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An Interactive Framework for Strategic Participation of a Price-Maker Energy Hub in the Local Gas and Power Markets Based on the MPEC Method

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Abstract: Power-to-gas (P2G) technologies within smart energy hubs (SEH) offer unprecedented operational flexibility to distribution networks. This is achieved by integrating various energy carriers both regionally and locally, particularly in the presence of renewable energy sources (RES). According to this subject, the present work outlines an interactive risk-based model and meticulous mathematical solution to justifiably incorporate the P2G units into the SEH to participate in the local electricity and natural gas markets strategically. As a price-maker prosumer, the SEH utilizes cross-product arbitrage strategies to optimize its proposals for power and gas exchanges in the local markets. The participation model for SEH is developed as a bi-level framework. At the top level, the goal is to maximize SEH's profit while accounting for the risks posed by RES. At the bottom level, the aim is to increase social welfare under network constraints through local market settlements. Finally, a mathematical program with equilibrium constraints (MPEC) is offered as a solution to solve the bi-level model. Using integer disjunctions on the complementarity and slackness criteria and the strong duality theory on the bilinear product terms, a mixed-integer linear programming (MILP) has been derived to approximate the suggested MPEC formulation. It can be concluded from the results that the integration of P2G technologies and the use of mutual product arbitrage in the local electricity and natural gas markets, not only increases the profit of the SEH, but also reduces operating costs and improves social welfare as well as cost-recovery of the entire network.

Keywords: Power-to-gas, Smart energy hub, local electricity and gas markets, MPEC.

1. Introduction

1.1 Concepts

Unrestrained and overindulgent use of various energy sources, including electricity and natural gas, has led to a notable increase in energy costs and is thus becoming an increasingly significant concern in the context of climate change. However, technological developments have made it easier to incorporate distributed generation and power-to-X (P2X) units into power systems' hierarchical structure, changing how energy networks are managed [1]. The advent of multi-carrier energy systems (MES) has resulted in their extensive application in contemporary energy infrastructures, successfully tackling the obstacles linked to various energy sources. The SEH as the main part of MES plays a crucial role in energy generation, transformation, commerce, and storage. It facilitates the interconnection of multiple energy sources and plays an important role in integrated infrastructures [2].

The SEH enables system operators to make more informed decisions. It boosts their flexibility by utilizing diverse elements such as boilers, P2G, wind turbines (WT), batteries, and thermal storage. While CHP converts natural gas into electricity and heat, a boiler converts electricity into heat. In addition, electricity and heat storage units enable storing excess energy during periods of low demand, making it available for subsequent use during periods of high usage [3]. These facilities may be used and controlled in real time to meet fluctuating energy needs, ensuring a steady and reliable energy supply. On the other hand, with the dramatic increase in penetration of RES and the need to increase the flexibility of the power system to control the extreme fluctuations of RES, the use of these multi-carrier energy equipment can provide the necessary platform for the integration of these variable generations [4].

In recent years, many models and architectures have been presented for the planning and operation of SEH from different points of view. However, their implementation and participation in the local markets as a price-maker agent must be considered in detail. While some researchers have examined the potential of peer-to-peer (P2P) energy trading between SEHs and the power market, the effects of its market power on the both electricity and natural gas markets and optimal offering techniques still needs to be explored. Thus, there is an urgent need to investigate the potential benefits and challenges of integrating SEH into present markets. In addition, it is essential to develop effective offering methods that maximize the value and impact of SEH participation while satisfying network requirements. Such initiatives can considerably improve the overall efficacy, stability, and resiliency of energy systems while increasing the integration of RES and lowering carbon emissions.

1.2 Literature review

The prevailing configuration of the power grid is based on a centralized production model characterized by a restricted number of producers and a multitude of consumers. This structure is not conducive to generations that are characterized to be distributed and modern market systems. One emerging market model that has been advocated recently is the local energy market, which prioritizes customer needs and promotes on-site production. Various innovative models for local markets have been proposed in the existing literature with the aim of promoting the active involvement of prosumers in energy trading. The authors in reference [3] have presented a novel local market structure that may be used in the context of distribution energy systems. This study utilizes the feed-in-tariff mechanism for electrical market energy trading. Furthermore, it proposes a linear optimization approach to examine the most effective tactics for market players with different configurations in this particular market. Paper [4], discusses the Turkish electricity market's market design and electricity trading and then seeks to maximize a coal-fired power plants profit by allocating its capacity to spot, derivative, and bilateral contract markets.

The advancement of design and management techniques for the transmission of energy, money, and information within local energy markets plays a crucial role in the progress of this particular area of research. For example, in [5] bilateral contract networks have been proposed for P2P energy trading among small-scale distributed energy resources completely decentralized using pioneering information transfer techniques between players. Similarly, the study conducted in [6] explores a paradigm of an energy market based on completely decentralized P2P blockchain technology. This paradigm enables small-scale prosumers to participate in bilateral energy token transactions with one another via the use of smart contracts. Accordingly, in reference [7], many clusters of adjacent residences establish a virtual local energy market (LEM) through collaborative efforts to integrate diverse load and renewable profiles. This article also incorporates the inclusion of electric vehicles (EVs) to enhance the flexibility in developing virtual LEM. The study conducted by the authors of [8] examines the P2P energy-sharing dynamics among 50 houses inside a local microgrid, taking into account the varying degrees of photovoltaic (PV) and electric vehicle (EV) infrastructures.

Generally, the prosumers are classified into distinct groups, where an aggregator manages these groups. The energy-sharing provider, an independent organization, determines the intra-group pricing. The primary aim of the LEM is to decrease energy costs, facilitate more market participation by competitors, and encourage investment in renewable energy sources and distributed generation. To achieve these objectives, the authors in reference [9] suggest using a community-based P2P local energy management architecture that incorporates principles from game theory. This article presents a paradigm centered on energy sector prosumers, highlighting several on-site production and consumption opportunities. In reference [10], a conceptual framework for a P2P power trading system consisting of three layers is presented. This system is specifically designed to cater to local communities with a significant adoption of residential PV systems. The trading system described has three distinct layers: a physical layer that relies on the power grid, an information layer that operates via a virtual network, and a market layer that functions using a double auction mechanism. The authors examined the security and privacy problems of P2P energy trading in LEM in reference [11]. To tackle these difficulties, blockchain technology has been proposed, and it has been determined that adopting it will prevent the need for a reliable intermediate. Game-theoretic-based P2P electricity trading in energy communities has been investigated in [12]. An energy-sharing scheme and the mechanism are developed in [13], in which the benefits of sharing distributed energy resources (DER) for peak shaving have been explored. Yang in [14] introduced a framework for automated demand response in local energy networks, focusing on ensuring secure trading.

The concept of SEH was first introduced in the influential publication titled "*Vision of Future Energy Networks*" [15]. Subsequently, the notable versatility shown by SEH, together with their significant contributions to carbon reduction and energy management, has garnered substantial attention. In recent years, there has been a notable focus on the market involvement of SEHs in various scholarly studies. The multi-stage energy management system presented by the authors in reference [15] aims to optimize the operational expenses of a multi-energy SEH operating in deregulated energy markets. This is achieved via the implementation of a multi-stage technique. The authors have presented a transactive energy solution in reference [16], which aims to optimize the functioning of SEHs by simultaneously considering the power and gas grids in a techno-environmental-economic framework. The research also employs the conditional value-at-risk (CVaR) approach to effectively represent the risks associated with the existence of SEHs in energy markets. Similarly, in [17], researchers explored the potential for an SEH to participate concurrently in isolated electricity and natural gas markets. This investigation's findings indicated that the use of cross-product arbitrage for the SEH in energy markets enhances decision-making capabilities and leads to energy cost savings. Authors in [18] have proposed a unique concept for a decentralized energy market architecture that prioritizes security. This model involves the active participation of SEHs, utility grids, and energy customers within the local market. This research employs a bi-level optimization approach to represent the interaction among these elements. Authors of [19] have presented a local market clearing framework considering the impact of energy storage devices (ESD) and reginal MES. Optimal scheduling of a SEH in the day-ahead and regulation markets is investigated in [20]. Reference [21] examines the functioning of a P2X integrated SEH within energy markets and draws the conclusion that the inclusion of P2X infrastructures reduces the required wholesale electricity trading volume for the SEH. The study conducted in reference [22] examines the interplay of many SEHs within a localized energy market. This research presents a suggested framework for effective energy management of SEHs, known as the Transactive Energy (TE) framework. Each SEH is a complex energy system that uses day-ahead energy management strategies to optimize the scheduling of its electrical, thermal, and cooling demand profiles. Additionally, it effectively utilizes its internal energy resources to minimize both overall energy expenditures and the release of CO_2 emissions. The study conducted in reference [23] has examined the relationships between many SEHs operating in various energy markets. This research aims to explore the strategies used by an SEH to optimize its income via active engagement in diverse local energy markets.

The literature study emphasizes notable progress and diverse strategies in incorporating SEH into local energy markets. Significantly, several studies have consistently shown that LEMs enable prosumers and distributed generating units to actively participate, thereby encouraging a decentralized approach to energy trading. Furthermore, the integration of SEHs in these markets has the potential to enhance the efficiency and responsiveness of energy systems. Optimization methodologies such as linear programming, game theory, and multi-stage procedures have shown that the strategic involvement of SEHs in electricity and natural gas markets may effectively decrease operating expenses and improve overall market efficiency. In addition, cross-product arbitrage tactics allow SEHs to take advantage of pricing differences across marketplaces, thereby increasing their earnings. Utilizing risk management technologies, such as CVaR, is essential for reducing the financial risks linked to the integration of RES. Prior research has shown that risk aversion measures may help stabilize SEH processes and guarantee more predictable economic results. Moreover, the integration of technologies such as P2G, combined heat and power (CHP), solar (PV) panels, WT, and energy storage systems in SEHs has been shown to improve the adaptability and durability of the energy grid. These technologies facilitate the effective conversion, storage, and consumption of energy, therefore reducing carbon emissions and enhancing grid stability. Based on these findings, our study suggests a dynamic risk-based framework for SEH involvement in regional electricity and natural gas markets. Our approach attempts to optimize earnings and mitigate the risks associated with RES by modelling the SEH as a price-maker prosumer and using cross-product arbitrage tactics.

1.3 Novelty and contributions

Following the assessment of the relevant literature that was presented in the previous section, it has become abundantly clear that important contributions have been made to the development of regional energy trading markets. The SEH, which serves as the backbone of modern multi-energy infrastructure, will play an essential role in future energy markets, particularly in the local markets owing to the fact that it is consumer-oriented rather than producer-oriented. Meanwhile, the incorporation of new technologies into the framework of the SEH makes it necessary to do research that is both in-depth and exact about energy management. A survey of the prior works finds that there has yet to be a study that models the interaction between electricity and gas markets via a price-maker P2G integrated SEH which uses cross-product arbitrage. By incorporating P2G technology along with other technologies into the SEH, its owner gains the ability to engage in both the day-ahead electricity and natural gas markets as a prosumer, enabling the use of cross-product arbitrage to mitigate expenses or potentially produce a surplus profit.

Table 1: A comparative analysis of previous research studies and the present work.

Ref.	Uncertainty management	Risk	Participation in markets		Local market	P2G	Market configuration
			Natural gas market	Electricity market			
[17]	Stochastic	✓	Price taker prosumer	Price taker prosumer	×	✓	Central
[18]	Robust	×	Consumer	Price maker prosumer	✓	×	P2P
[21]	Deterministic	×	Not considered	Price taker prosumer	×	✓	P2P
[22]	Stochastic	×	Not considered	Price maker prosumer	✓	×	P2P
[23]	IGDT	✓	Consumer	Price taker prosumer	✓	×	Central
This work	Stochastic	✓	Price taker prosumer	Price maker prosumer	✓	✓	Central

Table 1 presents a comparative analysis of the relevant studies on the SEH's market participation. As can be seen, the previous studies investigated the SEH’s involvement in energy markets as either a price-taker entity or as a result of P2P energy exchange among numerous participants. In this research, the SEH is characterized as a market-maker player that has the ability to influence prices in a local electricity market (LEM). This study focuses on analyzing the interactions between this SEH and other participants in the conventional market. The P2G-compliant SEH is recognized for its ability to fulfill both thermal and electrical load requirements while also actively engaging in the local electricity and natural gas markets at the distribution level. This enables the sale of power and gas to the local market or network, with the aim of optimizing income irrespective of the volatility in market pricing. Furthermore, given the presence of uncertainties in RES generation, SEH's profit may exhibit volatility. Consequently, the owner of SEH may have a vested interest in developing models to assess the risk associated with variations in profit. The suggested solution integrates the fluctuation in operational costs using the CVAR method. In summary, the primary contributions of this work could be outlined as follows:

- Developing an interactive risk-based model to incorporate the P2G units into the SEH to strategically participate in the local electricity and natural gas markets. The SEH is modelled as a price-maker prosumer that utilizes cross-product arbitrage strategies between power and gas markets to maximize its own profit.
- The participation model is structured as a bi-level framework; maximizing the SEH profit at the upper level considering the risk caused by the RES, and settling the local markets under spatial-temporal constraints of power system in lower level.
- To solve the bi-level model, a MPEC is suggested as a means to analyze the strategic actions of a profit-oriented SEH in the electricity and gas markets. The MPEC formulation is then approximated as a MILP by applying integer disjunctions and binary expansion approach to the complementarity and slackness requirements.
- The integration of P2G technology and the emphasis on renewable energy sources contribute significantly to sustainable energy practices. This research not only aims to enhance economic performance but also aligns with global efforts to reduce carbon emissions and promote renewable energy adoption.
- The study presents a sophisticated bi-level optimization framework that not only maximizes the SEH’s profit but also ensures social welfare in the local energy market. This dual focus ensures that the SEH’s operations are economically viable while also contributing positively to the broader energy market ecosystem.
- By applying the proposed model to a realistic 3-bus test system, the study provides valuable insights into the practical implementation of the model. The case study highlights the model’s effectiveness in real-world scenarios, demonstrating its potential for broader application in different market settings.

1.4 Paper organization

The remainder of this paper will be organized in the following manner. The core issue, uncertainty characterization, risk management methods, and SEH modelling are all discussed in the second section. In the third part, we give the problem formulation as well as models for a variety of technologies and techniques that are used inside the presumptive SEH. The presentation of numerical data, a comparison of case studies, and a commentary are included in Section 4. The conclusion is presented in section 5, along with a discussion of possible avenues for further investigation.

2. Problem explanation

In order to establish the SEH as a price-setting organization, it is necessary to implement a local electricity market framework because in the regular electricity market the SEH is a tiny organization and cannot deviate from market prices. This framework involves the formation of a neutral third-party institution known as the local energy market operator (LEMO), which is responsible for clearing the market on an hourly basis. The proposed SEH encompasses several components, including CHP, P2G, gas boiler, PV, gas-fired resources and energy storage along with WT. The use of a risk index (i.e., CVaR) will be outlined in section 2.2, serves the purpose of managing the potential outcomes stemming from uncertain circumstances. The primary objective of the decision-making mechanism used by the SEH operator is to maximize its own profits associated with the acquisition of energy carriers for its consumers. Simultaneously, the day-ahead marketplaces aim to achieve social welfare for their participants. The members of the proposed model include traditional distribution companies (DISCOs), generation companies (GENCOs), a large-scale SEH, an energy utility grid, and the LEMO. The interaction among these individuals is represented as a bi-level optimization problem, which has been converted into a single-level MILP by the application of the MPEC to put out a straightforward and resolvable model that offers an optimum global solution, capable of being efficiently solved by a commercially available solver.

2.1 Uncertainty characterization

This study focuses on the key sources of unpredictability in the key parameters of the problem, including natural gas prices, the supply of energy from RES, and the levels of energy consumption within the SEH. Probabilistic modeling is often used as the preferable methodology for constructing a stochastic framework, whereby each variable characterized by uncertainty is represented by a probability density function (PDF). The PDFs serve the purpose of ascertaining the likelihood of a particular random variable's occurrence, including a range of discrete probability values within each PDF [24]. There are three primary probabilistic methodologies: Monte Carlo simulation, analytical approaches, and approximation techniques [27]. This work uses an efficient scenario generation technique, namely SCENRED to develop a collection of different modeling scenarios that account for the inherent uncertainty inside our system. In order to alleviate the computational burden on the commercial solver, the Kantorovich scenario reduction approach [28] is used to decrease the quantity of scenarios.

2.2 Risk management

Neglecting additional qualities that specify the distribution of probable outcomes connected to random variables is a major downside of utilizing the anticipated value as a representation for a random parameter. For a random variable to have a projected value that is acceptable to decision-makers, it may have to contain the possibility of a non-zero likelihood of a loss. As a result, stochastic programming models should include risk management in order to reduce the likelihood of unfavorable characteristics in profit distributions. Current research mitigates risk for the SEH operator by including the CVaR risk hedging tool into the market participation issue. Actually, CVaR is a risk metric that quantifies losses at the extremes of a probability distribution [29]. When losses surpass the VaR threshold, CVaR gives a measure of the typical loss [30]. The following procedures are frequently used for calculating CVaR:

- **Determine the VaR:** To analyze losses across a time horizon, you must first establish the VaR. It is often represented as a percentage and is associated with a degree of certainty (such as 90% or 95%).
- **Identify the tail losses:** Once the VaR has been calculated, the "tail losses," or losses in excess of the VaR threshold, may be pinpointed.
- **Calculate the average of the tail losses:** The standard deviation of the tail losses is used to derive the CVaR. The number of observations is divided by summing up the total of the tail losses.

2.3 SEH modelling

An SEH often comprises equipment for energy conversion and storage, which facilitates the transformation of input energy into many different forms of energy to end-users. There are several architectural possibilities for establishing an SEH that depends on their purpose. The presumed SEH model is shown in Figure 1. It incorporates two primary input energy sources, namely electricity and natural gas. These inputs are used to meet the respective needs for electrical and thermal energy outputs. The internal components of this SEH consist of a CHP unit, a gas-powered boiler, two transformers, a P2G utility, as well as electricity and natural gas storage systems, along with PV and WT technologies. The responsibility for determining market participation strategy and meeting end-user requests lies with the SEH owner. Fig. 1 depicts the diagram of the SEH and its components, illustrating the intricate network of energy generation, transformation, storage, and distribution systems. The central component of the SEH is the CHP system, which utilizes natural gas to produce both electricity and thermal energy. The system efficiently harnesses surplus heat for heating needs. The gas boiler serves as a supplementary heat production device, turning natural gas into additional thermal energy. The P2G facility converts excess electricity into synthetic natural gas (SNG), enabling effective energy storage and subsequent consumption. Meanwhile, PV and WT are utilized to capture renewable energy sources, specifically solar and wind energy, to generate electricity. The SNG produced by the P2G facility is stored in the natural gas storage system, while the electrical energy storage system stores electricity. These stored resources are readily available for use during periods of high demand or can be sold in the market. Lastly, transformers guarantee the appropriate voltage levels to facilitate effective transmission and distribution of energy within the SEH and to external networks.

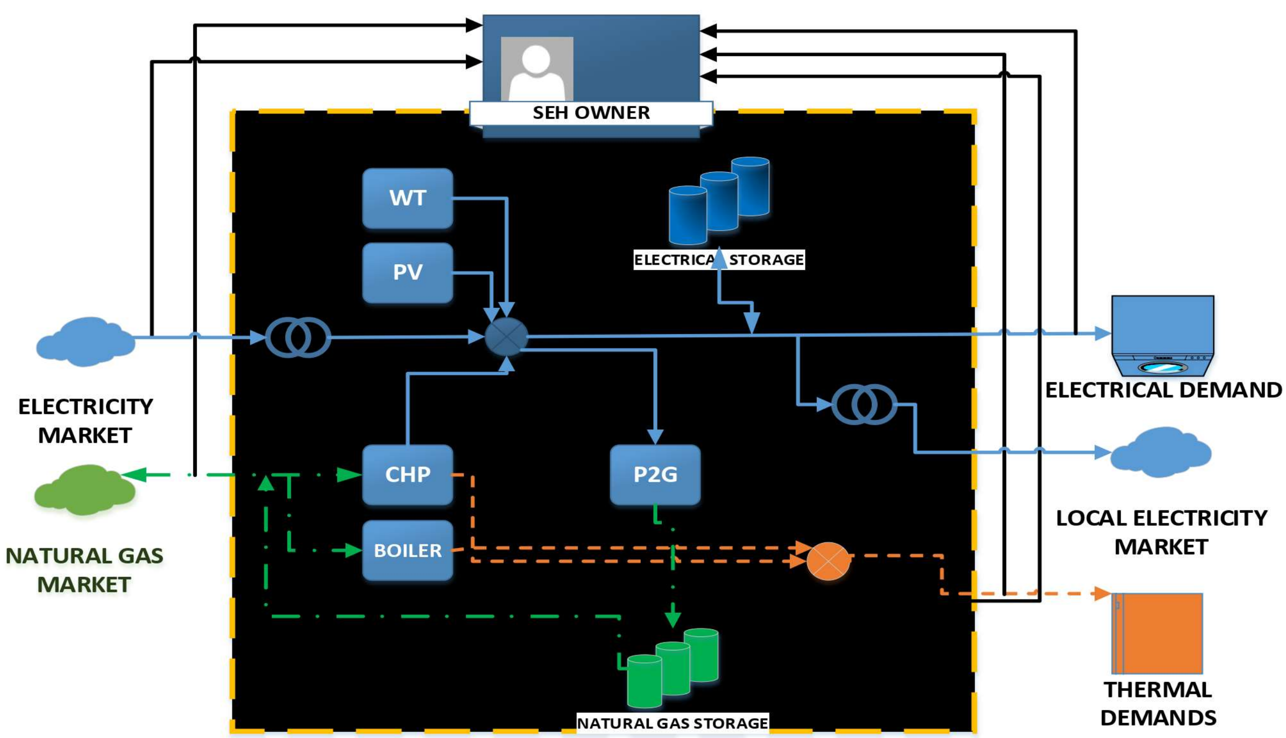

Fig. 1. The schematic structure for the SEH along with their equipment and connections.

2.4 Concept of LEM and SEH participation in it

The primary objective of competitive energy markets is to efficiently and economically provide power to customers while simultaneously meeting their specific demands. This objective can be achieved through various mechanisms, including competition and regulation. However, conventional electricity markets, encompassing wholesale and retail sectors, struggle integrating emerging small-scale power production sources, innovative technologies and infrastructure, increasing local demand, and adopting a consumer-centric market approach. Consequently, there has been a recent paradigm shift towards novel market designs to enhance operational efficiency and address these concerns [31].

One such initiative is the concept of the LEM. Utilizing local power production, storage, and demand response offers significant benefits, attracting diverse market participants. Information and communication technology further facilitates sustainable and efficient power distribution to end-users. Multiple LEMs can operate on a shared distribution network, fostering a collaborative energy ecosystem. Power sources generate electricity, while loads consume it. When electricity generation exceeds load demand, the surplus can be stored for use when demand surpasses production capacity. This system combines the advantages of decentralized energy generation from individual power plants with those of traditional centralized power plants. The local grid is specifically designed to accommodate various source and load sizes and different types of power output (AC/DC). Moreover, it operates on a P2P architecture, enabling all sources and consumers to actively participate in the grid through a high-speed information and communication network, making them integral to the solution.

The LEM becomes a remedy for energy market difficulties and a significant step towards dealing with global warming and minimizing carbon emissions. On the other hand, for its own power and heating needs, the SEH uses only electricity and natural gas as its main fuel sources. Furthermore, through conversion and storage facilities of the SEH, it can engage in the LEM to gain advantages from cross-product arbitrage between electricity and gas markets which result in cost reduction. Hence, by joining the LEM, the SEH could purchase or sell energy thus contributing to sustainable future. The day-ahead settlement is such that; every hour of operation is settled one day prior to delivery on both electricity and natural gas derivative contracts for LEM. However, this auction operates exclusively within 24 hours making it possible for participants to trade only through closed auctions systems. In addition, network constraints have to be considered while at same time optimizing participants' orders in order to achieve maximum social welfare by the LEM operator.

Fig. 2. The framework of competitive LEM for participation of SEH.

3. Problem formulation

Put simply, the SEH strives to fulfill its responsibilities while minimizing expenses in the presence of uncertainty. Participating in the gas market and employing internal CHP, furnace, transformer, WT, PV and P2G units, the manager of the SEH acquires the necessary energy to satisfy these demands. In the meantime, this SEH participates in local electricity and natural gas markets to make a profit. Due to the small scale of the considered LEM, SEH has the ability to deviate the market clearing prices (i.e., market power). Fig. 2 depicts the representation of a LEM, whereby an operator has the responsibility of overseeing and facilitating the management and clearing processes within this market. Within this framework, each individual participant endeavors to attain their own objectives. Retailers are actively seeking to get electricity at the most economically advantageous price, while GENCOs and SEH are striving to maximize their revenue by selling electricity at the highest feasible price.

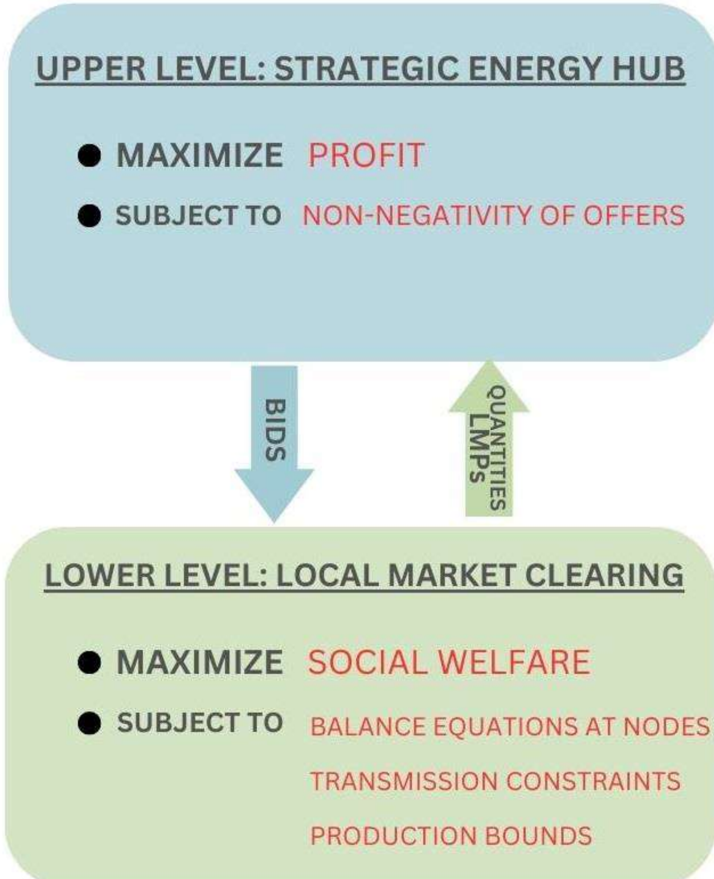

Fig. 3. The proposed bi-level strategy for SEH to participate into the LEM.

3.1 SEH objective function and it's components modeling

The SEH has emerged as dynamic and integrated system that aims to optimize energy resources and increase profitability. This system seek to participate actively in the LEM by leveraging their diverse portfolio of assets, which may include renewable energy generation, storage facilities, and P2G capabilities. By participating in energy markets, SEH can capitalize on price differentials, arbitrage opportunities, and market fluctuations to enhance their profits. However, the volatile nature of energy markets and the presence of uncertainties pose risks to the profitability OF SEH. To mitigate these risks and ensure stable financial performance, SEH employ robust risk management strategies such as CVaR. These strategies involve the identification, assessment, and quantification of risks associated with market price fluctuations, supply-demand imbalances, regulatory changes, and other uncertainties. By implementing risk management measures such as hedging, portfolio diversification, and financial instruments, SEH can reduce the impact of uncertainties and safeguard their profits. The integration of risk management practices with active market participation enables SEH to navigate the complex energy landscape, optimize their operations, and achieve sustainable financial success. In doing so, the predicted profit of SEH related to market participation and the CVaR instrument multiplied by the risk-aversion factor (β) are the two terms that make up the goal function of SEH (2). Note that the trade-off between predicted profit and CVaR is modelled by the proposed risk-aversion factor (β). The power contracted from each block of the forward contracting curve (P_{fj}^{F}) is limited by constraints (3). The block of the price-quota curve that corresponds to each selling price (λ_{ei}^{R}) is identified by constraints (4) and (5). The electric energy balance within the SEH is mandated by constraints (6) for each time period and scenario. The CVaR is calculated using the constraints (7), and ultimately, variable declarations (v_{ei}, η_{ω}) are found in lines (8) and (9).

$$Maximize_{P_{fj}^{F}, \lambda_{ei}^{R}, v_{ei}, E_{tw}^{P}, \zeta, \eta_{\omega}} \tag{1}$$

$$\sum_{\omega=1}^{N_\Omega} \pi_\omega \sum_{t=1}^{N_T} (\sum_{e=1}^{N_E} \sum_{i=1}^{N_I} \lambda_{ei}^{R} \overline{E}_{eti\omega}^{R} - \lambda_{t\omega}^{P} E_{t\omega}^{P} - \sum_{f \in F_t} \sum_{j=1}^{N_j} \lambda_{fj}^{F} P_{fj}^{F} d_t) + \beta(\zeta - \frac{1}{1-\alpha} \sum_{\omega=1}^{N_\Omega} \pi_\omega \eta_\omega) \tag{2}$$

$$0 \le P_{fj}^{F} \le \overline{P}_{fj}^{F} \qquad , \forall f, \forall j \tag{3}$$

$$\overline{\lambda}_{ei-1}^{R} v_{ei} \le \lambda_{ei}^{R} \le \overline{\lambda}_{ei}^{R} v_{ei} \qquad , \forall e, \forall i \tag{4}$$

$$\sum_{i=1}^{NI} v_{ei} = 1 \qquad , \forall e \tag{5}$$

$$\sum_{e=1}^{N_E} \sum_{i=1}^{N_I} \overline{E}_{eti\omega}^{R} v_{ei} = E_{t\omega}^{P} + \sum_{f \in F_t} P_f^{F} d_t + E_t^{PC} \qquad , \forall t, \forall \omega, \tag{6}$$

$$\zeta - \sum_{t=1}^{N_t} (\sum_{e=1}^{N_E} \sum_{i=1}^{N_I} \lambda_{ei}^{R} \overline{E}_{eti\omega}^{R} - \lambda_{t\omega}^{P} E_{t\omega}^{P} - \sum_{f \in F_t} \sum_{j=1}^{N_J} \lambda_{fj}^{F} P_{fj}^{F} d_t) \le \eta_\omega \qquad , \forall \omega \tag{7}$$

$$v_{ei} \in \{0,1\} \qquad , \forall e, \forall i \tag{8}$$

$$\eta_\omega \ge 0 \qquad , \forall \omega \tag{9}$$

To improve the applicability of optimization results, it is important to take into account the capacity limitations of the internal equipment and connecting points of SEH. Failure to adhere to these limitations may lead to a setup that is unfeasible in practical applications. Equitation (10) and (11) denote the constraint that governs the interconnection between the SEH and the LEM, whereas $P_{\max}^{E}$ represents the maximum allowable capacity for power importation from the electricity grid. The limitation is sometimes attributed to factors such as connecting line constraints within the electrical infrastructure. In the interim, $P_{\max}^{G}$ represents the utmost capacity of natural gas imported into/exported from the SEH.

Typically, Pipe line constraints impose this restriction. As shown in these equations, the energy under story only buys electricity from upper head electricity grid, while it imports or exports to natural gas network. It is due to the reason that for selling its electricity, SEH participates in LEM. The parameters $P_{trans}^{input}, P_{CHP}^{input}$, P_{chiler}^{input}, and P_{P2G}^{input} are used to define the upper limits of the electrical transformer (12), CHP (13), Boiler (14) and P2G systems (15) in terms of their maximum capacity.

$$0 \leq P_{e}^{DA}(t,s) \leq P_{\max}^{E} \tag{10}$$

$$-P_{\max}^{G} \leq P_{g}^{DA}(t,s) \leq P_{\max}^{G} \tag{11}$$

$$-P_{trans}^{input} \leq P_{trans}^{E}(t,s) \leq P_{trans}^{input} \tag{12}$$

$$0 \leq P_{CHP}^{G}(t,s) \leq P_{CHP}^{input} \tag{13}$$

$$0 \leq P_{Boiler}^{G}(t,s) \leq P_{Boiler}^{input} \tag{14}$$

$$0 \leq P_{P2G}^{E}(t,s) \leq P_{P2G}^{input} \tag{15}$$

3.1.1 CHP feasible region

CHP is a system that employs diverse technologies and fuels to concurrently generate electricity and thermal energy with a notable level of efficiency. On-site power generating systems have the advantage of minimizing losses and using excess heat that would otherwise be dissipated. This surplus heat may be effectively used for various facility loads within the SEH, such as process heating, steam generation, hot water supply, or even chilled water production. CHP systems have the potential to be situated inside a singular establishment or structure, or alternatively, they may be implemented within a district energy, microgrid, or utility resource. Furthermore, these systems may be integrated with other distributed energy technologies inside the SEH, such as and energy storage and RES. The CHP system is often regarded as a crucial component of SEH. In the present study, we use a standard CHP system fueled by natural gas. It is worth noting that the power capacity limitations are dependent on the heat outputs, and conversely, the heat outputs are influenced by the power capacity. As a result, the CHP has the capability to function within the region that equations (16)-(18) mathematically elucidate these restrictions [33].

$$P^{t} - P_{A} - \frac{P_{A} - P_{B}}{H_{A} - H_{B}}(H^{t} - H_{A}) \leq 0 \tag{16}$$

$$P^{t} - P_{B} - \frac{P_{B} - P_{C}}{H_{B} - H_{C}}(H^{t} - H_{B}) \geq 0 \tag{17}$$

$$P' - P_C - \frac{P_C - P_D}{H_C - H_D}(H' - H_C) \geq 0 \tag{18}$$

3.1.2 Energy storage modelling

Energy storage refers to the process of collecting and retaining energy that is produced at a certain point in time, with the intention of using it at a later period. This article incorporates both gas and electrical energy storages into the SEH to enhance its operational and decision-making flexibility within the LEM. In order to accurately represent the electrical storage system, it is necessary to include certain limitations (19)-(24) into the problem. Equation (19) depicts the energy equilibrium inside the storage, while equation (20) characterizes the energy dissipation of storage. The use of equation (21) is employed to ensure that the stored energy level remains within the acceptable range. The limitations on charging/discharging are shown in equations (22) and (23), in which β_{Min}^{E} and β_{Max}^{E} are minimum and maximum allowable charging rates, respectively. η_{ES}^{ch} and η_{ES}^{dis} are used to denote the efficiencies of charging and discharging. Eq. (24) serves as a constraint that ensures storage cannot work in both the charging and discharging modes concurrently.

$$P_s^E(t,s) = P_s^E(t-1,s) + P_{ch}^E(t,s) - P_{dis}^E(t,s) - P_{loss}^E(t,s) \tag{19}$$

$$P_s^E(t,s) = \alpha_{loss}^E P_s^E(t,s) \tag{20}$$

$$\alpha_{Min}^E P_{capaity}^E \leq P_s^E(t,s) \leq \alpha_{Max}^E P_{capacity}^E \tag{21}$$

$$\beta_{Min}^E P_{capacity}^E \left(1 / \eta_{ES}^{ch} \right) I_{ch}^E(t,s) \leq P_{ch}^E(t,s) \leq \beta_{Max}^E P_{capacity}^E \left(1 / \eta_{ES}^{ch} \right) I_{ch}^E(t,s) \tag{22}$$

$$\beta_{Min}^E P_{capacity}^E \eta_{ES}^{dis} I_{dis}^E(t,s) \leq P_{dis}^E(t,s) \leq \beta_{Max}^E P_{capacity}^E \eta_{ES}^{dis} I_{dis}^E(t,s) \tag{23}$$

$$0 \leq I_{dis}^E(t,s) + I_{ch}^E(t,s) \leq 1 \tag{24}$$

The direct injection of natural gas generated by P2G infrastructure into existing natural gas pipelines is not feasible. Initially, it is important to channel the natural gas into a designated system for storage. As a result, the model necessitates the implementation of a gas storage system. The natural gas storage system, like the electrical storage system, is subject to technological limitations that must be included in the suggested model. The constraints are elucidated by equations (25)-(30).

$$P_s^G(t,s) = P_s^G(t-1,s) + P_{P2G}^{ch}(t,s) - P_{P2G}^{dch}(t,s) - P_{loss}^G(t,s) \tag{25}$$

$$P_s^G(t,s) = \alpha_{loss}^G P_s^G(t,s) \tag{26}$$

$$\alpha_{Min}^G P_{capacity}^G \leq P_s^G(t,s) \leq \alpha_{Max}^G P_{capacity}^G \tag{27}$$

$$\beta_{Min}^{G} P_{capacity}^{G} \left(1 \big/ \eta_{G}^{ch} \right) I_{ch}^{G}(t,s) \le P_{P2G}^{ch}(t,s) \le \beta_{Max}^{G} P_{capacity}^{G} \left(1 \big/ \eta_{G}^{ch} \right) I_{ch}^{G}(t,s) \tag{28}$$

$$\beta_{Min}^{G} P_{capacity}^{G} \eta_{G}^{dis} I_{dis}^{G}(t,s) \le P_{P2G}^{dch}(t,s) \le \beta_{Max}^{G} P_{capacity}^{G} \eta_{G}^{dis} I_{dis}^{G}(t,s) \tag{29}$$

$$0 \le I_{dis}^{G}(t,s) + I_{ch}^{G}(t,s) \le 1 \tag{30}$$

3.1.3 P2G equipment

P2G is an emerging technology that facilitates the integration of electricity and natural gas networks. It is widely recognized as a crucial component within the SEH aimed at transitioning towards multi energy systems with lower carbon emissions. The P2G unit offers many notable advantages, e,g., it has the greatest energy storage density, it offers a diverse range of storage alternatives, encompassing compressed gas and liquefied hydrogen stored in tanks, as well as integration with the natural gas infrastructure. This integration is particularly advantageous for SEH due to its ability to optimize the utilization of the pre-existing infrastructure, thereby enhancing economic efficiency. Within our theoretical framework, the initial electrical energy undergoes a process known as electrolysis, resulting in the conversion of water into hydrogen. Subsequently, the hydrogen is further transformed into synthetic natural gas. A mixture of hydrogen and carbon dioxide can be utilized to produce a continuous flow of synthetic natural gas, which can be seamlessly integrated into the existing natural gas distribution infrastructure. The chemical equations corresponding to these steps are denoted in (31) and (32), whereas the its power generation/consumption is modeled using the equations (33)-(34). In these equations, η_{P2G}^{elec}, η_{P2G}^{methan} are the efficiencies of electric and electrolysis process.

$$2H_2O \rightarrow 2H_2 + O_2 \tag{31}$$

$$4H_2 + CO_2 \rightarrow 2H_2O + CH_4 \tag{32}$$

$$P_{Hydrogen}^{E}(t,s) = P_{P2G}^{E}(t,s)\eta_{P2G}^{elec} \tag{33}$$

$$P_{P2G}^{ch}(t,s) = P_{Hydrogen}^{E}(t,s)\eta_{P2G}^{methan} \tag{34}$$

3.1.4 PV generation

The power production of PV on an hourly basis is contingent upon many factors, including solar irradiation, temperature, and the specific properties of the panel. The output of PV panel is represented by equation (35), while the equation (36) denotes the energy transfer equation for the PV. The parameters pertaining to PV generation have been obtained from reference [34]. In this research, the same values for irradiance have been used for the SEH. The PV production is either equivalent to or lower than its rated capacity. The electrical output produced by PV may be used to meet the electrical demand of a system, such as an SEH, or it can be sent to the utility grid for sale or to P2G equipment (36).

$$P_{k,t}^{PV} = \frac{G_{k,t}^{a}}{G_{0}^{a}}[\overline{P}_{k}^{PV} + \mu_{\overline{P}}(T_{k,t}^{a} + G_{k,t}^{a}\frac{NOCT-20}{800} - T_{0}^{M})] \tag{35}$$

$$P_{k,t}^{PV} = P_{k,t}^{PV\to EL} + P_{k,t}^{PV\to G} P_{k,t}^{PV\to EES} P_{k,t}^{PV\to EHP} + P_{k,t}^{PV\to EH} \tag{36}$$

3.1.5 WT modelling

WT, being a kind of non-dispatchable energy source, provide a significant contribution towards fulfilling the power requirements. This study presents an analysis of wind energy production, with a particular focus on the omission of maintenance costs associated with wind technology. The real-time wind power shall not exceed its maximum value expected for wind speed as stated in equation (37). The equation (38) signifies the upper limit of WT production throughout the duration of energy scheduling. In actuality, the projected power for each temporal interval encompasses a degree of inaccuracy, hence leading to the potential for either greater or lower energy acquisition inside those intervals. The real-time wind energy deficit is either less than or equal to the numbers specified in (39).

$$P_{W}^{RT}(t,h,s) \le P_{W}^{f}(t,h,s) \tag{37}$$

$$0 \le P_{W}^{DA}(t) \le P_{W}^{\max} \tag{38}$$

$$P_{SW}^{RT}(t,h,s) \le P_{W}^{RT}(t,h,s) \tag{39}$$

3.2 Bi-level optimization problem

The proposed market participation strategy for P2G integrated SEH is modelled as a stochastic bi-level problem, formulated as an MPEC. In this formulation, the upper level focuses on maximizing the profit of SEH, while the lower level considers the clearance of the LEM aimed at maximizing the social welfare of whole system as shown in Fig. 3. The suggested bi-level formulation can be written as follows. The Objective function (40) maximizes the profit of SEH at the upper level, as given by (41), obtained by subtracting the profit from participation in the LEM and the cost of energy production within the SEH. It has written az a minimization problem because we have written it in its canonical form. Equations (42) and (43) also depict the objective function of the market settlement at the lower level, which will be optimized under the operation constraints of network. In particular, Eqs. (44) to (46) are related to linearized DC power flow calculations, Eqs. (47) and (48) demonstrate the allowed range of production and consumption power of players, and Eqs. (49) to (51) limit the power flow in the network lines within the permissible limit, and at the end of Equation (52) sets the power angle of slack bus to 0. It is important to mention that the variables written in front of each constraint represent the dual variables related to that equation.

$$Minimize\left\{c_1^g\right\} \mathrm{U}\left\{g_1, g_2, g_3, d_1, d_2, d_3, \theta_1, \theta_2, \theta_3\right\} \equiv SO \tag{40}$$

$$c_1^g g_1 - \alpha_1 g_1 \tag{41}$$

$$Minimize\; g_1, g_2, g_3, d_1, d_2, d_3, \theta_1, \theta_2, \theta_3 \tag{42}$$

$$\hat{c}_1^g g_1 + \sum_{i=2}^{3} c_i^g g_i - \sum_{i=1}^{3} c_i^d d_i \tag{43}$$

$$g_1 - d_1 - B_1(\theta_1 - \theta_2) - B_2(\theta_1 - \theta_3) = 0 \qquad (\alpha_1) \tag{44}$$

$$g_2 - d_2 - B_1(\theta_2 - \theta_1) - B_3(\theta_2 - \theta_3) = 0 \qquad (\alpha_2) \tag{45}$$

$$g_3 - d_3 - B_2(\theta_3 - \theta_1) - B_3(\theta_3 - \theta_2) = 0 \qquad (\alpha_3) \tag{46}$$

$$0 \le g_i \le g_i^{Max} \qquad (\phi_i^{g\min}, \phi_i^{g\max}), i = 1,2,3 \tag{47}$$

$$0 \le d_i \le d_i^{Max} \qquad (\phi_i^{d\min}, \phi_i^{d\max}), i = 1,2,3 \tag{48}$$

$$-f_1^{\max} \le B_1(\theta_1 - \theta_2) \le f_1^{\max} \qquad (\rho_1^{\min}, \rho_1^{\max}) \tag{49}$$

$$-f_2^{\max} \le B_2(\theta_1 - \theta_3) \le f_2^{\max} \qquad (\rho_2^{\min}, \rho_2^{\max}) \tag{50}$$

$$-f_3^{\max} \le B_3(\theta_2 - \theta_3) \le f_3^{\max} \qquad (\rho_3^{\min}, \rho_3^{\max}) \tag{51}$$

$$\theta_3 = 0 \qquad (\gamma) \tag{52}$$

In these equations, g_i indicates the production offer of GENCOs, d_i displays the consumption bides of retailers, *B* is susceptance of the lines, θ_n indicates the power angle of the bus-bars, and $f_l^{\max}$ indicates the maximum power of the network lines[35].

To solve the MPEC, we apply the Karush-Kuhn-Tucker (KKT) conditions to the lower-level problem and convert the bi-level problem into a single-level Mixed-Integer Linear Programming (MILP) problem. The MPEC formulation is then approximated as a MILP by applying integer disjunctions and the Big-M method to linearize complementarity constraints. In addition to the optimization variables used in the main problem, the MPEC problem also includes binary variables needed to linearize complementarity constraints using the Big-M technique. In the proposed bi-level optimization, a connection between the primal and dual issues is established using the Strong Duality theorem. We may turn the bi-level issue into a single-level one with linear components in the goal function by utilizing this duality. Optimal solutions for the primal and dual issues are equivalent under specific circumstances as shown by the Strong Duality theorem. Using this theorem, the dual variables of the non-linear components in the objective function will be substituted into the Lagrangian function.

Electricity supply and demand in competitive power markets may vary from one area to another due to variables including transmission limitations, grid losses, and differences in load profiles. Locational Marginal Prices (LMP) are often employed to represent these variations and provide economic signals to market players. In this research, we applied the LMP idea to the participation strategy, considering the transmission circumstances and market strength of SEH. It considers several variables such as generation costs, transmission congestion, and power losses.

Therefore, applying the optimality conditions on Eqs. (43) to (52) and deriving the Lagrange function with respect to the lower-level variables, the KKT equations can be written as (53) to (58). Subsequently, the complementarity conditions of the proposed bi-level model is organized as (59) to (71). In fact, the MPEC for the primal problem (42)-(52) is given in (53)-(77), that is produced by substituting the KKT condition for the equivalent lower-level problems (42)-(52), converting MPEC into an MILP.

$$\hat{c}_1^{g} - \alpha_1 - \phi_1^{g\min} + \phi_1^{g\max} = 0 \tag{53}$$

$$c_i^{g} - \alpha_i - \phi_i^{g\min} + \phi_i^{g\max} = 0 \qquad i = 2,3 \tag{54}$$

$$-c_i^{d} + \alpha_i - \phi_i^{d\min} + \phi_i^{d\max} = 0 \qquad i = 1,2,3 \tag{55}$$

$$B_1(\alpha_1 - \alpha_2 - \rho_1^{\min} + \rho_1^{\max}) + B_2(\alpha_1 - \alpha_3 - \rho_2^{\min} + \rho_2^{\max}) = 0 \tag{56}$$

$$B_1(-\alpha_1 + \alpha_2 + \rho_1^{\min} - \rho_1^{\max}) + B_3(\alpha_2 - \alpha_3 - \rho_3^{\min} + \rho_3^{\max}) = 0 \tag{57}$$

$$B_2(-\alpha_1 + \alpha_3 + \rho_2^{\min} - \rho_2^{\max}) + B_3(-\alpha_2 + \alpha_3 + \rho_3^{\min} - \rho_3^{\max}) + \gamma = 0 \tag{58}$$

$$0 \le g_i \perp \phi_i^{g\min} \ge 0, i = 1,2,3 \tag{59}$$

$$0 \le g_i^{\max} - g_i \perp \phi_i^{g\max} \ge 0, i = 1,2,3 \tag{60}$$

$$0 \le d_i \perp \phi_i^{d\min} \ge 0, i = 1,2,3 \tag{61}$$

$$0 \le d_i^{\max} - d_i \perp \phi_i^{d\max} \ge 0, i = 1,2,3 \tag{62}$$

$$0 \le B_1(\theta_1 - \theta_2) + f_1^{\max} \perp \rho_1^{\min} \ge 0 \tag{63}$$

$$0 \le f_1^{\max} - B_1(\theta_1 - \theta_2) \perp \rho_1^{\max} \ge 0 \tag{64}$$

$$0 \le B_2(\theta_1 - \theta_3) + f_2^{\max} \perp \rho_2^{\min} \ge 0 \tag{65}$$

$$0 \le f_2^{\max} - B_2(\theta_1 - \theta_3) \perp \rho_2^{\max} \ge 0 \quad (66)$$

$$0 \le B_3(\theta_2 - \theta_3) + f_3^{\max} \perp \rho_3^{\min} \ge 0 \quad (67)$$

$$0 \le f_3^{\max} - B_3(\theta_2 - \theta_3) \perp \rho_3^{\max} \ge 0 \quad (68)$$

$$\phi_i^{g\min}, \phi_i^{g\max} \ge 0, \qquad (\eta_i^{g\min}, \eta_i^{g\max}), i = 1,2,3 \quad (69)$$

$$\phi_i^{d\min}, \phi_i^{d\max} \ge 0, \qquad (\eta_i^{d\min}, \eta_i^{d\max}), i = 1,2,3 \quad (70)$$

$$\rho_i^{\min}, \rho_i^{\max} \ge 0, \qquad (\eta_i^{\min}, \eta_i^{\max}), i = 1,2,3 \quad (71)$$

$$0 \le \phi_i^{g\min} \perp \eta_i^{g\min} \ge 0, \qquad i = 1,2,3 \quad (72)$$

$$0 \le \phi_i^{g\max} \perp \eta_i^{g\max} \ge 0, \qquad i = 1,2,3 \quad (73)$$

$$0 \le \phi_i^{d\min} \perp \eta_i^{d\min} \ge 0, \qquad i = 1,2,3 \quad (74)$$

$$0 \le \phi_i^{d\max} \perp \eta_i^{d\max} \ge 0, \qquad i = 1,2,3 \quad (75)$$

$$0 \le \rho_i^{\min} \perp \eta_i^{\min} \ge 0, \qquad i = 1,2,3 \quad (76)$$

$$0 \le \rho_i^{\max} \perp \eta_i^{\max} \ge 0, \qquad i = 1,2,3 \quad (77)$$

In addition to the optimization variables used in the main problem (40)-(52), the MPEC problem also includes the binary variables needed to linearize complementarity constraints, which is done by Big-M technique [28] as described mathematically in Eqs. (78)-(80), in which a non-linear complementarity condition (78) is divided into two linear constraints (79)-(80) by Big-M method. Note that in the Big-M method, it is critical to choose the right values for the *M* constant, so that its value should be sufficiently big to ensure that the resultant linearized constraints can be satisfied. However, arithmetic challenges or suboptimal solutions may arise for *M* numbers that are too big. Sensitivity analysis and familiarity with the specifics of the situation should inform the selection of *M* values.

$$0 \le x \perp y \ge 0 \quad (78)$$

$$0 \le x \le M.u \quad (79)$$

$$0 \le y \le M.(1-u) \quad (80)$$

When dealing with non-linear components in a lower-level objective function, however, the Strong Duality theorem [30] may be used to achieve this goal. In the proposed bi-level optimization, a connection between the primal and dual issues is established using the Strong Duality theorem. We may turn the bi-level issue into a single-level one with just linear components in the goal function by taking use of this duality [32]. Optimal solutions for the primal and dual issues are equivalent under specific circumstances, as shown by the

Strong Duality theorem. Using this theorem, the dual variables of the non-linear components in the objective function will be substituted into the Lagrangian function, as shown in Eqs. (81)-(88).

$$\hat{c}_1^{g} + \sum_{i=2}^{3} c_i^{g} g_i - \sum_{i=1}^{3} c_i^{d} d_i = -\sum_{i=1}^{3} g_i^{\max} \phi_i^{g\max} - \sum_{i=1}^{3} d_i^{\max} \phi_i^{d\max} - \sum_{i=1}^{3} f_i^{\max} \rho_i^{\max} - \sum_{i=1}^{3} f_i^{\max} \rho_i^{\max} .(\delta) \quad (81)$$

$$\hat{c}_1^{g} = \alpha_1 + \phi_1^{g\min} - \phi_1^{g\max} \quad (82)$$

$$\hat{c}_1^{g} g_1 = \alpha_1 g_1 + \phi_1^{g\min} g_1 - \phi_1^{g\max} g_1 \quad (83)$$

$$\phi_1^{g\min} g_1 = 0 \quad (84)$$

$$\phi_1^{g\max} g_1 = \phi_1^{g\max} g_1^{\max} \quad (85)$$

$$\hat{c}_1^{g} g_1 = \alpha_1 g_1 - \phi_1^{g\max} g_1^{\max} \quad (86)$$

$$\hat{c}_1^{g} g_1 = -\sum_{i=2}^{3} c_i^{g} g_i + \sum_{i=i}^{3} c_i^{d} d_i - \sum_{i=1}^{3} g_i^{\max} \phi_i^{g\max} - \sum_{i=1}^{3} d_i^{\max} \phi_i^{d\max} - \sum_{i=1}^{3} f_i^{\max} \rho_i^{d\max} - \sum_{i=1}^{3} f_i^{\max} \rho_i^{\min} \quad (87)$$

$$\alpha_1 g_1 = -\sum_{i=2}^{3} c_i^{g} g_i + \sum_{i=i}^{3} c_i^{d} d_i - \sum_{i=2}^{3} g_i^{\max} \phi_i^{g\max} - \sum_{i=1}^{3} d_i^{\max} \phi_i^{d\max} - \sum_{i=1}^{3} f_i^{\max} \rho_i^{\max} - \sum_{i=1}^{3} f_i^{\max} \rho_i^{\min} \quad (88)$$

Electricity supply and demand in competitive power markets may vary from one area to another owing to variables including transmission limitations, grid losses, and differences in load profiles. Since supply and demand vary by location, Locational Marginal Prices (LMP) are often employed to represent these variations and provide economic signals to market players. In this research, we applied the LMP idea to the participation strategy, taking into account the transmission circumstances and market strength of SEH. It considers several variables, such as generation costs ($LMP_{Energy}^{b,s}$), transmission congestion ($LMP_{Congestion}^{b,s}$), and power losses ($LMP_{Loss}^{b,s}$), as indicated in Eqs. (89)–(94). In order to optimize its own profit, the SEH operator might react to LMP signals by changing its production or consumption offers.

$$LMP_{energy}^{b,s} = \lambda \quad (89)$$

$$LMP_{Loss}^{b,s} = \frac{\partial P_{Loss}}{\partial P_{net}} \lambda \quad (90)$$

$$LMP_{Congestion}^{b,s} = \sum_{l=1}^{N_l} \mu_L \frac{\partial P_L}{\partial P_{net}} \quad (91)$$

$$LMP_{total}^{b,s} = LMP_{Energy}^{b,s} + LMP_{Loss}^{b,s} + LMP_{Congestion}^{b,s} \tag{92}$$

$$LMP_{total}^{b,s} = \lambda + \lambda \frac{\partial P_{Loss}}{\partial P_{net}} + \sum_{l=1}^{N_L} \mu_L \frac{\partial P_L}{\partial P_{net}} \tag{93}$$

$$LMP_{total}^{b,s} = \lambda + \lambda_{L,b} + \lambda_{C,b} \tag{94}$$

4. Case study and Results

4.1 Data and study cases

In this part, we proceed with the implementation of the suggested model on a 3-bus test system in order to assess the effectiveness and comprehensiveness of the proposed local market paradigm. The test setup shown in Fig. 4 comprises an SEH situated at bus 1, together with two GENCOs positioned at buses 2 and 3. Each of these three buses is equipped with individual retailer that serve as the primary intermediaries between power producers and clients on their own buses. These retailers provide power and electricity-related services to both residential and commercial customers. The SEH is situated inside bus one and encompasses a gas boiler unit, CHP, P2G equipment, PV panel, WT, and energy storage for electricity and natural gas. This configuration enables the SEH to meet its requirements for both electrical power and heating, while also participating in the day-ahead natural gas and local electricity market. The problem is first presented as a bi-level problem and afterward transformed into MILP by executing MPEC. Numerical simulations are conducted inside the GAMS [36] and solved using the CPLEX solver on a personal computer including an Intel Core i7 CPU with 32 Gig of RAM.

Several disadvantages related to the intelligent methods led to the decision of employing the CPLEX solver and nonlinear problem transformation to solve the problem as a linear program. Intelligent methods, like those relying on genetic algorithms or particle swarm optimization, generally do not guarantee convergence to the optimum; they are computationally time-consuming and require thousands of iterations, demand the proper choice of parameters controlling the search process. Suffering from the problems of convergence, getting stuck in local optima, and involving complex implementation because of the custom solution strategies and different schemes of encoding. They present scalability issues, and also with the size of a problem, the computational effort involved by Intelligent algorithms increases. Also, the solutions provided by these algorithms may vary significantly, suffering from initial condition sensitivity or even inherent randomness and thus often produce inconsistent results. The very robust, efficient, and reliable process is the CPLEX solver's result when this is transformed for the application of linear problems and applied with strong duality theory, it guarantees global optimality and has reproducible results in consistent behavior. Therefore, the approach of linearization, along with the CPLEX solver, was more suitable for our optimization problem because, in this way, it presented a much more practical solution to our problem.

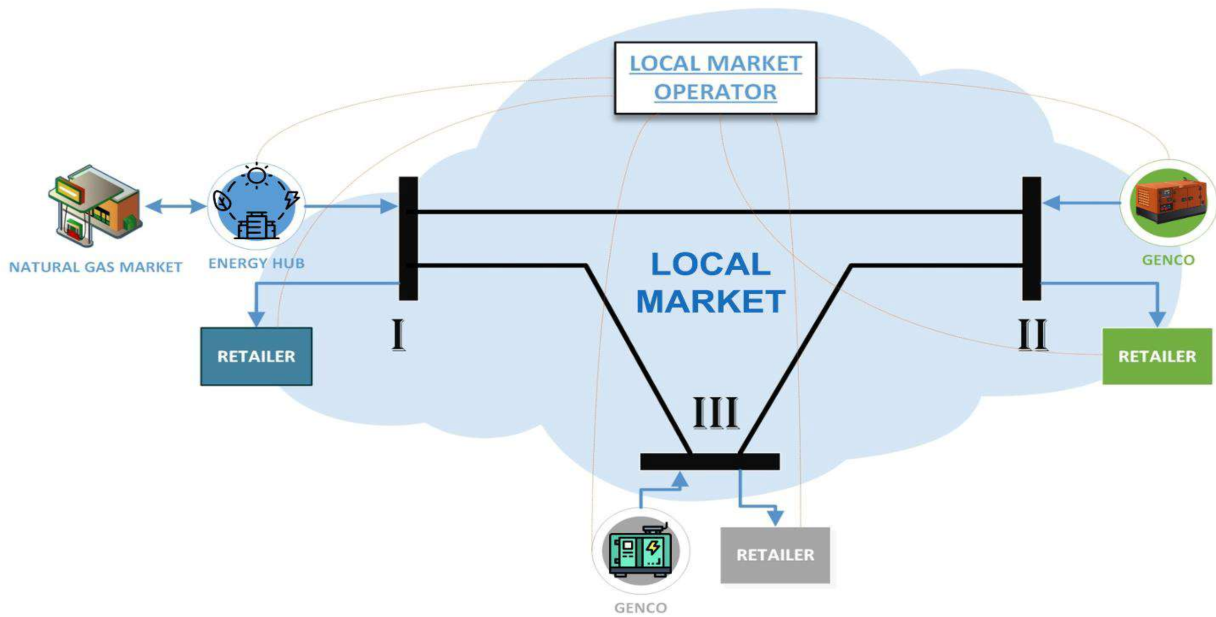

Fig. 4. Proposed 3-bus power grid structure for local market implementation.

The efficiencies and capacities of installed resources within the SEH including CHP, PV, WT, electricity and natural gas storage systems are given in Table 2 [24], [30], [33].

Table 2. internal equipment efficiencies and capacities

Equipment	Efficiency (%)		Max capacity
CHP	Thermal=0.3	Electrical=0.4	450
PV	0.85		350
WT	0.9		350
Electricity storage	Charge=0.9	Discharge=0.9	700
Natural gas storage	Charge=0.9	Discharge=0.9	1100
Transformer	0.9		1100
P2G facility	0.75		250

This research considers the assumption that the projected data is readily accessible. The projected data includes both electrical and thermal demands, as well as day-ahead market pricing for natural gas. The figures shown in Fig. 5 illustrate the electrical and thermal demands of an SEH, whereas Fig. 6 displays the day-ahead pricing of natural gas. It is important to acknowledge that the SEH operates as a very minor player within the natural gas market, and thus lacks the ability to significantly impact on gas market-clearing prices. However, in the context of the electricity LEM, where the scale is smaller, and the number of players is limited, clearing prices are susceptible to deviations resulting from the tactics used by individual participants. In other words, the SEH operates as a price-taker inside the natural gas market, meaning it must accept the prevailing prices established by the market. However, within the local electricity market, the SEH functions as a price maker, exerting influence on the pricing of electricity.

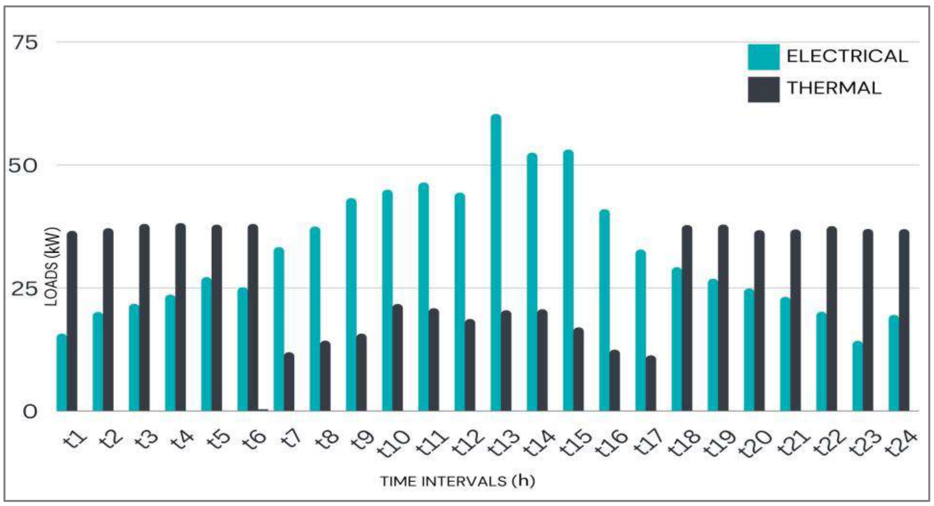

Fig. 5. Forecasted electrical and thermal demands of SEH during operating horizon.

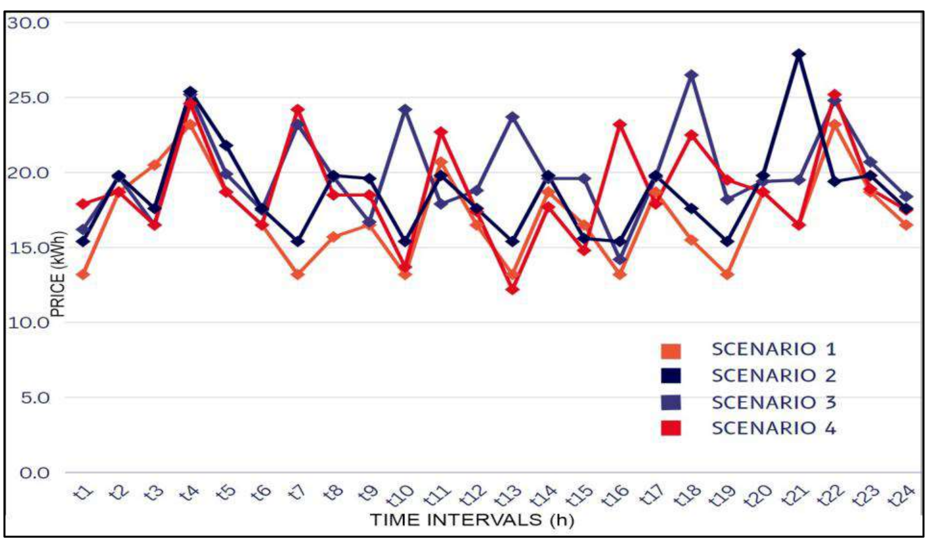

Fig. 6. Predicted scenarios for day ahead energy prices.

In recognizing the inherent randomness and volatility of renewable energy outputs, our methodology employs a probabilistic approach through scenario reduction techniques to ensure robust modeling of uncertainties. The present research used the Monte Carlo simulation to construct a comprehensive ensemble of 1000 potential scenarios for electricity, RES production, and natural gas pricing. For RES outputs, 1000 potential scenarios were generated to capture a comprehensive range of possible renewable energy outputs, encapsulating the inherent randomness and volatility. It is often believed that all possibilities exhibit equal probabilities. Stochastic prices are represented by a normal probability density function with parameters of a mean value of 1600 and a standard deviation of 3000, expressed as a percentage of the mean. The SCENRED subprogram, which has been included in the GAMS software, is used to efficiently reduce the overall number of scenarios to 4. This approach maintains computational feasibility while preserving the integrity of the uncertainty modeling. The confidence level for CVaR is set at 90%, while the risk aversion value is set at 0.2. The anticipated expense connected with SEH scheduling experiences a proportional increase when the risk-aversion parameter in the context of the decision-making problem pertaining to SEH is heightened, and concurrently, there is a decrease seen in the CVaR. It is essential to acknowledge that a relationship exists between lower levels of risk and higher anticipated costs, while higher levels of risk are associated with lower projected costs. The research concluded that it is crucial for SEH management to estimate the value of the risk-aversion parameter in order to assess the level of risk aversion accurately.

Furthermore, while real-time dynamic adjustments are crucial in practical applications, the primary aim of our study is to establish a strategic framework capable of adaptation in real-time systems. The chosen scenarios include extreme and moderate cases, providing a robust foundation for future real-time strategy adjustments. Our bi-level optimization framework and MPEC formulation inherently support the integration of real-time data updates, thus enabling dynamic adjustments. This ensures that our model not only simulates current market conditions accurately but also offers the flexibility needed for practical real-time applications. The use of CVaR further demonstrates our model's robustness in managing financial risks associated with renewable energy output fluctuations. This probabilistic and stochastic approach aligns with established methodologies in the field, reinforcing the validity and applicability of our findings.

4.2 Sensitivity Analysis for Big-M Value Selection

The Big-M method is employed to linearize the complementarity constraints in our MPEC formulation. The selection of an appropriate value for M is crucial to ensure that the resultant linearized constraints can be satisfied without causing arithmetic challenges or suboptimal solutions. To determine the appropriate value for M, we performed a sensitivity analysis, varying M and observing its impact on the solution feasibility and optimality.

Process of Selecting M:

1. *Initial Range Selection:* We start with an initial range for M based on preliminary estimates and literature review, typically ranging from 1,000 to 10,000.
2. *Incremental Testing:* We incrementally tested values of M within this range, observing the impact on the solution's feasibility and computational performance.
3. *Optimal Value Identification:* By evaluating the solutions obtained at different values of M, we identified the value that provided feasible solutions without significant computational burden or numerical instability.
4. *Final Selection:* The optimal value of M was determined to be 5,000, as it ensured the linearized constraints were satisfied, and the solver performance was optimal without encountering numerical issues.

4.3 Simulation results

This section presents and discusses the findings collected from the aforementioned case study. During the first phase, the SEH strategically organizes its internal components and assesses its surplus and deficit energy requirements. As previously stated, the SEH participates in the natural gas and local electricity market. Hence, the concept of engaging in both the natural gas and local power markets simultaneously as a prosumer is being contemplated.

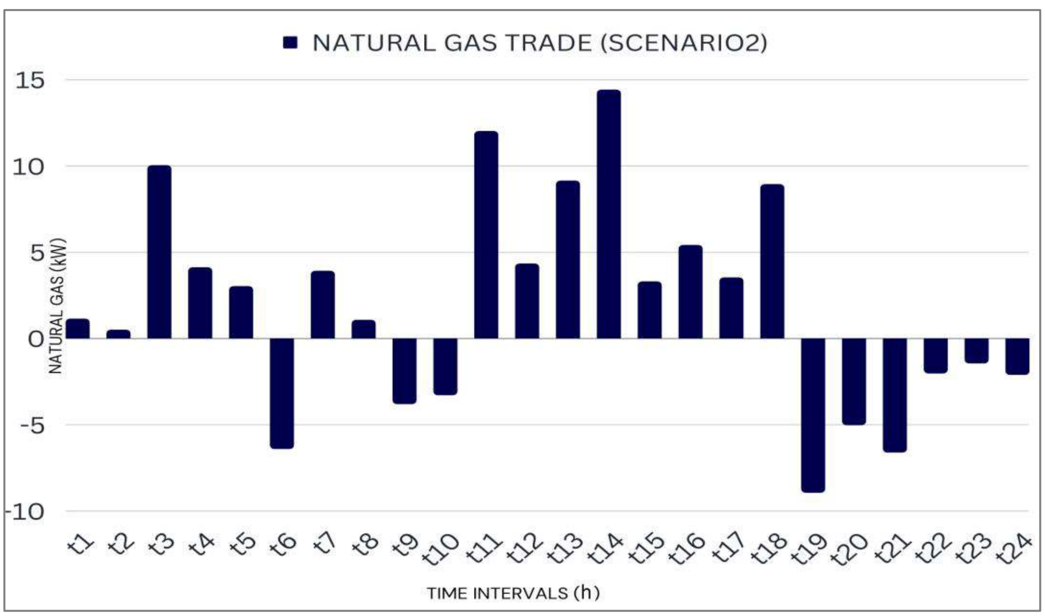

Fig. 7. Natural gas exchanges between SEH and gas market.

The SEH functions as a prosumer within the natural gas market and as a price-setter producer within the local electricity market. Hence, it is capable of using cross-product arbitrage in order to exploit disparities in prices between two distinct marketplaces. To clarify, the SEH engages in the procurement of energy within a certain market, subsequently conducting the processes of conversion or storage and ultimately vending this energy within a distinct market at an elevated price point. In this instance, it is important to take into account the necessary infrastructure inside the system. Fig. 7 illustrates the interchange of natural gas between the SEH and the regional gas market. In order to enhance conciseness and improve the legibility of data, only scenario number 2 (as an expected scenario with high probability) has been presented in this context. In this figure, the negative values represent the acquisition of energy, while positive values indicate the sale of power. It can be deduced that during the colder hours of the night (t_1 to t_5), the price of gas tends to increase as a result of heightened heating requirements from customers. Conversely, the demand for electricity in both the local energy market and SEH is reduced during this time. Consequently, it assumes the role of a producer throughout this time period. It is worth mentioning that during the hours of noon (t_{11} to t_{16}), the SEH engages in the sale of gas to the gas market. It may be posited that in instances when solar panels commence operation and there is a low demand for electricity, the SEH may choose to convert electricity to natural gas via the use of P2G infrastructure, hence maximizing profitability. However, throughout the hours of midday and night, there is a surge in electrical needs, resulting in higher electricity rates. During the specified time period (t_{19} to t_{21}), the SEH engages in the procurement of natural gas in order to meet its own energy requirements as well as cater to the needs of the local market.

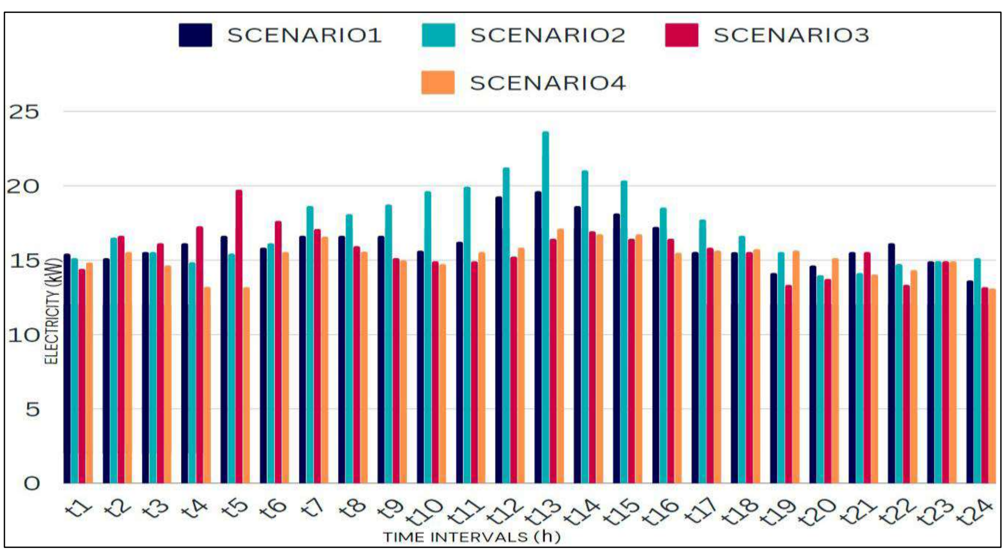

Fig. 8. The daily surplus power of SEH to submit into the local electricity market.

Before clearing the local electricity market, every participant has to prepare its bidding offers. Therefore, SHE, as a prominent participant in this market, must determine the maximum electricity power that can sell to this market. In this manner, after an internal economic dispatch, the manager of the SEH determines the net power to offer to local market. This power is consists of battery discharge, electricity produced by diesel generator, PV output, WT output and CHP. Fig. 8 demonstrates the net power SEH offers in local market in all scenarios. As can be seen, in midday hours, the net energy is higher, and in night hours, it is lower. It is because at noon the internal electricity usage of SEH is low, and the PV output is at its maximum, while at night, the PV output is zero, and internal demands are at maximum. Moreover, the strategic price offering of SEH in the local electricity market for 24 hours has been depicted in Fig. 9 for all scenarios.

The electricity prices shown in Fig. 9 are sourced from the local electricity market's market-clearing procedure. In its role as a price-maker, the SEH calculates its bids strategically using hourly demand and supply forecasts. By balancing the bids and offers provided, the market operator determines the clearing price for each hour, clearing the market. When making operational decisions, the SEH relies on these pricing, which impact its strategies for power generation, storage, and market involvement. To maximize earnings and improve the stability and efficiency of the local electricity market, the SEH uses precise forecasts and strategic bidding.

The market-clearing electricity prices have a big influence on our proposed model. SEH is a price maker because through strategic bids, it can affect the market-clearing price itself. In order to achieve profit maximization objectives, SEH uses accurate predictions and intelligent bidding strategies. The SEH may earn additional income during peak hours by selling excess electricity at higher clearing prices or store it for later use or even convert it into gas using P2G technology when rates are low. However, if the cost of electricity falls, It could decide to store electricity or convert it into gas. On the other hand, in case electricity's price increases drastically they might opt to sell more power into the grid. Thus, this model must be adaptable to changing pricing signals to the needs of reducing costs while increasing profits for SEH.

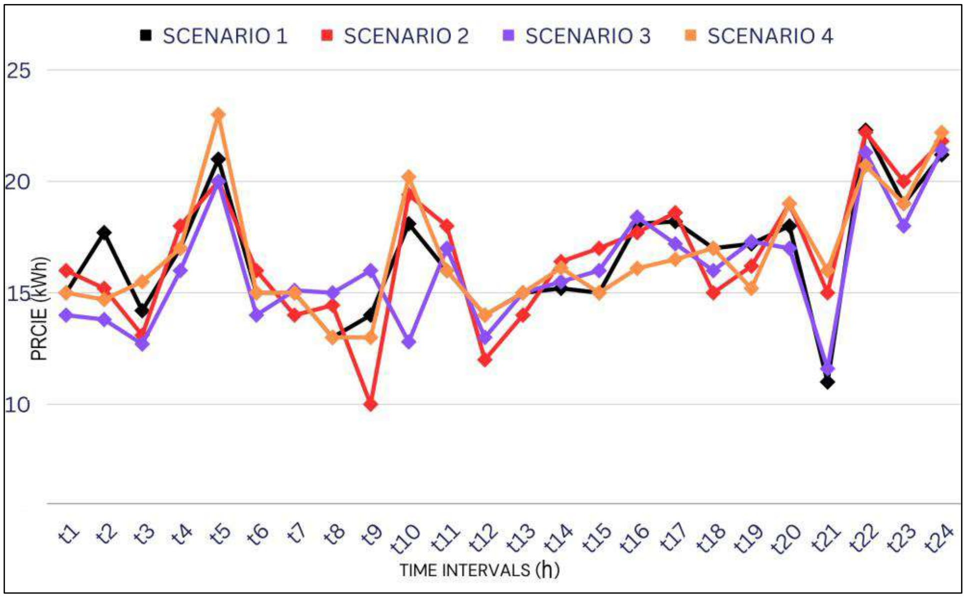

Fig. 9. Strategic price offering of SEH in the LEM for all scenarios.

After local market clearance, the sold electricity power of SEH is determined, which is shown in Fig. 10 and Fig. 11 for scenarios 2 and 4, respectively. As illustrated in these figures, the net power offered by SEH to the local electricity market is always more than the sold power after market clearance. The reason for this problem is the existence of network operation restrictions and uncertainties caused by RES inside the SEH, which leads to a decrease in the sold power of the SEH compared to the available amount. In addition, Fig. 12 and Fig. 13 demonstrate the clearing price of electricity in the local market for scenarios 2 and 4 and also the LMP at each node. As can be seen, the clearing price is precisely equal to LMP in node three because node number 3 is the slack bus, And whatever we move away from the slack bus, the difference between the market clearing price and LMP increases due to the presence of congestion and power losses of lines.

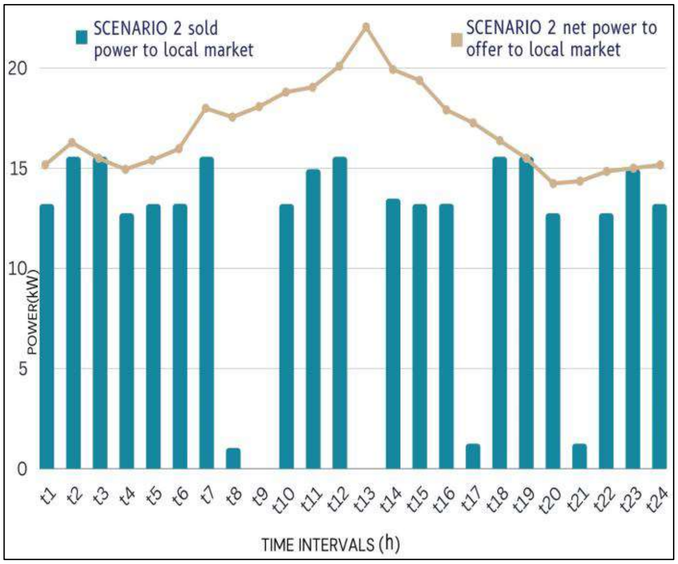

Fig. 10. SEH net electricity power versus cleared power in scenario 2

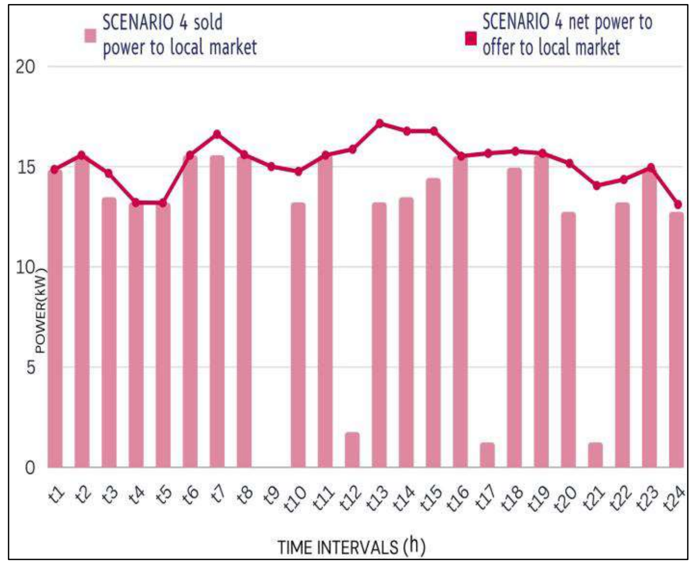

Fig. 11. SEH net electricity power versus cleared power in scenario 4

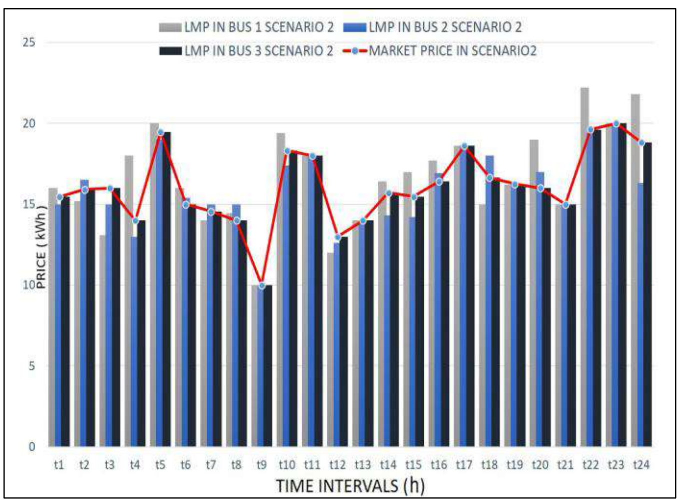

Fig. 12. Local market clearing price and LMPs in scenario 2

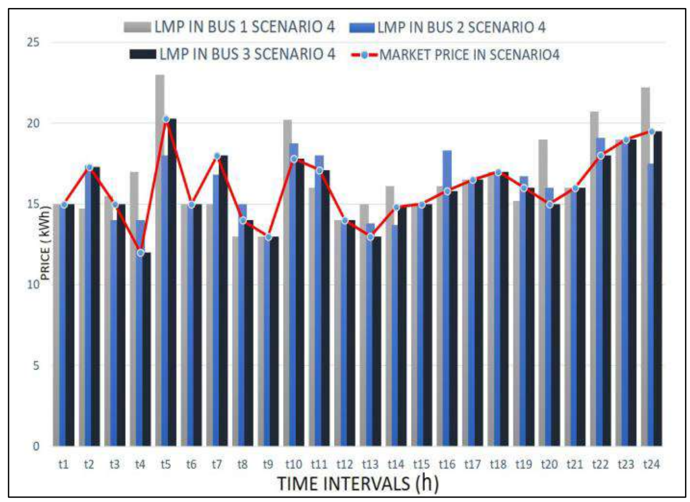

Fig. 13. Local market clearing price and LMPs in scenario 4

Based on Figs 10 to 13, the suggested SEH demonstrates a versatile and strategic approach to market participation in the electricity and gas sectors. By actively participating in both markets, the SEH can exploit the price differentials and leverage the exchange of power to increase its profits. One significant advantage of the SEH's participation in multiple markets is the ability to capitalize on the variations in electricity and gas prices. By strategically managing the timing and magnitude of power exchange between the two markets, the SEH can take advantage of favorable price disparities. For instance, according to Fig. 9, during periods of high electricity prices and low gas prices, the SEH can sell excess electricity to the electricity market and purchase cheaper gas from the gas market.

This dynamic approach allows the SEH to maximize its revenue potential and optimize its overall profitability, as shown in Table 3. Moreover, the implementation of a risk control index (CVaR) highlights the SEH's commitment to managing uncertainty and reducing potential risks. Uncertainties such as market price fluctuations, supply-demand imbalances, and regulatory changes can have a significant impact on the SEH's profitability, as can be seen in Table 4. By utilizing a risk control index, the SEH can assess and quantify potential risks, enabling proactive risk management strategies. These strategies may include hedging mechanisms, diversification of energy sources, and using financial instruments to mitigate the adverse effects of uncertainties. The risk control index acts as a valuable tool for decision-making, allowing the SEH to strike a balance between maximizing profits and minimizing exposure to market volatility.

However, it is essential to note that the success of the SEH's strategy relies on accurate market forecasting, effective decision-making, and the availability of reliable market data. Furthermore, regulatory frameworks and market rules must support the SEH's participation in both electricity and gas markets seamlessly because the presence of SEH will benefit the whole system, as shown in Fig. 14. In conclusion, the results of the SEH's participation in the local electricity and gas markets, combined with the utilization of a risk control index, demonstrate a strategic and dynamic approach to increasing profits while maximizing the social welfare of the system. The SEH's ability to leverage price differences, optimize power exchange, and implement risk mitigation measures positions it favorably in the energy landscape, enabling sustainable financial success.

Table 3. Operational cost, profit and total objective function of SEH.

Items	Amount ($)	Cost/Profit
Operation cost of SEH	4806.456	Cost
Profit of SEH	1072.898	Profit
Total objective function	3733.558	Cost

Table 4. Risk assessment analysis and its impact on profit of SEH.

Scenarios	CVaR ($)	Objective function ($)
Scenario 1	755.274	3817.36
Scenario 2	791.000	3749.51
Scenario 3	-610.546	3584.04
Scenario 4	-188.161	3697.25

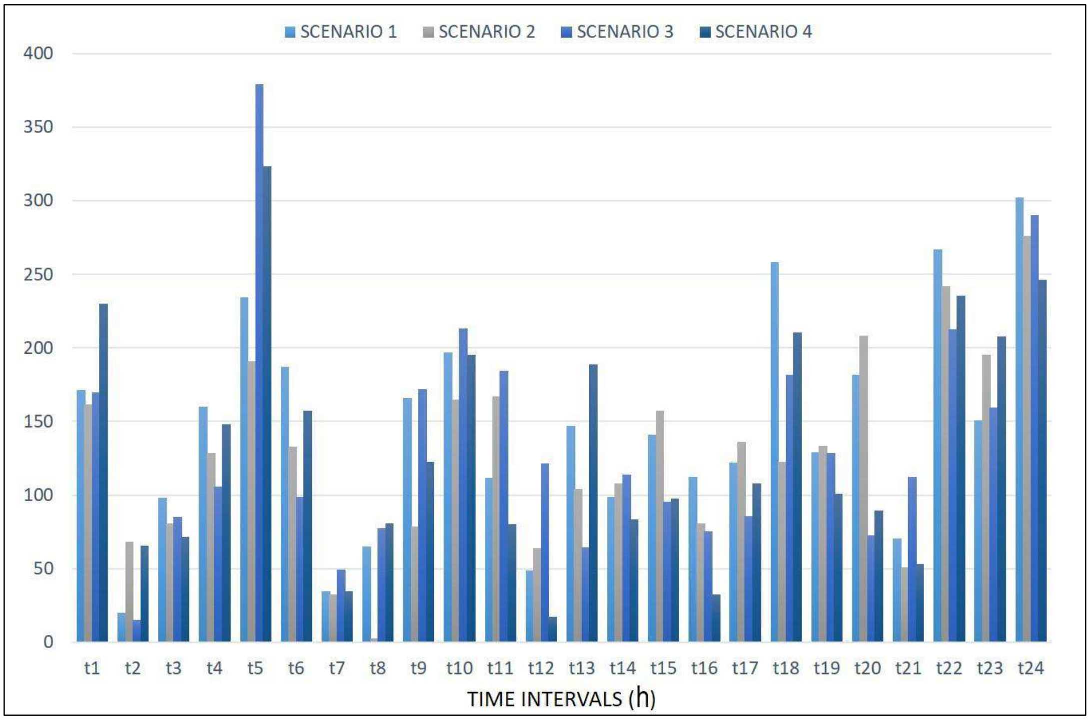

Fig. 14. The amount of social welfare of whole system at all scenarios.

5. Conclusion

This study presents a thorough framework for the modeling and computational analysis of a profit-motivated SEH that actively participates in regional electricity and gas markets as a price-setting agent. With market clearing concerns in mind, the formulation of the strategic bidding problem for the SEH is provided as a stochastic risk-constrained bi-level model. The MPEC method is then used to convert this model into a MILP structure. Using optimality condition transformation and strong duality theory, we have built a MILP approximation model to methodically approach this problem. According to empirical case studies, the profitability of an SEH is mostly influenced by fluctuations in electricity and natural gas prices and the efficiency of P2G and storage systems within a certain range. If gas fuel or electricity costs were to skyrocket, it would still be viable to maintain a modest profit by switching to other energy sources. In addition, the results confirmed that the SEH's profitability and cost recovery were both improved by the adoption of P2G technology and the execution of reciprocal product arbitrage in the regional electricity and gas markets. The results of this SEH's approach to market participation and risk control are promising. By optimizing the utilization of its assets, actively participating in electricity and gas markets, and leveraging price differences, the SEH can enhance its financial performance. The efficient power exchange between the two markets enables the SEH to capitalize on favorable market conditions and achieve revenue gains. Additionally, the integration of a risk control index ensures a proactive approach to risk management, reducing the potential negative impacts of uncertainties on the SEH's profitability. On the flip side, the proposed method has the potential to provide useful insights in a wide variety of contexts:

- ✓ SEH owners: To determine the most profitable bidding methods in the electricity and gas markets, the suggested approach may be used by SEH operators.
- ✓ Private investors: The model may be used by investors to determine whether or not a certain system design, such as P2G-integrated SEH, is financially viable.
- ✓ Market regulators: The model can be used by government agencies to assess the competitive strength of SEH and the equilibrium state of integrated energy systems, which in turn can inform crucial market parameters like the maximum offering price and guarantee the continued integrity of the market.

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