage 8: Update $E(y)$ and $E(y^2)$, using (40) and (41), respectively:

$$OF = \sum_t^T \pi_e(t) \cdot P_{e,n(t)} + \pi_g(t) \cdot V_{g,n(t)} + \varpi_{CO_2} \cdot \sum_t^T \varphi_e(t) \cdot P_{e,n(t)} + \varphi_g(t) \cdot V_{g,n(t)}; \forall t \in \Omega_T \quad (23)$$

$$E(y) \cong \sum_{n=1}^N \sum_{i=1}^2 p_{\gamma_{n,i}} \cdot f(\mu_{x_1}, \mu_{x_2}, \dots, u_{x_{n,i}}, \dots, \mu_{x_{N-1}}, \mu_{x_N}); \forall i \in \{1,2\} \quad (40)$$

$$E(y^2) = \sum_{n=1}^N \sum_{i=1}^2 p_{\gamma_{n,i}} \cdot f(\mu_{x_1}, \mu_{x_2}, \dots, u_{x_{n,i}}, \dots, \mu_{x_{N-1}}, \mu_{x_N})^2; \forall i \in \{1,2\} \quad (41)$$

- Stage 9: Compute the mean (expected value) and the standard deviation of the output variable y , according to (42) and (43), respectively:

$$\mu_y = E(y) \quad (42)$$

$$\sigma_y = \sqrt{\text{var}(y)} = \sqrt{E(y^2) - (E(y))^2} \quad (43)$$

- Stage 10: Set $n = n + 1$. If $n \leq N$, proceed to Stage 4; otherwise, move to the subsequent stage.
- Stage 11: Stop.

V. CASE STUDIES AND DISCUSSION

For illustration, the offered optimization model is implemented on an industrial μ MEH (building). The predicted values for electrical, heating, and cooling demand of this building as well as solar radiation intensity, are depicted in Fig. 2. Also, the predicted values for time-varying electricity and gas prices and the cost factor of the CO₂ emission are shown in Fig. 3. These prices are used according to Denmark's retail energy market [24]. Parameters related to the μ MEH's energy equipment and other essential simulation parameters are provided in Table II. Additional data can be found in [13], [14]. The proposed model is implemented in the GAMS environment using a Core i7 CPU clocked at 2.8 GHz and 32 GB of RAM. Also, two different scenarios are considered to evaluate the efficiency of the proposed model as follows:

- Scenario 1: The model ignores ES and TS.
- Scenario 2: The model considers ES and TS.

Optimal schedules of the μ MEH's energy equipment cluster under scenarios 1 and 2 and the hourly charging and discharging modes of ES and HS under scenario 2 are shown in Fig. 4 through Fig. 6, respectively.

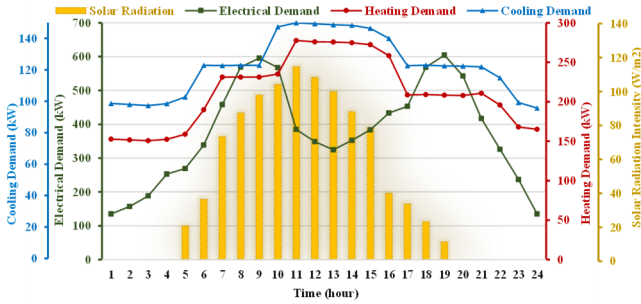


Fig. 2. The predicted values for electrical, heating, and cooling demand of the building as well as the solar radiation intensity

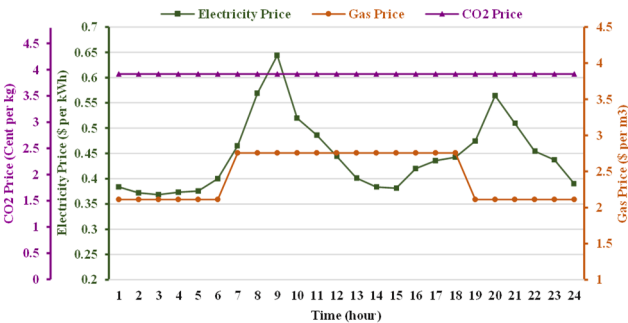


Fig. 3. Time-varying electricity and gas prices, and CO₂ emission price

TABLE II. INPUT PARAMETERS FOR DIFFERENT DEVICES

Parameter	Value	Parameter	Value
HP	50 kW _e	$\eta_{ch,es}$	0.95
ψ_{hp}	2.5	$\eta_{di,es}$	0.95
CHP	600 kW _e	χ_{es}	0.5% per hour
$\eta_{chp,gte}$	0.35	$E_{ch,es}^{max}$	20 kWh
$\eta_{chp,gth}$	0.45	$E_{di,es}^{max}$	20 kWh
AB	300 kW	$E_{es(t=0)}$	15 kWh
η_{ab}	0.8	TS	80 kWh
ACH	140 kW	$\eta_{ch,ts}$	0.9
η_{ach}	1.2	$\eta_{di,ts}$	0.9
PV	20 kW _p	χ_{ts}	0.08% per hour
S_{pv}	110 m ²	$E_{ch,ts}^{max}$	20 kWh
η_{pv}	0.157	$E_{di,ts}^{max}$	20 kWh
TR	650 kW	$E_{ts(t=0)}$	15 kWh
η_{tr}	0.98	φ_e	0.968 kg per kWh
ES	100 kWh	φ_g	0.22 kg per m ³

Also, the optimal values for the objective function under these case studies are given in Table III.

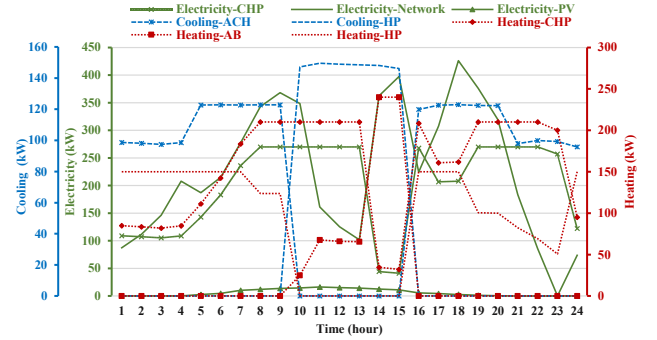


Fig. 4. Optimal schedule of the energy equipment cluster in Scenario 1

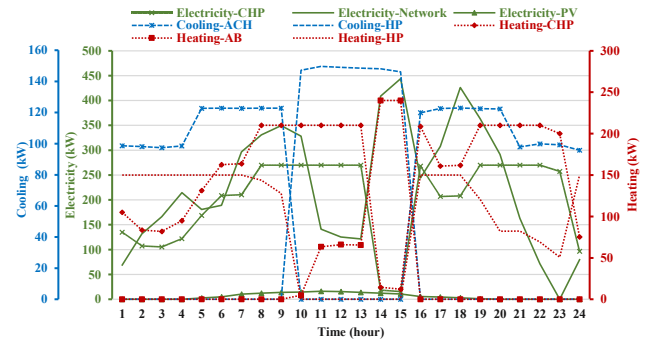


Fig. 5. Optimal schedule of the energy equipment cluster in Scenario 2

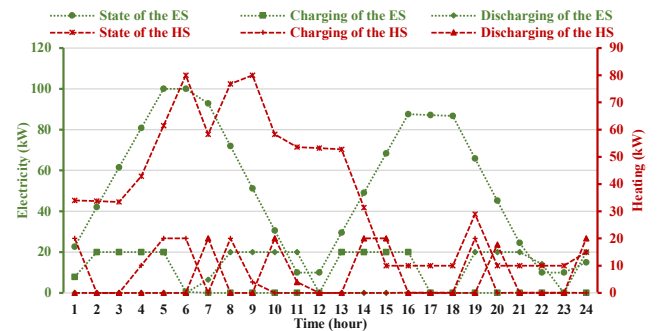


Fig. 6. Hourly charging/discharging mode of ES and HS in Scenario 2

TABLE III. OBJECTIVE FUNCTION VALUES IN CASE STUDIES 1 AND 2

Scenario number	The OC (\$)	The EC (\$)	The OF (\$)
Scenario 1	6204.8253	311.1905	6516.0158
Scenario 2	6056.6482	300.9827	6357.6309

Figs. 4 through 6, and Table III show that the optimal schedule of the μ MEH's energy equipment cluster in both scenarios connects the input energy carriers and output energy demands optimally and flexibly, which reduces the OC and EC. As a significant part of the proposed model, the ES and HS have a major impact on the energy management of the μ MEH. The time-varying electricity price, stochastic features of electrical, heating, and cooling demands, electricity and gas prices, and the production capacity of the PV system enable the operator to reduce the OC and EC by optimally charging and discharging the ES and HS (see Table III). Precisely, energy exchanges with upstream networks in more expensive hours are lower in scenario 2 than in scenario 1. Table IV gives the optimal result of implementing the proposed model under both scenarios with and without considering UIPs.

TABLE IV. RESULTS WITH AND WITHOUT CONSIDERING UIPs

Scenario number	Assumption	The OF (\$)
Scenario 1	Considering UIPs	6516.0158
	Ignoring UIPs	6584.3125
Scenario 2	Considering UIPs	6357.6309
	Ignoring UIPs	6412.6533

From Table IV, the value of the OF considering UIPs is less than the scenario where they are ignored. This trend is observed in both scenarios. Therefore, integrating UIPs in the optimization related to the operation of the μ MEH's energy equipment cluster using the TPE method allow the operator to avoid unnecessary OC and reduce the EC.

VI. CONCLUSION REMARKS

This article defined an optimization model to find an optimal operation plan for the buildings' energy equipment cluster under uncertain predictions. In this model, the EH concept was used to model the energy equipment cluster consisting of electric HP, CHP, AB, ACH, TR, PV, ES, and HS as well as their connections. In addition, the TPE method was used to integrate UIPs, electricity and gas prices, electrical, heating, and cooling demands, and the production capacity of the PV system in this model. Finally, this optimization model was applied to an industrial building. The obtained results show the feasibility and capabilities of the proposed model. Mainly, electrical and heating storages play a vital role in this model. They help match energy supply and demand better, reduce the need for an expensive and polluting energy mix, increase the share of RERs in building energy supply, provide cost savings for the building owner, and reduce GGEs, and others. Furthermore, it was also seen that considering different UIPs in the offered model could allow the operator to find a more flexible schedule for the building's energy equipment cluster to avoid unnecessary energy costs.

REFERENCES

- [1] "2018 revision of world urbanization prospects|multimedia library- united nations department of economic and social affairs." <https://www.un.org/development/desa/publications/2018-revision-of-world-urbanization-prospects.html>.
- [2] A. Kalua, "Urban residential building energy consumption by end-use in Malawi," *Buildings* 2020, Vol. 10, Page 31, vol. 10, no. 2, p. 31, 2020.
- [3] E. Papadis and G. Tsatsaronis, "Challenges in the decarbonization of the energy sector," *Energy*, vol. 205, p. 118025, 2020.
- [4] E. Litvinov, F. Zhao, and T. Zheng, "Electricity markets in the united states: Power industry restructuring processes for the present and future," *IEEE Power and Energy Magazine*, vol. 17, no. 1, pp. 32–42, 2019.
- [5] M. B. Bulut, M. Odlare, P. Stigson, F. Wallin, and I. Vassileva, "Active buildings in smart grids - Exploring the views of the Swedish energy and buildings sectors," *Energy Build*, vol. 117, pp. 185–198, 2016.
- [6] G. Schweiger *et al.*, "Active consumer participation in smart energy systems," *Energy Build*, vol. 227, p. 110359, 2020.
- [7] H. Lin, Y. Liu, Q. Sun, R. Xiong, H. Li, and R. Wennersten, "The impact of electric vehicle penetration and charging patterns on the management of energy hub—A multi-agent system simulation," *Appl Energy*, vol. 230, pp. 189–206, 2018.
- [8] N. H. Jabarullah, M. S. Shabbir, M. Abbas, A. F. Siddiqi, and S. Berti, "Using random inquiry optimization method for provision of heat and cooling demand in hub systems for smart buildings," *Sustain Cities Soc*, vol. 47, p. 101475, 2019.
- [9] H. R. Gholinejad, A. Loni, J. Adabi, and M. Marzband, "A hierarchical energy management system for multiple home energy hubs in neighborhood grids," *Journal of Building Engineering*, vol. 28, p. 101028, 2020.
- [10] D. Huo, S. Le Blond, C. Gu, W. Wei, and D. Yu, "Optimal operation of interconnected energy hubs by using decomposed hybrid particle swarm and interior-point approach," *International Journal of Electrical Power & Energy Systems*, vol. 95, pp. 36–46, 2018.
- [11] N. Zhang, L. Yang, | Qiuye Sun, and Y. Li, "Matrix modelling and optimisation calculation method for large-scale integrated We-Energy," *IET Energy Systems Integration*, pp. 2–3, 2022.
- [12] J. Li, D. Li, Y. Zheng, Y. Yao, and Y. Tang, "Unified modeling of regionally integrated energy system and application to optimization," *International Journal of Electrical Power & Energy Systems*, vol. 134, p. 107377, 2022.
- [13] A. Eshraghi, G. Salehi, S. Heibati, and K. Lari, "An enhanced operation model for energy storage system of a typical combined cool, heat and power based on demand response program: The application of mixed integer linear programming," vol. 40, no. 1, pp. 47–74, 2018.
- [14] A. Eshraghi, G. Salehi, S. Heibati, and K. Lari, "Developing operation of combined cooling, heat, and power system based on energy hub in a micro-energy grid: The application of energy storages," vol. 30, no. 8, pp. 1356–1379, 2019.
- [15] G. Quirosa, M. Torres, and R. Chacartegui, "Analysis of the integration of photovoltaic excess into a 5th generation district heating and cooling system for network energy storage," *Energy*, vol. 239, p. 122202, 2022.
- [16] F. Kienzle, P. Ahčin, and G. Andersson, "Valuing investments in multi-energy conversion, storage, and demand-side management systems under uncertainty," *IEEE Trans Sustain Energy*, vol. 2, no. 2, pp. 194–202, 2011.
- [17] M. Roustai, M. Rayati, A. Sheikhi, and A. M. Ranjbar, "A scenario-based optimization of smart energy hub operation in a stochastic environment using conditional-value-at-risk," *Sustain Cities Soc*, vol. 39, pp. 309–316, 2018.
- [18] M. Yan, N. Zhang, X. Ai, M. Shahidehpour, C. Kang, and J. Wen, "Robust two-stage regional-district scheduling of multi-carrier energy systems with a large penetration of wind power," *IEEE Trans Sustain Energy*, vol. 10, no. 3, pp. 1227–1239, 2019.
- [19] L. Ma, N. Liu, J. Zhang, and L. Wang, "Real-time rolling horizon energy management for the energy-hub-coordinated prosumer community from a cooperative perspective," *IEEE Transactions on Power Systems*, vol. 34, no. 2, pp. 1227–1242, 2019.
- [20] X. Lu, Z. Liu, L. Ma, L. Wang, K. Zhou, and N. Feng, "A robust optimization approach for optimal load dispatch of community energy hub," *Appl Energy*, vol. 259, p. 114195, 2020.
- [21] D. S. Shafiqullah, P. P. Vergara, A. N. M. M. Haque, P. H. Nguyen, and A. J. M. Pemen, "Gaussian mixture based uncertainty modeling to optimize energy management of heterogeneous building neighborhoods: A case study of a Dutch university medical campus," *Energy Build*, vol. 224, p. 110150, 2020.
- [22] P. Mancarella, "MES (multi-energy systems): An overview of concepts and evaluation models," *Energy*, vol. 65, pp. 1–17, 2014.
- [23] M. Kiani-Moghaddam, M. N. Soltani, S. A. Kalogirou, O. Mahian, and A. Arabkoohsar, "A review of neighborhood level multi-carrier energy hubs—uncertainty and problem-solving process," *Energy*, p. 128263, 2023.
- [24] M. Kiani-Moghaddam, M. Shivaie, and P. D. Weinsier, "A techno-economic multi-objective model for hybrid harmonic filter planning considering uncertainty in non-linear loads," *International Journal of Electrical Power and Energy Systems*, vol. 112, 2019.
- [25] "Energinet." <https://energinet.dk/>.