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A max-min-max robust optimization model for multi-carrier energy systems integrated with power to gas storage system

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Abstract

The volatile nature of the electricity market prices and renewable resources imposes remarkable challenges for multi-energy systems operators to make the appropriate decisions. Therefore, this paper offers a linear *max-min-max* robust optimization-based decision-making tool that incorporates both uncertainties of the electricity market price and the wind generation. Besides interaction with the electricity market, the EH purchases natural gas to feed the combined heat and power (CHP) and boiler units and supply gas demands. An electrical storage system is also used to smooth the unfavorable volatility nature of the electricity market price. Besides, an uncertainty budget model is proposed to consider both negative and positive deviation of electricity market prices, which gives the capability to increase the robustness of the system against the error of forecasting uncertainty sources. The nonlinearities arisen from the model are linearized using effective approaches and the resulted linear mathematical model is solved by GAMS. Moreover, the power to gas (P2G) storage system is integrated with the EH in order to create a link between the electrical and natural gas networks by converting the electricity to hydrogen and then to natural gas. Simulation results demonstrate that using P2G saves 6.9% in gas purchase cost and 2.13%

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in total cost.

Keywords: Energy hub, power to gas storage system, robust optimization, uncertainty budget.

Nomenclature

A. Sets and Indexes:

T	Set of time intervals.
t	Index of time.

B. Constants:

$\bar{\lambda}_t^m$	Expected electricity market price (€/kWh).
$Dev_{\max}^p$	Maximum deviation of electricity price.
Γ^p	Uncertainty budget of electricity price.
N_p	Number of hours allowed to be affected by uncertainties.
$\bar{P}_t^w$	Expected wind generation (kW).
Γ^w	Uncertainty budget of wind turbine generation.
ϕ_w	Maximum deviation of wind turbine generation (kW).
λ_t^g	Natural gas price (¢/kWh).
c^{p2g}	Discharging coefficient of P2G storage system (¢/kW).
c^{em}	Emission coefficient.
η^{ge}/η^{pe}	Gas/electricity conversion coefficient to emission (kg/kWh).
c^{ch}, c^{dch}	Charging/discharging cost coefficient (¢/kWh).
ED_t	Electricity demand (kW).
HD_t	Heat demand (kWth).
GD_t	Gas demand (kW).
η^b	Conversion coefficient of the boiler unit (¢/kWh).
$\eta^{e,CHP}, \eta^{h,CHP}$	Electrical/ thermal coefficient of the CHP unit (¢/kWh).
$p_{\min}^{CHP}, p_{\max}^{CHP}$	Minimum/maximum electricity generation of the CHP (kW).
η^{P2G}	Gas to electricity conversion coefficient of P2G system.
$P_{\max}^{P2G}$	Maximum electricity entered the P2G (kW).
$Gdch_{\max}^{P2G}$	Maximum discharging of the P2G system (kW).

$GS_{\min}, GS_{\max}$	Minimum/maximum capacity of P2G storage system (kWh).
$E_{\max}^{ST}$	Maximum capacity of the ESS (kWh).
$\eta_{ch}^{ST}/\eta_{Dch}^{ST}$	Charging/discharging efficiency of the battery storage system.
$E_{\min}^{ch}, E_{\max}^{ch}$	Charging/discharging limit of the ESS (kWh).
M	Big number.

C. Variables:

λ_t^m	robust electricity market price (¢/kWh).
P_t^m	Purchased electricity from electricity market (kW).
$\phi_{\lambda t}$	Deviation of electricity price (euro cent/kWh).
P_t^w	Robust wind turbine generation (kW).
k_t	Binary variable associated with the wind generation.
C_t^m	Electricity market cost (¢).
C_t^g	Gas network cost (¢).
C_t^{P2G}	P2G storage system cost (¢).
C_t^{em}	CO_2 emission cost (¢).
C_t^{ESS}	Electrical storage system cost (¢).
$P_t^{m,LD}$	Purchased electricity from market to transfer to the load (kW).
$P_t^{m,ST}$	Purchased electricity from market to feed the ESS (kW).
P_t^{P2G}	Purchased electricity from market to feed the P2G system (kW).
P_t^{CHP}	Electrical output of the CHP (kW).
P_t^{dch}	Discharging power of the ESS (kW).
P_t^g	Gas entering the EH (kW).
$Gdch_t^{p2g}$	Discharging gas from P2G storage system (kW).
h_t^b	Output of the boiler (kWth).
H_t^{CHP}	Thermal output of the CHP (kWth).
g_t^{CHP}	Gas entering the CHP (kW).

g_t^b	Gas entering the boiler (kW).
E_t	State of charge of ESS (kWh).
Gch_t^{P2G}	Charging gas of P2G storage system (kWh).
GS_t	State of charge of the P2G storage system (kWh).
Z_t	An auxiliary variable for linearization (kWh).
$\xi_t, \overline{\delta}_t, \underline{\delta}_t, \sigma_t, \underline{\sigma}$	Dual variables of the inner objective function for the electricity price uncertainty.
$\alpha_t, \beta_t, \gamma_t$	
$\chi_t, \epsilon_t, \varepsilon_t$	
ν_t, κ_t, μ_t	
$\theta_t, \overline{\varpi}_t, \underline{\varpi}_t$	
$\varrho_t, \rho_t, \iota_t, \varsigma_t, \tau_t$	Dual variables of the main problem constraints.
$\zeta_t^1, \zeta_t^2, \zeta_t^3$	Dual variables of feasible operation region of CHP.

1. Introduction

The rapid development of technologies resulted in amplifying the joint operation of the multi-generation systems [1]. This highlights the importance of focusing on multiple alternatives such as integration of renewable energy sources (RES) [2], renewable energy integration for combined heat and power production [3], effective energy conservation [4], energy storage [5], etc. One of the most effective solutions to managing energy is the energy hub (EH). The EH is a concept that takes care of different types of energy such as electricity, gas, heat, and at times cooling networks [6]. The EH may consist of, e.g., wind turbine (WT), photovoltaic (PV), combined heat and power (CHP) plant, boiler, absorption chiller, electric vehicles (EV), electrical energy storage (ESS), power to gas (P2G), electrical or thermal energy storage systems [7], as well as renewable power sharing [8]. In addition, since there is a wide range of energy types in EHs that can easily be converted to each other, stored, and managed to supply the demands, it gives more economical solutions for the system operator and society. Therefore, EH is taken into account as a solution to enhance the usage of existing energy resources [9]. The uncertainty arising from various sources imposes unfavorable effects on the operation of multi-energy systems. However, robust optimization (RO) is an effective tool to deal with uncertainty, and energy storage systems are instrumental in smoothing the volatile nature of the uncertainties.

1.1. Literature review

This literature review aims at indicating the optimization goals, applied algorithm, and uncertainty issues presented in the recent works. A trade-off between the reduction of the operation and emissions costs and increasing the risk aversion for the EH operation was proposed in [10]. The problem was solved by deploying a risk-constrained stochastic scheduling model while using the conditional value-at-risk as a risk measure. A combination of electrical, gas, thermal and cooling demands was included in the presented model considering the uncertainties of RES, EV, and electricity prices. The authors used a K-means cluster analysis method to handle the uncertainties issues. In [11], a stochastic-based model was proposed to include the plug-in hybrid electric vehicles into the residential EH management problem. A k-means clustering method was used to address the uncertainties related to electricity prices and PV generation. The authors in [12] developed a stochastic programming model to solve the energy management problem of the EH, taking into account both the electrical and thermal demand response in the presence of the probabilistic problem of demands, market prices, and wind speed. [13] proposed a multi-stage stochastic programming model to minimize the total procuring cost of electricity and natural gas markets subject to wind and electricity price uncertainties. Indeed, the mentioned article does not investigate the EH operation in the worst-case realization of the uncertainties. A two-stage robust–stochastic approach and Benders decomposition algorithm was proposed in [14] to build a proper interaction between the industrial EH and renewable energy sources. An optimization model of EH in point of maximizing profits from electric energy selling and minimizing input energies costs was proposed in [15] and handled using the particle swarm optimization algorithm. The authors in [16] proposed a stochastic optimization model for EH operation considering components availability using N-1 contingency criteria. In [17], a mixed-integer linear programming model was developed to handle the multi-objective problem of EH aiming at reducing the operating cost and CO_2 emission level. The optimal scheduling of an EH was investigated in [18], while taking into account the uncertainties of WT and PV generation, load demands, natural gas, and electricity prices. Incorporating the regulation market in the energy hub integrated with electric vehicles was investigated in [1], and a modified grey wolf optimization was used to handle this problem. The authors in [19, 20] proposed a mixed-integer nonlinear programming model for residential load management in an energy hub aiming at optimizing the operation of the EH units under dynamic pricing and performing optimal load management. The other common investigation direction is the optimal EH capacity configuration in many works. In [21], a two-stage planning method was proposed to find the optimal sizing of EH elements. In this article, a Group Search Optimizer method was applied to determine the optimal size of EH units, while a mathematical programming method was developed to assure the optimal operations of the EH. The authors in [22] addressed the EH optimal dispatch and sizing simultaneously. The objective function was to minimize the total capital and operational cost of the EH based on a double-layer firefly optimization algorithm. A distributed auction mechanism for EH scheduling using the alternating direction method of multipliers was proposed in [23]. In this work, the EH unit is a solar combined system as an element to cover the electrical and heating demands. In [24], the authors aimed to address the distributed planning of electricity and natural gas networks and energy hubs. The distributed planning framework in this work was based on the alternating direction method of multipliers (ADMM). ADMM is a method to solve the problems with the different independent entities which have their local scheduling problem. The author of this paper has considered the distribution network operator and the EHs owners as independent entities. A fully decentralized model was proposed in [25] to investigate the capability of electricity trading using peer-to-peer (P2P) mode in EHs. The ADMM algorithm was deployed to coordinate the electricity exchange between EHs. Also in [26], a decentralized framework was presented to manage the electricity trading between an EH and EV parking lot, taking into account the uncertainties of electricity market prices and driving patterns of EVs by developing a hybrid stochastic programming and RO method.

In addition to the works above, some works in the literature deployed the information gap decision theory (IGDT) to solve the self-schedule operation of renewable energy-based EH [27]. One of the initial works related to the operation of EH using IGDT was proposed in [28], considering the uncertainties of the generations and demands and disregarding the uncertainty of electricity prices. Circumstances like operating costs, curtailed renewable power, and CO_2 emission factors were included during the optimization process in [29]. The problem constitutes from both the optimal operation of the EH and securit-constrained unit commitment using a nonlinear IGDT mathematical model. A robust optimization (RO) approach looks for a solution to an optimization problem that is feasible for any realization of the uncertainties within the uncertainty set and gives the optimal solution for the worst-case realization of these uncertain parameters. In [30], the electricity market retailer was equipped with the EH aims at maximizing the retailer profit. The lower level problem and its constraints were relaxed using the Karush-Kuhn-Tucker (KKT) conditions first, and then the RO method was applied to the problem. In [31] and [32], a *min-max* robust optimization model was suggested for dealing with the electricity price uncertainty in the EH disregarding other types of uncertainties. The authors in [31] tried to minimize the total operation and emission costs of the EH, while in [32], the goal was to minimize the total management cost of hydrogen-based EH . In [33], both the electricity prices and renewable energy resources were taken into account in managing the EH, while the worst-case realization was only conducted on electricity price uncertainty. A distributed robust optimization has also been studied in [34] investigating the electricity price uncertainty in local scheduling of energy hub. In [35] a distributionally robust optimization (DRO) was proposed to deal with the uncertainty of PV generation for the problem of EH operation neglecting the uncertainty of the electricity prices. The DRO is utilized when there is imperfect information regarding the mean value of the probability distribution function of the uncertainty source. A P2G-based multi-objective method was proposed in [36] to deal with maximum operation profit and minimum operation risk developing the uncertainties of output power coming from renewable energy resources. In [37] the uncertainty of wind power was included using the RO approach to reach the worst-case realization of wind power generation. The uncertainty of electricity market prices was disregarded in this reference.

1.2. The challenges and paper contributions

The literature review reveals that limited works have focused on the worst-case realization of both electricity prices and renewable energy resources. Although, several works have considered the uncertainties of the electricity prices and renewable energy sources by hybrid methods. For instance, [38] has considered both uncertainties by means of a hybrid method, including RO and IGDT approach, where the IGDT copes with the wind speed uncertainty and the RO deals with the electricity market prices uncertainty. The hybrid utilization of stochastic programming and RO have been deployed in [39, 40] to deal with the mentioned uncertainties. However, non of them have used only RO to take into account both uncertainties. Indeed, taking into account the both uncertainty sources simultaneously complicates the mathematical model from a *max-min* or *min-max* model to a *max-min-max* one. To emphasize the distinction of the current work with [31], [32] and [34], it is essential to mention that these works have only deployed the RO approach to take into account the uncertainty of the electricity market prices. Although the uncertainties of both electricity prices and wind speed have been addressed in [33], the worst-case realization has only been considered for the electricity prices. However, in our proposed work, we develop the RO approach to reach the worst-case realization of both electricity market prices and wind power generations. It is worth mentioning that addressing both uncertainties using the IGDT is also possible, but it converts the problem to a nonlinear one due to the bi-linear term arising from electricity price uncertainty [41]. Therefore, this paper tries to develop the models presented in [31, 33, 32, 34] to have a more realistic and practical model that aims to realize the worst-case situation for both the electricity prices and wind turbine generation in the frame of a *max-min-max* robust optimization model. Consequently, the main contributions of the article are as follows.

- Proposing a linear *max-min-max* model for robust operation of EH considering the worst-case realization of wind and electricity price uncertainties.
- Presenting an uncertainty budget model for controlling the volume of uncertainties. In other words, the uncertainty budgets model are proposed for both uncertainty sources to manage the robustness against different uncertainty conditions. The proposed uncertainty budget model is able to consider both positive and negative deviations of uncertainty sources.
- Integrating the proposed *max-min-max* RO model with P2G technology for the first time by extending the presented model in [42] to the energy hub. Moreover, the effects of the P2G on the robust operation cost are investigated.

1.3. Paper organization

The rest of this paper is organized as follows. The problem description is presented in Section 2. The problem modeling and formulation, including the main model, the P2G model, and the main mathematical model, are given in Section 3. The solution methodology is presented in Section 4. Section 5 provides the numerical results, and finally, the conclusion is given in Section 6.

2. Problem description

The EH is a concept that takes into account different types of energy. In this paper, a short-term robust optimization model is developed for the optimal operation of EH integrated with P2G technology. The EH system structure used in this paper is depicted in Fig. 1. The intended energy hub encloses the electricity market, wind turbine generation, and natural gas network as the inputs, while the outputs are electricity, heat, and gas demands. The electricity demands are met through wind generation, electricity market, an electrical energy storage system (ESS), and a CHP unit. The heat demands are satisfied through the boiler and CHP units. The natural gas network and P2G storage system supply the gas demands. The EH operator is also the owner of the EH that aims to minimize the total costs. The boiler and CHP are also fed through the natural gas network.

Due to the concerns about global warming and releasing CO_2 emissions from fossil fuel into the environment, the cost related to this pollution is also incorporated in the objective function. Moreover, the P2G technology, as one of the newest technologies, has been deployed in order to help in meeting the natural gas demands as well as better operation of the electricity market in the off-peak periods. The P2G storage system is fed by electricity and generates natural gas, and is presented as a storage system in the mathematical model. We have added a new explanation to the paper in the current version of the paper to show this aim. The electricity prices and wind generations are subject to uncertainties. Robust optimization is an effective approach to address uncertainties, ensuring the optimal operation. Therefore, the main purpose of this scheduling is to minimize the total operation cost of procuring the energy carriers while meeting the demands on a short-term horizon via a robust optimization model.

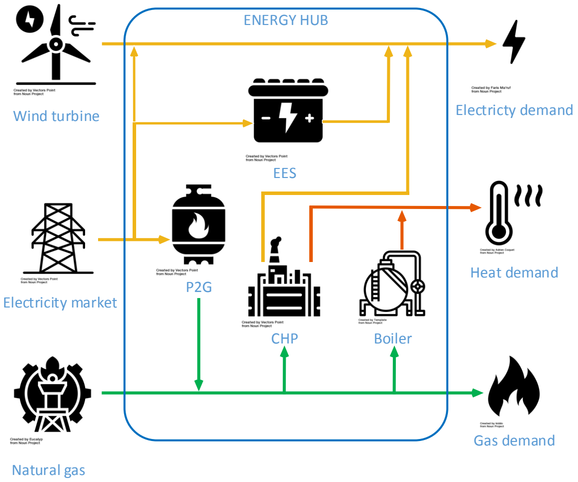


Figure 1: Energy hub under study

3. Problem modeling and formulation

3.1. P2G storage system

The P2G storage system is a valuable technology that creates an opportunity to use the electricity surplus from the renewable generation or the electricity market to generate natural gas. In other words, at peak hours, the P2G storage system discharges natural gas from P2G storage to the natural gas network to make the operator needless to procure the gas from the natural gas market. The process of converting electricity to natural gas has two main steps. The water is electrolyzed in the first step by means of electricity, and hydrogen (H_2) is released. The released hydrogen is combined with carbon dioxide and results in producing methane (CH_4). This procedure is called methanization and is conducted in the second step. The main component of natural gas is methane. Then, the methane is compressed and injected into the natural gas network [43]. It is worth mentioning that the hydrogen generated in the first step is also useful for industries. Here, P2G efficiency η^{P2G} shows the ratio of the electricity converted to the natural gas in the mentioned process. The equivalent gas entered the P2G storage system is obtained as follows.

$$Gch_t^{P2G} = \eta^{P2G} P_t^{P2G} \tag{1}$$

The P2G storage system acts as an energy storage and the energy balance equation (state of charge of the storage) is presented as follows.

$$GS_t = GS_{t-1} + Gch_t^{P2G} - Gdch_t^{P2G} \tag{2}$$

The amount of charge is calculated based on the previous state of charge and charging/discharging of natural gas.

3.2. Uncertainty modeling

In this paper, the uncertainties related to the electricity price and wind generation are taken into account.

The electricity price is multiplied by the amount of electricity purchased from the market, and it is positioned in the inner part of the main mathematical model. The uncertainty model is presented by (3)-(6). Eq. (3) shows the inner objective function, which aims to maximize the electricity prices in order to reach the worst-case realization. The electricity price deviation can be either positive or negative in (4), and it is limited by a maximum deviation in (5). The robustness level of the model with respect to the electricity prices uncertainties can be managed using the parameter of price uncertainty budget in (6). This parameter is controlled by the number of hours that can be accompanied by uncertainty (N_p). The greater the numerical value in the scheduling horizon, the greater is the value of the robustness.

$$\max_{\phi_\lambda} \sum_{t=1}^{T} \lambda_t^m P_t^m \quad \forall t = 1, ..., T \tag{3}$$

$$\lambda_t^m = \bar{\lambda}_t^m + \phi_{\lambda t} \quad : \xi_t \quad \forall t = 1, ..., T \tag{4}$$

$$\mid \phi_{\lambda t} \mid \leq Dev_{\max}^p \bar{\lambda}_t^m \quad : \underline{\delta_t}, \overline{\delta_t} \quad \forall t = 1, ..., T \tag{5}$$

$$\sum_{t=1}^{T} \mid \phi_{\lambda t} \mid \leq \Gamma^{p} \quad : \underline{\sigma}, \sigma_t \quad \forall t = 1, ..., T$$
$$\Gamma^{p} = N_p Dev^{p}_{\max} \frac{\sum_{t=1}^{T} \bar{\lambda}^{m}_{t}}{T} \tag{6}$$

The degree of the wind generation uncertainty is modeled by introducing uncertainty budget parameter Γ_w which is represented as follows.

$$P^{w}_{t} \epsilon \{\bar{P}^{w}_{t} - k_t \cdot \phi_w,\ \bar{P}^{w}_{t}\} \quad k_t \epsilon \{0, 1\} \tag{7}$$

k_t is a binary variable to control the maximum wind generation deviation ϕ_{wt} from the expected generation in time t and the total amount of uncertainty is controlled by (7). In other words, it determines the number of hours allowed to be affected by the uncertainty.

$$\sum_{t=1}^{T} k_t \leq \Gamma^{w} \tag{8}$$

3.3. Main model

The objective function in (9) aims at minimizing the total cost of the system, including the market cost, natural purchased gas cost, P2G operation cost, CO_2 emission cost, and energy storage costs, presented in (10)-(14), respectively. Constraints (15)-(17) declare the demand balances for the electricity, heat, and gas, respectively. The electricity market, CHP, wind turbine, and energy storage participate in the EH to meet the electricity demands, while the boiler and CHP satisfy the heat demands. The gas demands and the required gas of boiler and CHP are met by directly purchasing from the gas network and generating gas by the P2G system. Constraints (18)-(20) indicate the relation of the generated heat by the boiler and generated electricity and heat by CHP, respectively. The feasible operation region of the CHP production is given in (21)-(23). The feasible operation region is enclosed by coordinates A, B, C and D as shown in Fig. 2 [13]. Eq. (24) shows the gas charged to the P2G storage system. The P2G storage balance equation is considered in (25). The upper limitations of the P2G, discharged gas from the P2G storage system, and the energy capacity of the P2G storage system are presented in (26)-(28), while (29) stands for the lower limit of the P2G storage. The energy balance of the electrical storage system is presented in (30) [44]. The state of charge of the ESS and charging/discharging electricity to/from ESS are given in (31)-(33) [45, 46]. Finally, (34) indicates that one part of the purchased electricity from the market is transferred into the output directly, and the other part is stored in the ESS. The dual variable of each constraint is provided in front of each constraint following a colon.

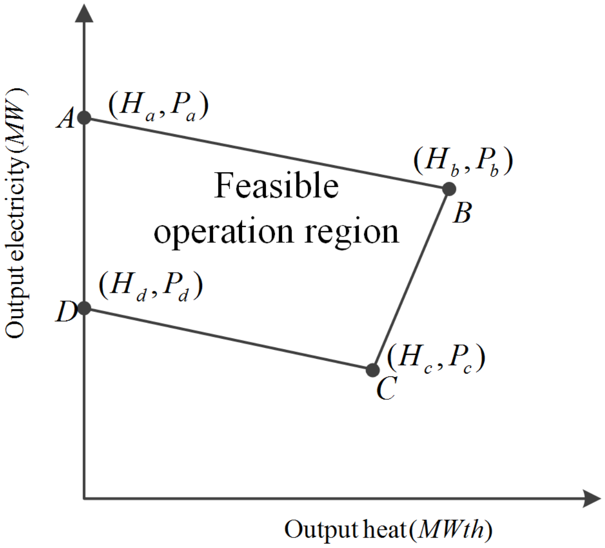


Figure 2: Feasible operation region of the CHP

$$\max_{\phi_w}\min_{\Phi}\max_{\phi_\lambda}\sum_{t=1}^{t=T} C_t^m + C_t^g + C_t^{P2G} + C_t^{em} + C_t^{ESS} \tag{9}$$

Subject to (4)-(6) and:

$$C_t^m = \lambda_t^m P_t^m \tag{10}$$

$$C_t^g = \lambda_t^g P_t^g \tag{11}$$

$$C_t^{P2G} = c^{p2g} Gdch_t^{p2g} \tag{12}$$

$$C_t^{em} = c^{em}(\eta^{ge} P_t^g + \eta^{pe} P_t^m) \tag{13}$$

$$C_t^{ESS} = pf \cdot (c^{ch} P_t^{m,ST} + c^{dch} P_t^{dch}) \tag{14}$$

$$P_t^{m,LD} + P_t^{CHP} + P_t^w + P_t^{dch} = ED_t \quad : \alpha_t \tag{15}$$

$$h_t^b + H_t^{CHP} = HD_t \quad : \beta_t \tag{16}$$

$$P_t^g + Gdch_t^{P2G} - g_t^{CHP} - g_t^b = GD_t \quad : \gamma_t \tag{17}$$

$$h_t^b - \eta^b g_t^b = 0 \quad : \chi_t \tag{18}$$

$$P_t^{CHP} - \eta^{e,CHP} g_t^{CHP} = 0 \quad : \epsilon_t \tag{19}$$

$$H_t^{CHP} - \eta^{h,CHP} g_t^{CHP} = 0 \quad : \varepsilon_t \tag{20}$$

$$P_t^{CHP} - \frac{P_a - P_b}{H_a - H_b} H_t^{CHP} \leq P_a - \frac{P_a - P_b}{H_a - H_b} H_a \quad : \zeta_t^1 \tag{21}$$

$$P_t^{CHP} - \frac{P_b - P_c}{H_b - H_c} H_t^{CHP} \geq P_b - \frac{P_b - P_c}{H_b - H_c} H_b \quad : \zeta_t^2 \tag{22}$$

$$P_t^{CHP} - \frac{P_c - P_d}{H_c - H_d} H_t^{CHP} \geq P_c - \frac{P_c - P_d}{H_c - H_d} H_c \quad : \zeta_t^3 \tag{23}$$

$$Gch_t^{P2G} - \eta^{P2G} P_t^{P2G} = 0 \quad : \nu_t \tag{24}$$

$$GS_t - GS_{t-1} - Gch_t^{P2G} + Gdch_t^{P2G} = 0 \quad : \kappa_t \tag{25}$$

$$P_t^{P2G} \leq P_{\max}^{P2G} \quad : \mu_t \tag{26}$$

$$Gdch_t^{P2G} \leq Gdch_{\max}^{P2G} \quad : \theta_t \tag{27}$$

$$GS_t \leq GS_{\max} \quad : \overline{\varpi}_t \tag{28}$$

$$GS_t \geq GS_{\min} \quad : \underline{\varpi}_t \tag{29}$$

$$E_t - E_{t-1} - \eta_{ESS}^{ch} P_t^{m,ST} \Delta t + (\frac{1}{\eta_{ESS}^{dch}}) P_t^{dch} \Delta t = 0 \quad : \varrho_t \tag{30}$$

$$E_t \leq E_{\max}^{ST} \quad : \rho_t \tag{31}$$

$$P_t^{m,ST} \leq E_{\max}^{ch} \quad : \iota_t \tag{32}$$

$$P_t^{dch} \leq E_{\max}^{dch} \quad : \varsigma_t \tag{33}$$

$$P_t^{m} - P_t^{m,ST} - P_t^{m,LD} - P_t^{P2G} = 0 \quad : \tau_t \tag{34}$$

4. Solution methodology

The uncertainties associated with electricity prices and wind generation result in difficulties in the optimal decision-making process of the EH operation. Therefore, it is crucial to use a useful approach to tackle the uncertainties. Contrary to the stochastic programming method, the robust approach does not need too many scenarios and information. Therefore, in this work, the

RO method is employed to model the uncertainties in the scheduling horizon. The RO method paves the way for the system operator (or the owner) to make the appropriate decision in a risk-averse manner through changing the budget of uncertainties. In the proposed problem, the robust objective function is represented as follows.

$$
\begin{aligned}
&\max_{\phi_w} \min_{\Phi} \{ \sum_{t=1}^{T} \lambda_t^g P_t^g + pf^{P2G} c^{p2g} Gdch_t^{p2g} + c^{em} (\eta^{ge} P_t^g + \eta^{pe} P_t^m) + \\
&pf \cdot (c^{ch} P_t^{m,ST} + c^{dch} P_t^{dch}) + \max_{\phi_\lambda} \sum_{t=1}^{T} \lambda_t^m P_t^m \} \qquad (35) \\
&\Phi \, \epsilon \{ P_t^g, Gdch_t^{p2g}, P_t^m, P_t^{m,ST}, P_t^{dch}, P_t^{m,LD}, P_t^{CHP}, P_t^{P2G}, h_t^b, H_t^{CHP}, \\
&g_t^{CHP}, g_t^b, Gch_t^{P2G}, GS_t, E_t \}
\end{aligned}
$$

The inner maximization optimization problem aims to find the worst-case realization of the price uncertainty, and the outer maximization objective deals with finding the worst-case situation of wind generation. The steps of obtaining the final robust model are summarized as follows.

- Step 1: linearizing the uncertainty model of electricity prices using (A.1)-(A.5), see appendix Appendix A.
- Step 2: transferring the linear version of the electricity prices to a minimization problem using duality theory (the inner layer).
- Step 3: transferring the collected middle and the inner minimization problem to a maximization model using duality theory.
- Step 4: linearizing the bi-product of wind generation term and dual variable using (B.1)-(B.5), see appendix Appendix B.

By conducting Steps 1 to 3, the objective function (35) and constraints (15)-(15), (7)-(8), and (4)-(6) are transferred into the equivalent dual model in (36)-(56).

$$\begin{aligned}&\max\sum_{t=1}^{T}\{(ED_t-P_t^{w})\alpha_t+HD_t\beta+GD_t\gamma_t+(P_a-H_a\frac{P_a-P_b}{H_a-H_b})\zeta_t^{1}\\&+(P_b-H_b\frac{P_b-P_c}{H_b-H_c})\zeta_t^{2}+(P_c-H_c\frac{P_c-P_d}{H_c-H_d})\zeta_t^{3}+P_{\max}^{P2G}\mu_t\\&+Gdch_{\max}\theta_t+GS_{\max}\overline{\varpi}_t+GS_{\min}\underline{\varpi}_t+E_{max}^{ST}\rho_t+E_{max}^{ch}\iota_t+E_{max}^{dch}\varsigma_t\}\end{aligned} \tag{36}$$

$$\alpha_t-\tau_t\leq 0 \quad : P_t^{m,LD} \tag{37}$$

$$\alpha_t+\epsilon_t+\zeta_t^{1}+\zeta_t^{2}+\zeta_t^{3}\leq 0 \quad : P_t^{CHP} \tag{38}$$

$$\gamma_t\leq\lambda_t^{g}+c^{em}\eta^{ge} \quad : P_t^{g} \tag{39}$$

$$-\tau_t-\eta^{P2G}\nu_t+\mu_t\leq 0 \quad : P_t^{P2G} \tag{40}$$

$$\alpha_t+\eta_{ESS}^{dch}\varrho_t\Delta t+\varsigma_t\leq c^{dch} \quad : P_t^{dch} \tag{41}$$

$$\beta_t+\chi_t\leq 0 \quad : h_t^{b} \tag{42}$$

$$\beta_t+\varepsilon_t-\frac{P_a-P_b}{H_a-H_b}\zeta_t^{1}-\frac{P_b-P_c}{H_b-H_c}\zeta_t^{2}-\frac{P_c-P_d}{H_c-H_d}\zeta_t^{3}\leq 0 \quad : H_t^{CHP} \tag{43}$$

$$\gamma_t+\kappa_t+\theta_t\leq c^{P2G} \quad : Gdch_t \tag{44}$$

$$-\gamma_t-\eta^{e,CHP}\epsilon_t-\eta^{h,CHP}\varepsilon_t\leq 0 \quad : g_t^{CHP} \tag{45}$$

$$-\gamma_t-\eta^{b}\chi_t\leq 0 \quad : g_t^{b} \tag{46}$$

$$\nu_t-\kappa_t\leq 0 \quad : Gch_t^{P2G} \tag{47}$$

$$\kappa_t - \kappa_{t-1} + \overline{\varpi} + \underline{\varpi} \leq 0 \quad : GS_t \tag{48}$$

$$\rho_t + \varrho_t - \varrho_{t-1} \leq 0 \quad : E_t \tag{49}$$

$$-\eta^{ch}_{ESS}\varrho_t \Delta t + \iota_t - \tau_t \leq c^{ch} \quad : P_t^{m,ST} \tag{50}$$

$$\tau_t - \varnothing_t \leq c^{em}\eta^{pe} \quad : P_t^{m} \tag{51}$$

$$-\omega_t + \varnothing_t = \bar{\lambda}_t \quad : \zeta_t \tag{52}$$

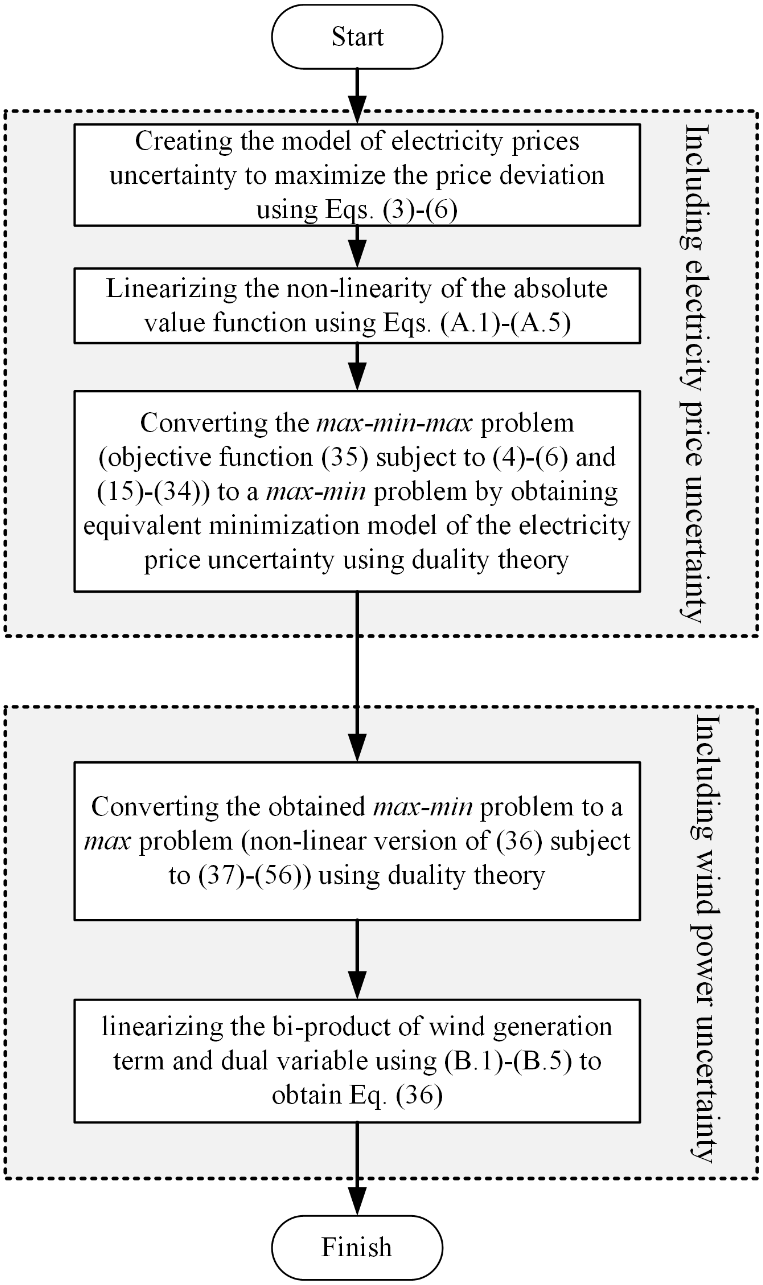
$$\omega_t \leq Dev^{p}_{\max} \cdot \bar{\lambda}_t \quad : \overline{\delta_t} \tag{53}$$

$$\omega_t \geq -Dev^{p}_{\max} \cdot \bar{\lambda}_t \quad : \underline{\delta_t} \tag{54}$$

$$\omega_t - \pi_t + \vartheta_t = 0 \quad : \sigma_t \tag{55}$$

$$\sum_{t=1}^{T} \pi_t + \vartheta_t \leq \Gamma^{p} \quad : \underline{\sigma} \tag{56}$$

$(ED_t - P_t^{w})\alpha_t$ makes a nonlinear bi-product. For the linearization, the method presented in (B.1)-(B.5) is used and the bi-product terms are recast into equivalent linear expressions. The constraints are also added to the final model. Fig. 3 shows the steps of considering both uncertainties and converting the initial *max-min-max* problem into a *max* problem using RO.



Creating the model of electricity prices uncertainty to maximize the price deviation using Eqs. (3)-(6)

Linearizing the non-linearity of the absolute value function using Eqs. (A.1)-(A.5)

Converting the *max-min-max* problem (objective function (35) subject to (4)-(6) and (15)-(34)) to a *max-min* problem by obtaining equivalent minimization model of the electricity price uncertainty using duality theory

Converting the obtained *max-min* problem to a *max* problem (non-linear version of (36) subject to (37)-(56)) using duality theory

linearizing the bi-product of wind generation term and dual variable using (B.1)-(B.5) to obtain Eq. (36)

Figure 3: Flowchart of considering uncertainties.

5. Numerical results

5.1. Case study

To assess the effectiveness of the proposed robust optimization model, the EH presented in Fig. 1 is considered. The EH consists of the CHP and boiler units, the P2G system, an ESS, and the wind turbine to satisfy the electrical, heat, and natural gas demands. The electricity price and wind generation are subject to uncertainties. The electricity and natural gas prices data patterns are adopted from [47] and [32]. Fig. 4 shows the prices. The gas price, compared to the electricity prices, shows lower fluctuation, therefore in this paper, just two values are considered for gas price. The demands are borrowed from [47] and are depicted in Fig. 5. The main characteristics of the P2G storage system are obtained from [48], while for the sake of adaptability with the proposed model, the size and the other details of the P2G are considered to be two times bigger. The maximum generation of the boiler is assumed to be equal to the maximum amount of the heat demands with an efficiency of 85%. The feasible operation region of the CHP is enclosed by coordinates $A(0,95)$, $B(100,105)$, $C(70,58)$, $D(0,0)$. As mentioned earlier, heat and electricity in the CHP model have a mutual dependency on each other. The conversion coefficients for electricity and heat are 0.45 and 0.4, respectively. The characteristics of the P2G and electrical storage systems are also provided in table 1. The expected value of wind generation is depicted in Fig. 6. The expected values of wind power is the forecasted values for the wind power. The simulations are performed in two main parts. The value of N_p and N_w are initially set to 12, while in the second part of the simulation, sensitivity analyses are conducted on these values.

Table 1: Details of the P2G and ESS systems

Device	Parameter	Value
P2G	$P_{\max}^{P2G}$	140 kWh
	$GS_{\min}$	40 kWh
	$GS_{\max}$	360 kWh
	$Gdch_{\max}$	100 kWh
	η^{P2G}	0.75
Electrical storage	$E_{\max}^{ST}$	150 kWh
	$E_{\max}^{dch}$	40 kWh
	$E_{\max}^{ch}$	40 kWh
	η^{ch}, η^{dch}	0.95

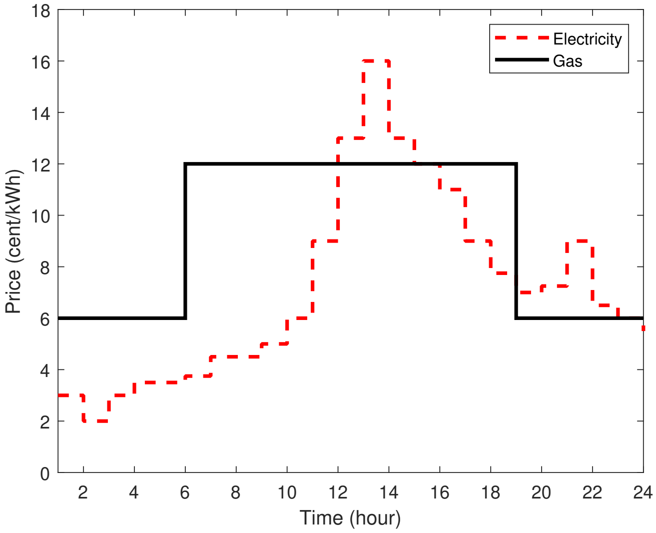


Figure 4: Electricity and natural gas prices [47, 32]

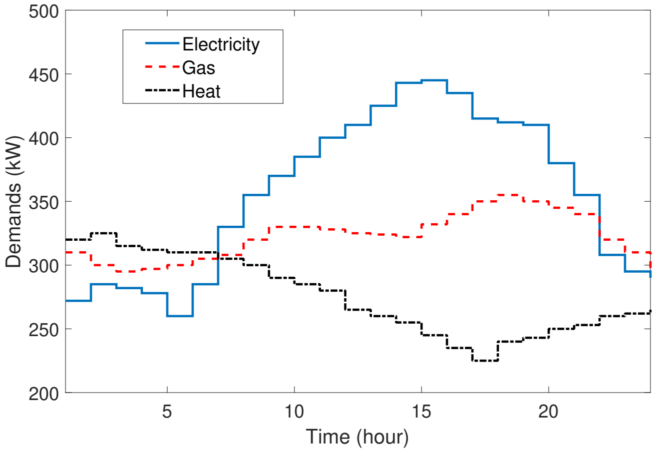


Figure 5: Electricity, natural gas and heat demands [47]

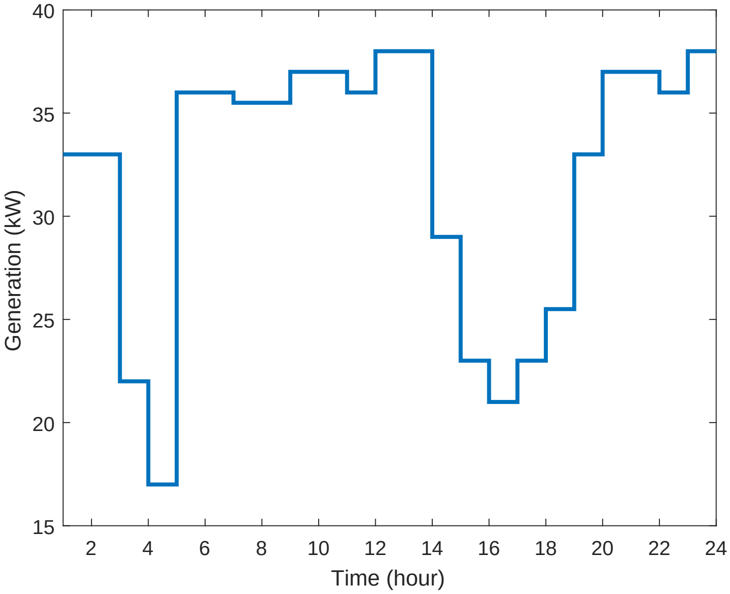
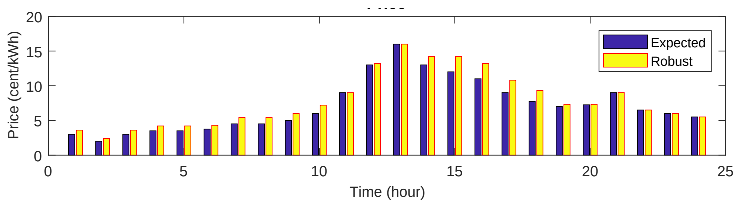


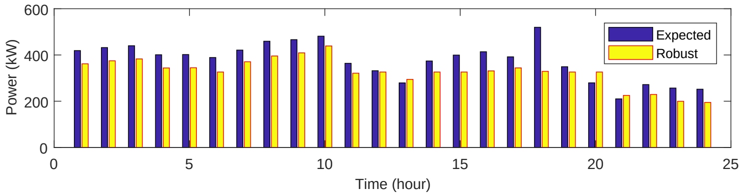
Figure 6: Expected wind generation [49]

5.2. Discussion

To evaluate the behavior of the proposed robust model, the results are shown in Figs. 7-15. Fig. 7-a shows both the expected and robust electricity prices. They are identical in a few hours, e.g., hours 20 to 24, while the robust prices show higher values in most hours. Due to the increasing electricity prices in the robust state, the electricity purchased in the electricity market is reduced in 7-b compared to the expected purchased electricity. However, the robust electricity price is not the only reason for such a reduction in purchasing electricity. As can be seen from Fig. 8, the amount of electricity generated by wind turbines decreases after hour 10, which corresponds to the hour with the highest electricity price. In other words, the robust electricity prices and wind generation impose the worst-case to the system simultaneously. Therefore, decreasing wind generation is another significant factor that affects the amount of electricity procured in the electricity market. Fig. 9 demonstrates the gas that entered the EH, CHP, and the boiler. Fig. 9-a is the total amount of gas entering the EH, which constitutes from the gas entered the boiler and CHP and served the gas demands. According to Fig. 9-b, the amount of gas entering the CHP changes significantly in order to compensate for the lack of procuring electricity from the market and wind turbine generation in the robust solution. As shown in the figure, generating electricity through the CHP is the primary source of compensating for the reduction of robust wind generation. This is due to the lower gas prices compared to the robust electricity prices. Fig. 9-c represents the amount of gas entering the boiler as the main source of supplying the heat demands. The similarity between the pattern of this figure and heat demands (5) verifies the satisfying the heat demands. In a robust solution, less gas has entered the boiler, mainly due to higher electricity generated by the CHP, resulting in higher heat generation. Indeed, the difference between the robust outcome and expected gas entered the CHP is compensated by CHP, as shown in Fig. 9-b.



a) Electricity price



b) Purchased electricity

Figure 7: Robust and expected electricity prices

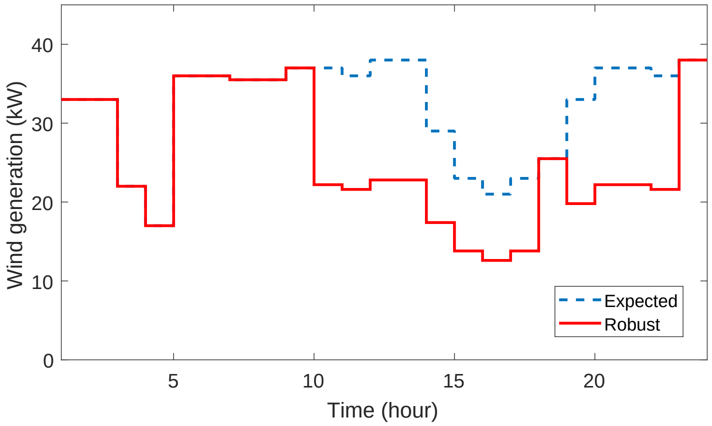


Figure 8: Robust and expected wind turbine generation

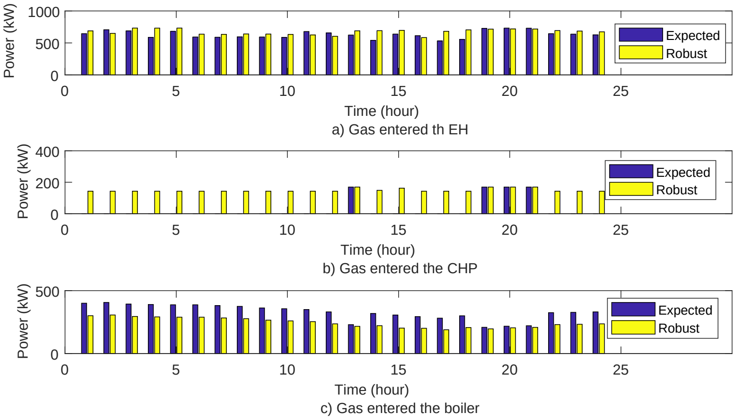
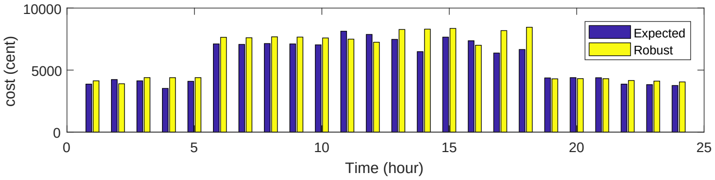
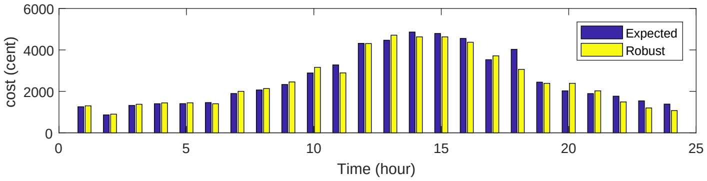


Figure 9: Total gas entered the EH and the devices

The hourly cost of the electricity market and natural gas operation is represented in Fig. 10. Fig. 10-a demonstrates the cost of purchasing gas from the gas market. The cost in hours 6-18 has the highest values due to the higher gas prices in the corresponding hours. Moreover, the higher costs of the robust model are related to the greater volume of purchased gas to guarantee the robustness of the decision. On the other hand, there is no significant distinction between hourly expected and robust electricity market costs. It means less electricity has been purchased with the higher price in the robust mode. Since the boiler and CHP are fed by natural gas and the heat and gas demands are only supported by natural gas, the entered gas to the EH is high, and as a result, the total cost of gas is higher than the electricity cost. The charging/discharging of the ESS is depicted in Fig. 11. The ESS is charged in the beginning hours with the lower electricity prices and discharged in the middle of the duration (peak electricity price hours). That is, charging electricity in off-peak hours (with the lower price) and discharging it in peak hours (with the higher price) results in reducing the electricity procuring cost. The state of charge of the ESS is shown in Fig. 12 accordingly, where the state of charge increases when the ESS is charged and decreases when it discharges.



a) Gas network cost



b) Electricity market cost

Figure 10: Natural gas and electricity price costs

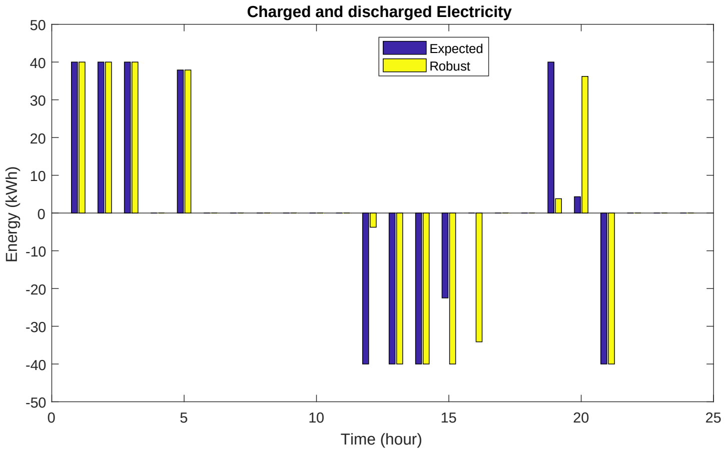


Figure 11: Charging and discharging of ESS

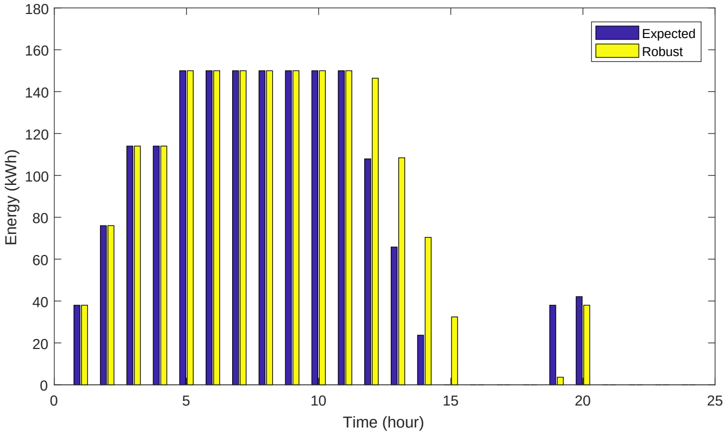
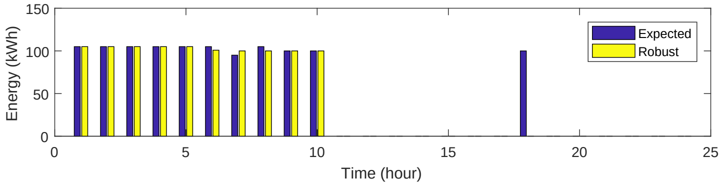
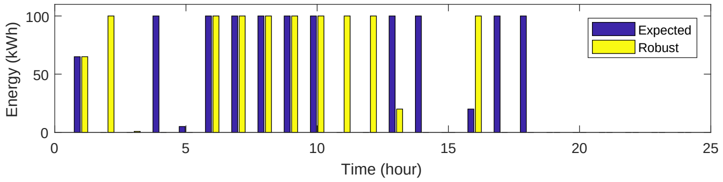


Figure 12: State of charge of the ESS

Fig. 13 presents charging and discharging of the P2G storage. The P2G is fed by the electricity market and discharged by generating natural gas. According to this figure, the P2G is charged in the range of the first and tenth hours, which corresponds to the off-peak prices of the electricity market. On the other hand, it is mostly discharged in the hours when the gas is more expensive. Generating part of the natural gas by the P2G system means a decrease in purchasing gas from the gas market. For a better assessment, Fig.14 shows the effect of the P2G in reducing the amount of gas required for the EH. As can be seen, the main difference occurs in the range when the gas prices are higher. For instance, in hour 12, without using the P2G storage, the purchased natural gas is 704.05 kW, while it decreases to 604 kW using the P2G system. On the whole, it means a reduction in total cost spent on purchasing electricity, as given in Table 2. Using P2G reduces the natural gas operation cost from €1589 to €1479 while it increases the electricity market operation cost from €547.1 to €605.06. Totally, using P2G decreases the total cost from €2290 to €2241, which means a saving of about 2.13%. Finally, Fig. 15 depicts the hourly cost of emission. Since the shortage of purchasing from the electricity market in the robust mode is compensated by natural gas and due to the closeness of the emission coefficients for the electricity and gas, there is no significant difference between the expected and robust operation for the emission cost. It should be noted that the obtained cost for the emission depends on all demands including electricity, heat, and gas demands, where natural gas is involved to supply all demands type.



a) Charging gas to GS



b) Discharging gas from GS

Figure 13: Charging and discharging of P2G storage

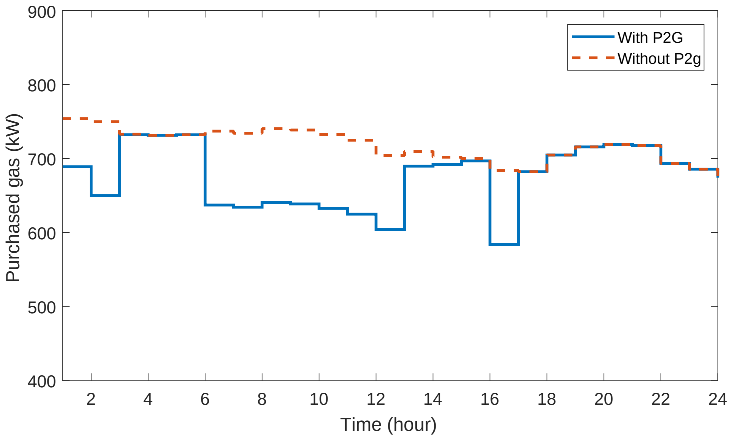


Figure 14: Effect of P2G on the entered gas

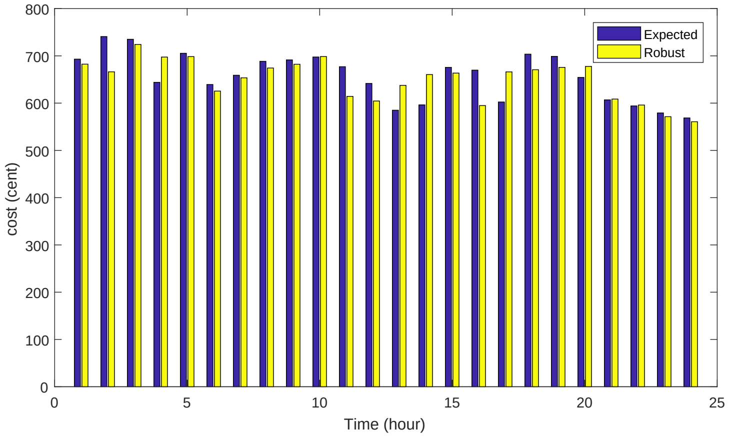


Figure 15: Emission costs

Table 2: Effect of P2G on output costs (€)

	Without P2G	With P2G
Electricity market cost	547.1	605.06
Natural gas cost	1589	1479
Total cost	2290	2241

5.3. Sensitivity analysis

The selection of the robust optimization parameters changes the decision-making results. Therefore, this section investigates the effects of different uncertainty budgets on the robustness of the problem against the different volumes of electricity prices and wind turbine generation uncertainties. In the other words, the volume of uncertainties is increased, and then the results are investigated. Γ^p is a parameter showing the budget of uncertainty for increasing or decreasing electricity prices. It changes with choosing the maximum number of prices (N_p) which are allowed to vary, i.e., the maximum value N_p is equal to 24. Table 3 provides the results of the cost with respect to changing the (N_p). Larger (N_p) means more uncertainty is allowed to affect the operation process. By increasing the uncertainty budget, the electricity prices increase in order to reach the worst-case, and consequently, the electricity market operation cost goes up while the electricity purchase reduces. On the other hand, the gas network operation

Table 3: Effect of electricity price uncertainty budget on operation cost (€)

N_p	Electricity cost	gas cost	Emission cost	Total cost
0	556.46	1465.04	156.34	2178.2
4	571.73	1473.5	156.2	2201.8
8	588.65	1476.8	156.11	2221.93
12	605.06	1479.4	156.05	2240.9
16	621.7	1481.7	156.1	2259.3
20	636.9	1482.61	156.2	2275.83
24	647.8	1484.06	156.12	2288.3

cost also increases due to higher electricity generation for compensating the shortage of purchasing electricity from the market. The emission cost does not have remarkable variation since, on the one hand, the electricity purchased decreases, and on the other hand, higher amounts of gas are purchased from the gas market. On the whole, the total operation cost increases from €2178.2 to €2288.3 when the uncertainty budget of electricity prices goes up.

In a similar way, the wind generation uncertainty is controlled by wind uncertainty budget N_w. It can range from 0 to 24, which means any hours could be affected by the uncertainty. The maximum deviation for each hour is considered to be 40%. Table 4 represents the results of sensitivity analysis on N_w. Results demonstrate that the bigger N_w brings greater operation cost. The main reason is that the greater N_w indicates higher uncertainty, so a higher decrease in wind generation, as a cost-free source, occurs. In this situation, the shortage of the generation is supplied by the electricity market, and the generation by natural gas does not change significantly. Therefore, the emission cost increases due to the raising in the purchased electricity from the electricity market. Finally, as can be seen in Table 4, the total cost of operation goes up from €2223.7 to €2249.7 by increasing the wind generation uncertainty budget from 0 to 24. As can be seen from the Tables 3 and 4, different realizations of the uncertainties cannot be an obstacle for the proposed mathematical model to operate under the worst-case realization in each state. It means the proposed mathematical model is capable of obtaining the robust solutions in various realizations of the

Table 4: Effect of wind uncertainty budget on cost (€)

N_w	Electricity cost	gas cost	Emission cost	Total cost
0	588.57	1479.8	155	2223.7
4	597.1	1478.8	155.38	2231.49
8	600.51	1480	155.74	2236.6
12	605.06	1479.4	156.05	2240.9
16	608.64	1479.84	156.42	2244.85
20	611.99	1478.88	156.80	2248.02
24	613.39	1479	157.08	2249.70

uncertainties.

6. Conclusion

In this paper, a robust optimization model has been developed to investigate the robust operation of an energy hub integrated with P2G technology, considering the uncertainties of the electricity market prices and wind turbine generation. The problem is modeled as a *max-min-max* robust optimization aiming to help the operator of an EH in making appropriate decisions regarding the dispatch of the generating units and energy procurement. The model also considered the imposed cost due to the releasing of CO_2 emission. Results show that the robust electricity prices increase most of the time, and consequently, the purchased electricity from the market is reduced. On the other hand, the CHP increases the generation in the robust mode to compensate for the lack of electricity purchasing from the electricity market. Meanwhile, compared with the expected mode, the total operation cost of the natural gas increases in the robust mode due to the increase in gas entering the CHP. The P2G storage system buys electricity from the market in the off-peak period and discharges into the gas network during the period of high gas prices. It decreases the gas purchasing cost by 6.9% and total operation cost by 2.13%. Finally, sensitivity analysis on the uncertainty budgets of the wind generation and electricity prices reveals that the proposed model is robust against different levels of the uncertainty budget for both electricity market prices and wind turbine generation, although the total cost raises by increasing the budget of uncertainty.

A network constrained decentralized framework of the operation of multi-EHs is introduced as a perspective of future work including the effect of power to gas storage systems.

Acknowledgment

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Appendix A. Linearization of absolute value function

The model of the inner maximization problem makes nonlinearity because of the presence of the absolute value. First of all, the inequalities (5)-(6) are reformulated as follows.

$$\lambda_t^m = \bar{\lambda}_t^m + \phi_{\lambda t} \quad : \xi_t \tag{A.1}$$

$$\phi_{\lambda t} \leq Dev_{\max}^p \bar{\lambda}_t^m \quad : \overline{\delta}_t \tag{A.2}$$

$$\phi_{\lambda t} \geq -Dev_{\max}^p \bar{\lambda}_t^m \quad : \underline{\delta}_t \tag{A.3}$$

$$\phi_{\lambda t} - \phi_{\lambda t}^+ + \phi_{\lambda t}^- = 0 \quad : \sigma_t \tag{A.4}$$

$$\sum_{t=1}^{T} \phi_{\lambda t}^+ + \phi_{\lambda t}^- \leq \Gamma^p \quad : \underline{\sigma} \tag{A.5}$$

Appendix B. Linearization of nonlineaity of bi-product of continuous and binary variables

If we consider (7) the term $(ED_t - P_t^w)\alpha_t$ will make a nonlinearity due to the bi-product of $k_t\alpha_t$. By taking into account the auxillary variable Z_t instead, the Eqs. (B.2)-(B.5) linearize the equations as follows.

$$Z_t = k_t \alpha_t \tag{B.1}$$

$$Z_t \leq \alpha_t + (1 - k_t)M \tag{B.2}$$

$$Z_t \geq \alpha_t - (1 - k_t)M \tag{B.3}$$

$$Z_t \leq k_t M \tag{B.4}$$

$$Z_t \geq -k_t M \tag{B.5}$$

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