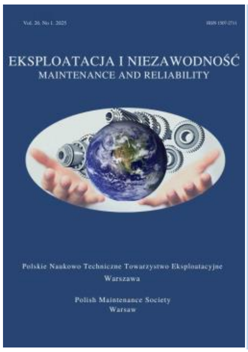

Eksploatacja i Niezawodnosc – Maintenance and Reliability

Volume 27 (2025), Issue 1

journal homepage: http://www.ein.org.pl

Article citation info:
Yu J, Hao S, Han J, Optimizing Virtual Energy Hub's for Enhanced Market Participation and Operational Resilience, Eksploatacja i Niezawodnosc – Maintenance and Reliability 2025: 27(1) http://doi.org/10.17531/ein/193171

Indexed by: Web of Science Group

Optimizing Virtual Energy Hub's for Enhanced Market Participation and Operational Resilience

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Highlights

- Innovative Modeling: Optimal market engagement with robust stochastic optimization.
- Interactive EMM: Free energy trading platform for VEHs, ensuring dynamic planning.
- Market-Based DRPs: Integrating direct load control and demand response applications.
- Diverse Supply Integration: CHP, PV, and varied storage options for risk mitigation.
- Dynamic Optimization: Focus on economic viability and sustainability in VEH operation.

Abstract

In this study, the IEEE 14-bus test system is employed to evaluate the proposed energy management strategy for Virtual Energy Hubs (VEHs). The results demonstrate significant cost reductions with the integration of the interactive Energy Market Management (EMM) system. In the baseline scenario, operating costs were reduced by 10.01% when the EMM was introduced, and further reduced by 13.11% with the addition of direct load control programs. The most significant cost reduction of 56.39% was achieved in scenarios incorporating both EMM and ancillary service demand response programs. Additionally, the use of direct load control programs alone resulted in a 6.02% reduction in operating costs, while ancillary service demand response programs contributed an additional 2.29% cost savings. These findings underscore the substantial potential for cost reduction and efficiency improvements through advanced energy management strategies.

Keywords

industrial energy hubs, energy management, market participation strategy, stochastic optimization, ancillary services

1. Introduction

Virtual Energy Hubs (VEHs) are emerging as pivotal components in the modern energy market, addressing several critical challenges and leveraging recent industry trends. One of the primary roles of VEHs is the integration of renewable energy sources, such as solar and wind, into the energy grid [1]. As the global energy market transitions towards sustainable solutions to combat climate change, VEHs manage the variability and intermittency of renewable energy generation, ensuring a stable and reliable energy supply. This capability is essential as renewable energy adoption continues to grow. Additionally, VEHs enhance grid flexibility and resilience, which are significant concerns for the modern energy grid. By providing ancillary services such as frequency regulation, voltage support, and demand response, VEHs contribute to grid stability. This capability enables the grid to handle fluctuations and disruptions more effectively, improving overall system reliability [2]. The importance of these services is magnified in light of increasing grid complexity and the integration of diverse energy sources. The role of VEHs in enabling advanced demand response programs and improving energy efficiency is also noteworthy. VEHs facilitate dynamic adjustments in energy consumption based on real-time market signals and demand

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conditions, reducing peak demand, lowering energy costs, and enhancing energy efficiency. This aligns with the trend towards smarter, more responsive energy systems, which are crucial for meeting future energy demands sustainably. The ongoing decentralization and digitalization of the energy market further highlight the significance of VEHs. By leveraging digital technologies such as smart meters, IoT devices, and advanced analytics, VEHs optimize energy management. This decentralization empowers consumers, prosumers, and local energy communities, fostering a more participatory and resilient energy ecosystem [3]. The ability of VEHs to operate efficiently within this decentralized framework is a testament to their adaptability and importance. Economic benefits and enhanced market participation are additional advantages provided by VEHs. They optimize energy procurement and sales across various markets, including Day-Ahead Markets (DAM) and Real-Time Markets (RTM), enabling VEHs to capitalize on price arbitrage opportunities, reduce operational costs, and generate additional revenue streams through demand response and ancillary services. This economic optimization is critical for the financial sustainability of energy systems in the evolving market landscape. Moreover, governments and regulatory bodies worldwide increasingly recognize the importance of VEHs in achieving energy transition goals. Supportive policies and incentives are being implemented to promote the adoption and integration of VEHs into the energy market. This regulatory support underscores the critical role of VEHs in the future energy landscape, providing a conducive environment for their growth and development [4].

The VEH framework adeptly oversees multiple IEHs, each featuring renewable energy sources (RES), energy-converting infrastructure, and energy storage systems (ESSs). These VEHs are intricately designed to efficiently and reliably fulfill energy requirements, offering ancillary services across diverse electricity markets through a unified operational strategy. Empirical findings suggest that VEHs hold the potential to trim overall operating costs for IEHs and commercial customers while reducing impacts of variable parameters, all without compromising the operational resilience of the power grid. Consequently, there is a pressing need to craft a more intricate planning framework that can extract the best possible involvement approach of a VEH in energy markets. This framework should empower the VEH operator to deliver advanced ancillary services while meticulously addressing technical constraints and uncertainties associated with various parameters.

The existing body of literature provides many insights on optimizing the exploitation strategies of IEHs for their seamless integration into diverse energy markets. Various mathematical optimization techniques have been applied to achieve a wide range of objectives, including distributed subservices and operational constraints.

1. 1. Literature Review

Jadidbonab et al. [5] addressed challenges in multicarrier energy systems, focusing on energy hub interactions in diverse markets. They introduced the VEH, which combines energy hub architecture with a self-scheduling approach to maximize revenue in electrical and thermal markets. The VEH achieved higher benefits and optimal facility operation by integrating these markets. To handle uncertainties in renewable resources, a non-probabilistic information gap method was used, allowing for risk-averse or risk-seeker strategies. A compressed air energy storage unit mitigated wind power volatility. The model was validated with a test case, proving its effectiveness. Li et al. [6] explored the integration of electricity and heat distribution networks to enhance system flexibility and energy efficiency. They emphasized the energy hub (EH) in energy production, conversion, and storage within these integrated systems. Li et al. proposed a mathematical program with equilibrium constraints (MPEC) model to study the strategic behaviors of a profit-driven EH in deregulated electricity and heating markets. The EH submitted bids to both markets, which then determined energy contracts. Network constraints were represented through optimal power and thermal flow problems. The MPEC model was approximated using a mixed-integer linear program with integer disjunctions and binary expansion techniques. Case studies validated the effectiveness of this approach. Marsyukov et al. [7] reviewed the principles of wireless power transfer (WPT), focusing on the inductive WPT technique. They thoroughly studied the concept behind WPT and conducted simulations to understand its operational mechanism. Significant attention was given to WPT using overhead high voltage power lines (HVPL). Marsyukov et al. explained that the studied concept involved extracting energy from HVPL using an energy harvesting device and transferring it to a consuming device via magnetically coupled transmitting and receiving coils. Their simulations demonstrated that energy transfer efficiency and transmission stability depended on the frequency of power transfer. While energy transfer efficiency increased with frequency, transmission stability decreased. Another simulation investigated the relationship between distance and efficiency. The results showed that as the distance increased, the voltage of the overhead line declined drastically. Zhang et al. [8]studied the distributed energy network (DEN), which connected distributed energy systems in multiple energy stations through energy interchanges, enhancing energy sharing and balance. They proposed a collaborative optimization model based on the energy hub concept to improve DEN's energy, economic, and environmental performances. Their case study verified the model's effectiveness, showing that collaborative optimization increased the primary energy saving ratio by 5.3%, annual total cost saving rate by 5.1%, and carbon dioxide emission reduction by 1.1%. It also reduced gas turbine power output by 7.6%, increasing efficiency, and decreased excess heat and electricity by 16.5% and 1.1%, respectively. This demonstrated the benefits of collaborative optimization for DEN design and energy management. Kuspan et al. [9] studied the impact of Electric Vehicles (EVs) on the power system network, emphasizing their potential to replace fossil-fuel-based cars due to lower pollution. However, they noted that high EV penetration could significantly increase power demand and affect the performance of distribution components, particularly transformers. The purpose of their research was to analyze the influence of EV charging on the thermal performance of oil-filled distribution transformers. They developed a transformer thermal mathematical model and introduced different EV penetration scenarios for simulation. Each scenario demonstrated how various levels of EV connection affected the transformer's lifetime. The simulation results were crucial for assessing the ability of currently exploited distribution transformers to support EVs. The evaluation was based on three criteria: load limit, ageing rate, and transformer life loss. Mohammadi et al. [10] studied electricity load forecasting for optimal power system operation, highlighting the complexity of short-term load forecasting (STLF) due to the volatile nature of load time series, especially at the building level. To address this, they proposed a new prediction model using a feature selection algorithm and a hybrid forecast engine combining an enhanced empirical mode decomposition (sliding window EMD) with an intelligent algorithm. The forecast engine was further optimized with shark smell optimization for increased accuracy. They validated the model's effectiveness through a real-world engineering test case, demonstrating superior performance compared to other prediction models. Javadi et al. [11] presented a robust chance-constrained optimization framework for managing an EH with electrical, heating, and cooling demands, and renewable power generation. This strategy aimed to optimize decision-making for EH operators and energy providers. They used an electrical energy storage device to handle operational fluctuations due to uncertainties. A robust chance-constrained close-to-real-time model was adopted to manage hourly demand and renewable power generation uncertainties. The EH followed a centralized framework, with operators responsible for optimal day-ahead scheduling. They analyzed energy flows with different carriers and performed a numerical stability test on time step size selection to ensure time resolution independence. Oskouei et al. [12] studied the impact of multi-energy consumers in the industrial sector, emphasizing their role in exchanging electricity, heat, and natural gas. They introduced a multi-energy retailer to meet both flexible and non-flexible energy demands with high reliability. Equipped with cogeneration facilities and power-to-x storage technologies, the retailer exploited arbitrage opportunities in various energy markets. The model aimed to maximize profit and enhance consumer welfare. They used a hybrid robust-stochastic approach to address uncertainties in electricity prices and consumer demands, ensuring optimal day-ahead scheduling. They estimated the retailer's profit considering conversion facilities, demand response programs, and market uncertainties based on actual data. Sobhani et al. [13] studied energy hubs as key components of future energy networks, highlighting their role in enhancing grid efficiency and reliability. They modeled the interaction between energy hubs as a congestion game, where operators aimed to maximize their payoff in a dynamic energy pricing market. They proposed a distributed algorithm that ensured a Nash equilibrium and developed two signaling types (price-based and load-based). Simulations showed that both setups reduced the peak-to-average ratio in electricity and natural gas networks. Their analysis revealed that each setup had advantages in terms of generation costs, convergence rate, price level, and stability, allowing energy providers and consumers to choose based on their needs. Zhao et al. [14] explored electricity-gas demand response (EGDR) programs within EH systems, which involve electric, heating, and cooling loads. They addressed the lack of systematic approaches to obtaining the electricity-shifting curve (ESC) by proposing a quantitative model based on aggregated utility curves of multi-energy demands. They adopted an ESC based on consumer behavior, aggregated utility curves into a single curve, and combined it with consumer choice theory. They analyzed factors affecting the shifting curves and provided guidelines for improving the ESC through case studies. They found that multi-energy users with a higher heating-to-electricity ratio (HER) performed better in achieving a broader shifting area, while those with a lower HER had a larger shifting amount within the common price ratio range. Eladl et al. [15]addressed increasing environmental concerns, fossil fuel scarcity, and uncontrolled demand growth, which led to the upgrading and restructuring of existing energy systems. They emphasized that sustainable multi-energy systems (MESs) would dominate future energy production and highlighted the need for integrated management systems to plan and control these MESs for optimal operation. They reviewed the concept of EHs as a promising solution for optimal management in sustainable MESs, noting their crucial role in advancing sustainable energy models. Eladk et al. provided a comprehensive overview of EH concepts, applications, and the benefits of integrating different energy sources. They also discussed the impact of renewable energy resources, MESs, demand-side management, and energy storage systems. Mansouri et al. [16] examined the integration of electricity and natural gas, highlighting its efficiency and economic benefits. They developed a two-stage stochastic model for energy hub planning and operation, addressing uncertainties from load forecasts and solar PV output. Using Monte-Carlo simulation and a backward scenario reduction technique, they managed these uncertainties. They also explored the effectiveness of demand response programs (DRPs). In the first stage, they optimized energy hub design with particle swarm optimization (PSO), considering continuous asset capacities. The second stage focused on optimal energy hub operation, formulated as mixed-integer non-linear programming (MINLP). Their simulation with a typical energy hub verified the model's effectiveness and efficiency. Wang et al. [17] studied the impact of energy market reforms and the resulting competition among emerging market organizations, addressing environmental pollution and rising energy demands. They proposed a collaborative optimization strategy for a low-carbon economy in the integrated energy system (IES) using a carbon trading mechanism and Stackelberg game theory. They introduced a multistakeholder low-carbon transaction mechanism, considering energy supply, demand, and storage. They proposed a reward and punishment carbon trading mechanism and an integrated demand response strategy based on price information and carbon compensation. They developed mathematical models for each stakeholder and solved them with a two-stage optimization algorithm. Their simulations showed that all stakeholders benefited from the proposed mechanism, achieving economical and environmentally friendly optimal scheduling of the IES. Nezhad et al. [18] presented a model for self-scheduling using a home energy management system (HEMS) with solar photovoltaic (PV) panels and an air conditioner (AC) with an inverter. The model adopted a time-of-use (TOU) tariff to minimize the daily electricity bill. They formulated the scheduling of home appliances as a mixed-integer linear programming (MILP) problem, incorporating a PV system and electrical energy storage (EES) to handle uncertain solar power and optimize load serving during peak hours. The indoor temperature was maintained within a predefined margin based on an indoor-outdoor temperature model. They demonstrated that the AC significantly contributed to the daily bill during peak hours. Shams et al. [19] explored the challenges of managing multiple energy carrier microgrids due to increasing energy demand and the volatile nature of renewable resources. They developed a min-max-min robust framework for the short-term operation of microgrids with natural gas networks, addressing uncertainties in wind generation and electrical/thermal loads. They solved the linearized model using the column-and-constraint generation (C&CG) procedure, decomposing it into a master problem (minimizing unit commitment cost) and a sub-problem (determining dispatch cost under worst-case uncertainties). Polyhedral uncertainty sets with a budget parameter were used to balance operation cost and robustness. Their 21-node microgrid simulations showed that the framework improved system robustness against uncertainties. They also converted the sub-problem's dual variables into primary variables to evaluate unit commitment and energy dispatch results.

1. 2. Innovation

In the realm of optimization of VEHs, it is evident that developing a robust operational framework for VEHs to effectively participate in diverse energy markets is an ongoing challenge. Significantly, there is a lack of widely accepted and scalable solutions to tackle these intricate large-scale issues. In light of these existing limitations, the main goals of presented strategy are to minimize operational costs of VEH, comprising both IEHs and various industrial energy consumers, in order to mitigate operational risks and navigate challenges arising from uncertainties. Optimizing operating costs of VEHs depends on developing a detailed EM strategy for each IEH. In addition, it relies on the skillful management of energy consumption among industrial consumers, which is facilitated through the deployment of advanced ancillary services. This study will show several contributions in this field, which are briefly listed below:

- **Innovative modeling approach:** The paper introduces an optimal market engagement strategy designed to ascertain optimal functioning of a VEH encompassing IEHs and various energy consumers. This strategy adeptly considers the operational constraints linked to energy trading across diverse markets, including DAM, R-TM, local electricity market, and NGM. A central aspect of this model involves addressing the uncertainties caused by factors such as pool market, energy demand and RES through a two-stage robust stochastic optimization approach.
- **Interactive Energy Management Mechanism:** An innovative sub-service called Interactive EMM is introduced. This mechanism facilitates the creation of a free energy trading platform exclusively for VEHs. This mechanism enables virtual energy operators to set energy dispatch planning in a general way for all energy hubs within the overall framework of the local electricity market.
- **Market-based demand response programs:** This strategy considers the integration of relevant market-based DRPs by separating itself from previous studies. In particular, it incorporates direct load control and demand response applications as ancillary services, which are strategically coordinated with the activity plans of industrial consumers in day-ahead and R-TMs. This approach injects a sense of practicality into the planning problem, ensuring that the execution of the DRP does not compromise the well-being of industrial consumers.
- **Diverse supply possibilities:** In addition to incorporating CHP units and photovoltaic systems, this strategy leverages the capabilities of various storage options, such as compressed air energy storage and P2H storage. These facilities are seamlessly integrated into the IEH framework, fostering coordinated communication among energy supply sources. This comprehensive approach not only mitigates technical and economic risks but also unlocks latent economic opportunities across diverse energy markets.

Basically, this innovative strategy not only seeks to dynamically optimize the operation of the VEH, but also provides a comprehensive framework to ensure the economic viability and sustainability of industrial energy systems. Through unique modeling techniques, pioneering ancillary services, and a nuanced approach to market-based DRPs, this strategy provides a forward-looking vision for the integration of IEHs into the evolving energy landscape.

1. 3. Paper Organization

In the rest of the article, the following topics will be discussed in separate sections. Following the introduction, the second half of the document focuses on modeling, where the suggested technique is thoroughly examined. This part comprises of two sub-sections. The first sub-section explores the constraints of VEH, while the second sub-section delves into the restrictions of IEHs. The final section analyzes the suggested two-step method. The fourth section of the report focuses on the analysis and investigation of the exchange energy management plan. The fifth section of the document contains numerical findings and a sensitivity analysis. In the sixth part, the ultimate conclusion is provided along with recommendations for future developments to sustain this trajectory.

2. Modeling

The proposed method for implementing the VEH system in an industrial complex is shown visually in Fig. 1. In this context, we investigate a VEH configuration that includes several IEHs. These IEHs, along with various industrial consumers, with the main purpose of operating a VEH, efficiently meet the electrical and thermal energy needs of consumers, while minimizing operating costs and maximizing compatibility. delivered, they work.

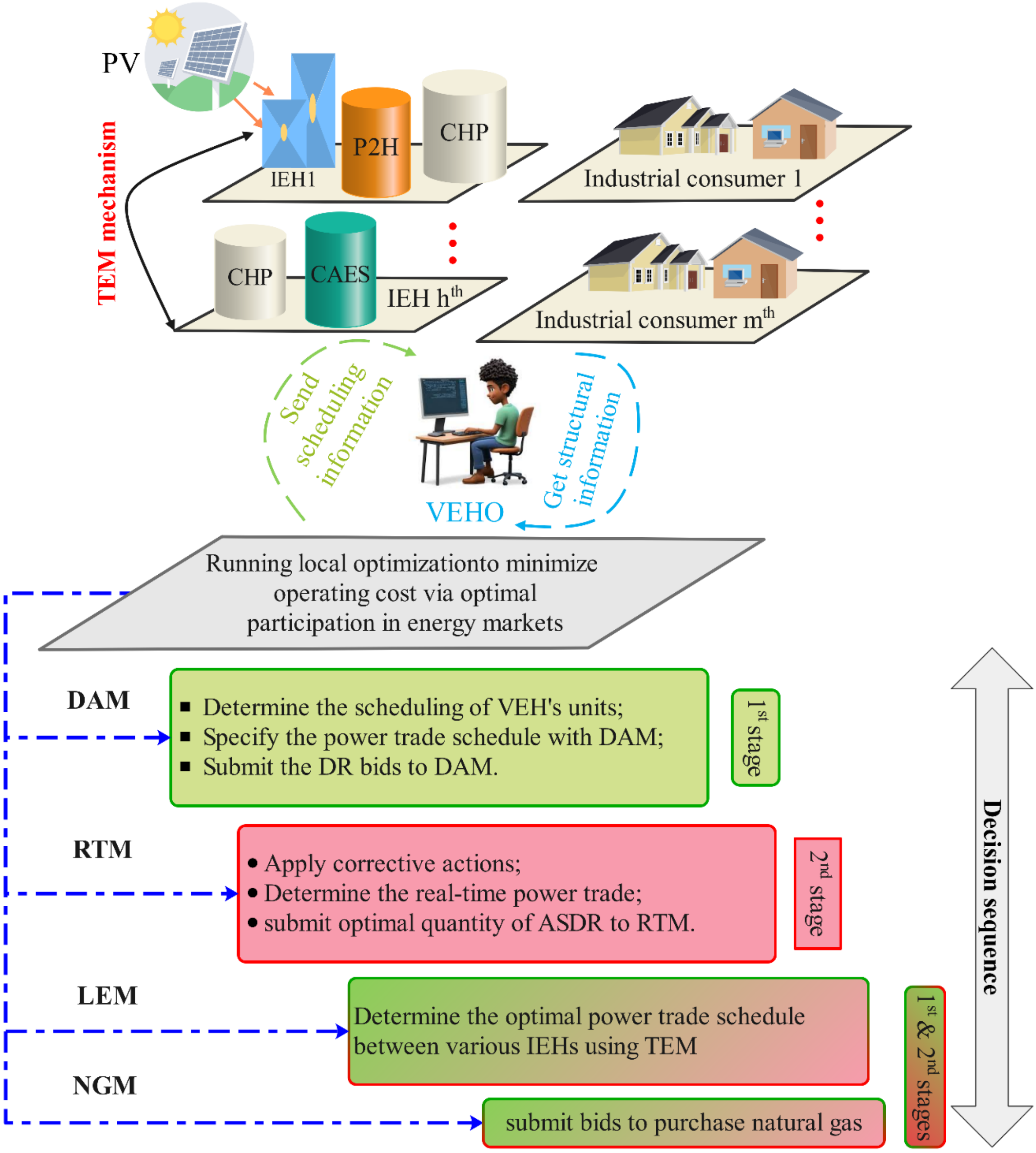


Figure 1. Schematic of a VEH in Energy Markets, Illustrates the integration of a VEH across various energy markets.

Fig. 1 provides an overview of IEHs that include various components such as CHP unit, P2H storage system, compressed air ESS and photovoltaic. In the energy market, the VEH acts as a price-taking entity, allowing it to actively participate in several market mechanisms, including DAMs, R-TMs, local energy markets, and the NGM. These partnership options serve to meet energy needs of industrial complex. Moreover, a strategically governed VEH possesses the capability to capitalize on economic prospects within energy markets, including DRPs and energy exchange market mechanisms. The aim of the VEH is to reduce cost of imbalance in R-TM by combining these advanced ancillary services and increase the reliability and overall security of system.

2. 1. Limitations of the virtual energy hub

The operating limits for the first stage are defined in Eq. 4 to Eq. 6, which cover different aspects of VEH operation. Eq. 4 establishes an equality constraint for the net active power injection at each bus, with P^{Da} representing the power exchange at the common integration point. Eq. 5 uses the DC load distribution equation to model the power flow in the VEH system and provides insights into energy distribution. Eq. 6 is very important to ensure system reliability by setting lower and upper limits for the branch current. Also, by applying Dugan's theory and integrating uncertainty for R-TM, relevant limits will be written in form of Eq. 4 to Eq. 6.

$$P^{Da}(t)\big|i \in PCC + \sum_{h\in\mathscr{H}} P(h,t)\cdot KN(i,h) - \sum_{m\in\mathscr{M}} PD^{Fin}(m,t)\cdot KN(i,m) = \sum_{j\in\mathcal{J}} PF(ij,t)\cdot KN(i,j) \tag{1}$$

$$PF(ij,t) = \frac{(\delta(i,t)-\delta(j,t))}{x(i,j)} \tag{2}$$

$$-PF(ij,t)^{Max} \le PF(ij,t) \le PF(ij,t)^{Max} \tag{3}$$

$$P^{Re}(s,t) - \Delta P^{Re}(s,t)\big|i \in PCC + \sum_{h\in\mathscr{H}} P(h,s,t)\cdot KN(i,h) - \sum_{m\in\mathscr{M}} PD^{Fin}(m,t)\cdot KN(i,m) = \sum_{j\in\mathcal{J}} PF(ij,s,t)\cdot KN(i,j) \tag{4}$$

$$PF(ij,t) = \frac{(\delta(i,s,t)-\delta(j,s,t))}{x(i,j)} \tag{5}$$

$$-PF(ij,t)^{Max} \le PF(ij,s,t) \le PF(ij,t)^{Max} \tag{6}$$

2. 2. Limitations of industrial energy hub

Industrial integrated energy hubs are equipped with a set of energy systems, including photovoltaic arrays, CHP unit, compressed air ESS and P2H storage. In our proposed mathematical model, we take into account all the operational limitations associated with this IEH equipment, which are fully mentioned in the references [9,12]. These references provide the necessary information to define the minimum and maximum. It provides power and heat production limits as well as possible operating ranges for CHP units. Additionally, when modeling compressed air energy storage and P2H storage systems, charging and discharging rates are considered along with reservoir energy level constraints. Furthermore, to guarantee the equilibrium of multiple energy sources in each IEH during the initial decision stage, we enforce constraints 7 to 9. It is important to highlight that these operational limits and energy balance constraints should also be adhered to during real-time operations. To accomplish this objective, we modify constraints 7 to 9 to represent real-time operational decisions using Eq. 10 to Eq. 12.

$$P(h,t) = \sum_{k\in\mathcal{K}} P(k,t)\cdot KN(h,k) + \sum_{e\in\mathcal{E}}\big(P^{Dis}(e,t) + P^{Si}(e,t) - P^{Ch}(e,t)\big)\cdot KN(h,e) - \sum_{q\in Q} P(q,t)\cdot KN(h,q) + \sum_{v\in\mathcal{V}} P(v,t)\cdot KN(h,v) + PT^{In}(h,t) - PT^{Out}(h,t) \tag{7}$$

$$\sum_{q\in Q}\big(H^{Dis}(q,t) - H^{Ch}(q,t) + H^{Dir}(q,t)\big)\cdot KN(h,q) + \sum_{k\in\mathcal{K}} H(k,t)\cdot KN(h,k) - \sum_{n\in\mathcal{N}} HD^{Fin}(n,t)\cdot KN(h,n) = 0 \tag{8}$$

$$\sum_{e\in\mathcal{E}} G^{CAES}(e,t) + \sum_{k\in\mathcal{K}} G^{CHP}(k,t) = GC^{Wh}(t) \tag{9}$$

$$P(h,s,t) = \sum_{k\in\mathcal{K}} P(k,s,t) - \Delta P(k,s,t)\cdot KN(h,k) + \sum_{e\in\mathcal{E}}\big(P^{Dis}(e,t) + P^{Si}(e,t) - P^{Ch}(e,t)\big)\cdot KN(h,e) - \sum_{q\in Q} P(q,s,t) - \Delta P(q,s,t)\cdot KN(h,q) + \sum_{v\in\mathcal{V}} P(v,t)\cdot KN(h,v) + PT^{In}(h,t) - PT^{Out}(h,t) \tag{10}$$

$$\sum_{q\in Q}\big((H^{Dis}(q,s,t) - \Delta H^{Dis}(q,s,t)) - (H^{Ch}(q,s,t) - \Delta H^{Ch}(q,s,t)) + (H^{Dir}(q,s,t) - \Delta H^{Dis}(q,s,t))\big)\cdot KN(h,q) + \sum_{k\in\mathcal{K}} H(k,s,t)\cdot KN(h,k) - \sum_{n\in\mathcal{N}} HD^{Fin}(n,t)\cdot KN(h,n) = 0 \tag{11}$$

$$\sum_{e\in\mathcal{E}} G^{CAES}(e,s,t) + \sum_{k\in\mathcal{K}} G^{CHP}(k,s,t) = GC^{Wh}(t,s) \tag{12}$$

3. The proposed two-step algorithm

In the framework of the participation strategy in the VEH market, our main goal is to minimize total operating cost during entire planning period. We formulate this objective in a two-stage MILP programming framework, as shown in Eq. 13. In this equation, we introduce different terms to obtain the necessary cost and revenue components related to the utilization of the VEH. ε_1 represents the cost (or revenue) associated with scheduled energy trading in DAM and participation in the NGM. ε_2 is related to operating costs of CHP units located in IEHs. ε_3 accounts for the operating costs associated with P2H storage systems. ε_4 represents the operating costs associated with compressed air ESSs. ε_5 earns revenue from VEH's participation in direct load control programs and ancillary service DRPs during DAM. Taking into account the decisions made in the second stage, ε_6 represents cost associated with the deviation in load exchange during real-time operations compared to the planned values from the previous day's process. Obviously, parameters such as P^{Da} and ΔP^{Re} can have positive values based on buying power or positive values based on selling power in DAM and the market in R-TM. To ensure stability in scheduled power during real-time operation, we determine R-TM price, λ^{Re}, through a two-step settlement process, specified in Eq. 14, where These factors are in the relative differences between the market prices of the previous day and R-TM in scenarios of increasing or decreasing regulation (σ_+ and σ_-). In addition, ε_7 to ε_9 correspond to the operating costs associated with CHP units, P2H storage and compressed air ESSs in the second stage, respectively. Finally, ε_{10} represents the income from the implementation of ancillary service DRPs in the R-TM.

$\mathrm{Min: TC}$

$$
\begin{aligned}
\mathrm{TC} = \sum_{t\in\mathcal{T}} \Bigg[& \underbrace{\left(P^{Da}(t)\cdot\lambda^{Da}(t)\right) + \left(GC^{Wh}(t)\cdot\lambda^{G}(t)\right)}_{\varepsilon_1} + \underbrace{\sum_{k\in\mathcal{K}} P(k,t)\cdot\rho(k)}_{\varepsilon_2} + \underbrace{\sum_{q\in Q}\left(H^{Dis}(q,t)+H^{Ch}(q,t)\right)\cdot\rho(q)}_{\varepsilon_3} + \\
& \underbrace{\sum_{e\in\varepsilon}\left((P^{Si}(e,t)+P^{Dis}(e,t))\cdot\left(\rho^{Voc}(e)+\lambda^{G}(t)\cdot HR(e)\right)+\left(P^{Si}(e,t)+P^{Ch}(e,t)\right)\cdot\rho^{Voc}(e)\right)}_{\varepsilon_4} - \underbrace{R^{DLC}(t)-R^{ASDR}(t)}_{\varepsilon_5}\Bigg] + \\
& \sum_{t\in\mathcal{T}}\sum_{s\in S}\pi_a\cdot\Bigg[\underbrace{\left(\Delta GC^{Wh}(s,t)\cdot\lambda^{G}(t)\right)+\left(\Delta P^{Re}(s,t)\cdot\lambda^{Re}(t)\right)}_{\varepsilon_6} + \underbrace{\sum_{k\in\mathcal{K}}\Delta P(k,s,t)\cdot\rho(k)}_{\varepsilon_7} + \\
& \underbrace{\sum_{q\in Q}\left(\Delta H^{Ch}(q,s,t)+\Delta H^{Dis}(q,s,t)\right)\cdot\rho(q)}_{\varepsilon_8} + \\
& \underbrace{\sum_{e\in\varepsilon}\left((\Delta P^{Si}(e,s,t)+\Delta P^{Dis}(e,s,t))\cdot\left(HR(e)\cdot\lambda^{G}(t)+\rho^{Voc}(e)\right)+\left(\Delta P^{Si}(e,s,t)+\Delta P^{Ch}(e,s,t)\right)\cdot\rho^{Voc}(e)\right)}_{\varepsilon_9} - \underbrace{R^{ASDR}(s,t)}_{\varepsilon_{10}}\Bigg]
\end{aligned}
\tag{13}
$$

$$
\lambda^{Re}(t) = \begin{cases} \lambda^{Da}(t).(1+\sigma_+) & \Delta P^{Re}(s,t)\geq 0 \\ \lambda^{Da}(t).(1-\sigma_-) & \Delta P^{Re}(s,t) < 0 \end{cases}
\tag{14}
$$

In Eq. 13, we have ignored the uncertainty of the previous day's market prices by considering complete forecasts. However, realizing the high importance of DAM price uncertainty, we adopt a robust approach to address this uncertainty parameter [20,21]. As shown in the relation, to increase the transparency of the model, we keep the uncertainty parameter λ^{Da} in the objective function and replace other parameters with $\Upsilon(s,\varphi)+\Phi(\varphi)$.

$$
C = \sum_{t\in\mathcal{T}}\sum_{s\in S}\pi(s)\cdot[\Upsilon(s,\varphi)+\Phi(\varphi) + (P^{Da}(t)\cdot\lambda^{Da}(t))]
\tag{15}
$$

The uncertainty determined for DAM prices is specified in Eq. 16 to Eq. 18, which calculates the uncertainty budget, Γ. Here, $\bar{\lambda}^{Da}$ represents the predicted DAM price, while $\tilde{\lambda}^{Da}$ represents max deviation from predicted amount. To generate most demanding circumstances for VEH power trading in DAM, we set power buying and selling modes as shown in Eq. 19.

$$
\lambda^{Da}(t)\in\left[\bar{\lambda}^{Da}(t)-\tilde{\lambda}^{Da}(t)\cdot\vartheta(s,t),\bar{\lambda}^{Da}(t)+\tilde{\lambda}^{Da}(t)\cdot\vartheta(s,t)\right]
\tag{16}
$$

$$0 \leq \vartheta(s,t) \leq 1 \tag{17}$$

$$\sum_{t=1}^{24} \vartheta(s,t) \leq \Gamma \tag{18}$$

$$\lambda^{Da}(t) = \begin{cases} \bar{\lambda}^{Da}(t) + \vartheta(s,t) & P^{Da}(t) \geq 0 \\ \bar{\lambda}^{Da}(t) - \vartheta(s,t) & P^{Da}(t) < 0 \end{cases} \tag{19}$$

Utilizing robust model for DAM prices, we modify initial objective function as stated in (15) into the expression presented in Eq. 20. By adding an additional continuous factor, ϑ (s, t), divergence from expected value can be maximized in order to reach a solid resolution. This results in a two-level Min-Max optimization problem.

$$\text{Min: TC} = \begin{cases} \sum_{t\in\mathcal{T}} \sum_{s\in S} \pi(s) \cdot \left[\underset{\vartheta(s,t)}{\text{Max}} \left\{ \tilde{\lambda}^{Da}(t) \cdot \vartheta(s,t) + \bar{\lambda}^{Da}(t) \right\} \cdot P^{Da}(t) + \Upsilon(s,\varphi) + \Phi(\varphi) \right] & P^{Da}(t) \geq 0 \\ \sum_{t\in\mathcal{T}} \sum_{s\in S} \pi(s) \cdot \left[\underset{\vartheta(s,t)}{\text{Max}} \left\{ \tilde{\lambda}^{Da}(t) \cdot \vartheta(s,t) + \bar{\lambda}^{Da}(t) \right\} \cdot P^{Da}(t) + \Upsilon(s,\varphi) + \Phi(\varphi) \right] & P^{Da}(t) < 0 \end{cases} \tag{20}$$

We transform the two-level Min-Max optimization problem in a single-level Min-Min problem using Dugan's theory [22]. Eq. 21 to Eq. 23 represent final form of resilient stochastic combinatorial optimization problem after applying Dugan's theory. To simplify the application of the dual theory, we denote β(s, t) and ε(s) as auxiliary dual variables related to original robust stochastic combinatorial problem.

$$\text{Min: TC} = \begin{cases} \sum_{t\in\mathcal{T}} \sum_{s\in S} \pi(s) \cdot \left[\bar{\lambda}^{Da}(t) \cdot P^{Da}(t) + \left(\varepsilon(s).\Gamma + \beta(s,t)\right) + \Upsilon(s,\varphi) + \Phi(\varphi) \right] & P^{Da}(t) \geq 0 \\ \sum_{t\in\mathcal{T}} \sum_{s\in S} \pi(s) \cdot \left[\bar{\lambda}^{Da}(t) \cdot P^{Da}(t) - \left(\varepsilon(s).\Gamma + \beta(s,t)\right) + \Upsilon(s,\varphi) + \Phi(\varphi) \right] & P^{Da}(t) \geq 0 \end{cases} \tag{21}$$

$$\varepsilon(s) + \beta(s,t) \geq \tilde{\lambda}^{Da}(t).P^{Da}(t) \tag{22}$$

$$\varepsilon(s) + \beta(s,t) \geq 0 \tag{23}$$

4. Exchange energy management strategy

The formulation of the exchange energy management (EEM) model can be expressed through Eq. 24 to Eq. 28, which check the presented assumptions. Inequality (24) specifies that each IEH cannot simultaneously receive and transmit electricity to and from the local energy market. Relying on Eq. 25 and Eq. 26, we make sure that the traded power does not exceed allowed limit. Power balance constraints in EEM framework, applicable to any IEH and throughout the planning horizon, are applied by Eq. 27 and Eq. 28. In order to maintain compliance with the EEM rules in real time operation decisions, it is necessary that constraints expressed in Eq. 25 to Eq. 28 are satisfied for each scenario with dual theory, which are in Eq. 29 to Eq. 32 is given. In these relations, $PT^{In}(h,s,t)$ and $PT^{Out}(h,s,t)$ are part of the set of decision variables of the second stage. Here, $\Delta PT^{In}(h,s,t)$ and $\Delta PT^{Out}(h,s,t)$ represent the regulated power transferred from and to the local energy market and IEHs during the step decisions. The second one ensures the integrity of the exchange EMM during decision making [4]:

$$u^{In}(h,t) + u^{Out}(h,t) \leq 1 \tag{24}$$

$$PT^{In}(h,t) \leq PT^{Max}(h).u^{In}(h,t) \tag{25}$$

$$PT^{Out}(h,t) \leq PT^{Max}(h).u^{Out}(h,t) \tag{26}$$

$$\sum_{t\in T} PT^{In}(h,t) = \sum_{t\in T} PT^{Out}(h,t) \tag{27}$$

$$\sum_{h\in H} PT^{In}(h,t) = \sum_{h\in H} PT^{Out}(h,t) \tag{28}$$

$$(PT^{In}(h,s,t) - \Delta PT^{In}(h,s,t)) \leq PT^{Max}(h).u^{In}(h,t) \tag{29}$$

$$(PT^{Out}(h,s,t) - \Delta PT^{Out}(h,s,t)) \leq PT^{Max}(h).u^{Out}(h,t) \tag{30}$$

$$\sum_{t\in T} (PT^{In}(h,s,t) - \Delta PT^{In}(h,s,t)) = \sum_{t\in T} (PT^{Out}(h,s,t) - \Delta PT^{Out}(h,s,t)) \tag{31}$$

$$\sum_{h\in H} (PT^{In}(h,s,t) - \Delta PT^{In}(h,s,t)) = \sum_{h\in H} (PT^{Out}(h,s,t) - \Delta PT^{Out}(h,s,t)) \tag{32}$$

Demand Response programs (DRP) play a critical role in the modern electricity market by enabling consumers to adjust their power consumption in response to electricity price signals or other incentives. These programs help in balancing supply and demand, reducing peak loads, and improving the overall efficiency and reliability of the electricity grid. Let's consider a mathematical formulation for a price-based demand response program with the objective of minimizing the electricity cost for a consumer while ensuring their demand is met. The employed symbols defined as:

T: Total number of time periods (e.g., hours in a day)

t: Index for time periods, t=1,2,…,T

P_t: Electricity price at time t

D_t: Demand (load) at time t

L_t: Load reduction at time t

C: Total electricity cost

α_t: Maximum allowable load reduction at time t

The objective is to minimize the total electricity cost C:

$$min\ C = \sum_{t=1}^{T} P_t\,(D_t - L_t) \tag{33}$$

Subject to:

$$0 \le L_t \le \alpha_t, \quad \forall t \tag{34}$$

$$\sum_{t=1}^{T}(D_t - L_t) \ge \sum_{t=1}^{T} D_t \tag{35}$$

$$L_t \ge 0, \quad \forall t \tag{36}$$

5. Numerical results

In this section, we utilize the IEEE 14-bus test system to evaluate the effectiveness of our proposed approach [4, 20], which acts as a representative model for our surrogate industrial park. The IEEE 14-bus system is a well-established benchmark in power systems research, offering a detailed framework to assess various energy management strategies. The IEEE 14-bus test system is utilized as the foundation for evaluating the proposed energy management approach. This benchmark system, originally designed for medium-sized power networks, includes 14 buses, 5 generators, and 20 transmission lines. For the purpose of this study, the system is adapted to represent an industrial park environment by integrating four Integrated Energy Hubs (IEHs), each equipped with a combination of energy generation and storage technologies. As depicted in Figure 2, our analysis focuses on a Virtual Energy Hub (VEH) that incorporates four Integrated Energy Hubs (IEHs). Each IEH is equipped with a combination of energy generation and storage technologies, tailored to simulate a real-world industrial park environment. The system under investigation includes four thermal loads and eleven electrical loads, with Bus 1 serving as the central connection point for the entire network. This configuration allows for a thorough examination of energy distribution and management across different components of the system. For a comprehensive understanding of the original IEEE 14-bus test system, please refer to reference [23], which provides detailed insights into its structure and operational parameters. Table 1 offers an in-depth breakdown of the various units within each IEH, detailing the specific types of energy resources and storage capabilities present.

Table. 1. Specifications of energy hubs in the energy system.

Energy hubs	Bus	PV	CHP	CAES	P2H2
IEH 1	2	×	✓	✓	×
IEH 2	3	✓	✓	×	✓
IEH 3	6	✓	×	×	✓
IEH 4	8	×	✓	✓	×

The table categorizes the IEHs based on their components, such as Combined Heat and Power (CHP) systems, Compressed Air Energy Storage (CAES), and Power-to-Heat (P2H) storage units. Technical limitations and operational features of these units are elaborated in references [5, 9, 23], which provide crucial information on the constraints and functionalities of each component. These references detail the performance characteristics, efficiency metrics, and operational constraints of the units used in our simulations, ensuring that our evaluation reflects realistic conditions and technical feasibility. By leveraging this detailed configuration and the accompanying technical references, our study aims to provide a robust assessment of the proposed energy management approach, ensuring its applicability and effectiveness in real-world scenarios.

Additionally, Fig. 3 displays the estimated power generation from photovoltaic systems as well as energy demand projections. Every photovoltaic system has a maximum capacity of 15 MW. Furthermore, we have taken into account that Hub Energy's peak electrical and thermal loads are 176 MW and 53 MW, respectively, and that the thermal load distribution in buses 2, 3, 6, and 8 is taken into account to be 17%, 55%, 13%, and 15% of the system's total thermal load demand, respectively.

In the field of energy pricing, we have adopted the values [12] for DAM and NGM. The R-TM prices for both increasing and decreasing regulations are set at 1.2 and 0.8 times the respective market prices of the previous day. The parameters and information governing direct load control and ancillary service DRPs are taken from references [9] and [11] and provide a realistic basis for our evaluations. For the time dimension, our exploitation horizon spans a 24-hour period with a time step of 1 hour. To effectively implement our mathematical model, we have used GAMS software relying on CPLEX solver. It is important to emphasize that our proposed strategy is structured as a MILP programming problem, which inherently offers significant scalability advantages. This design characteristic allows researchers to increase test system's dimensions without compromising system's ability to scale harmoniously between its constituent parts. This includes considerations such as line capacity and features of IEHs, all of which can be seamlessly configured to accommodate larger and more complex energy systems.

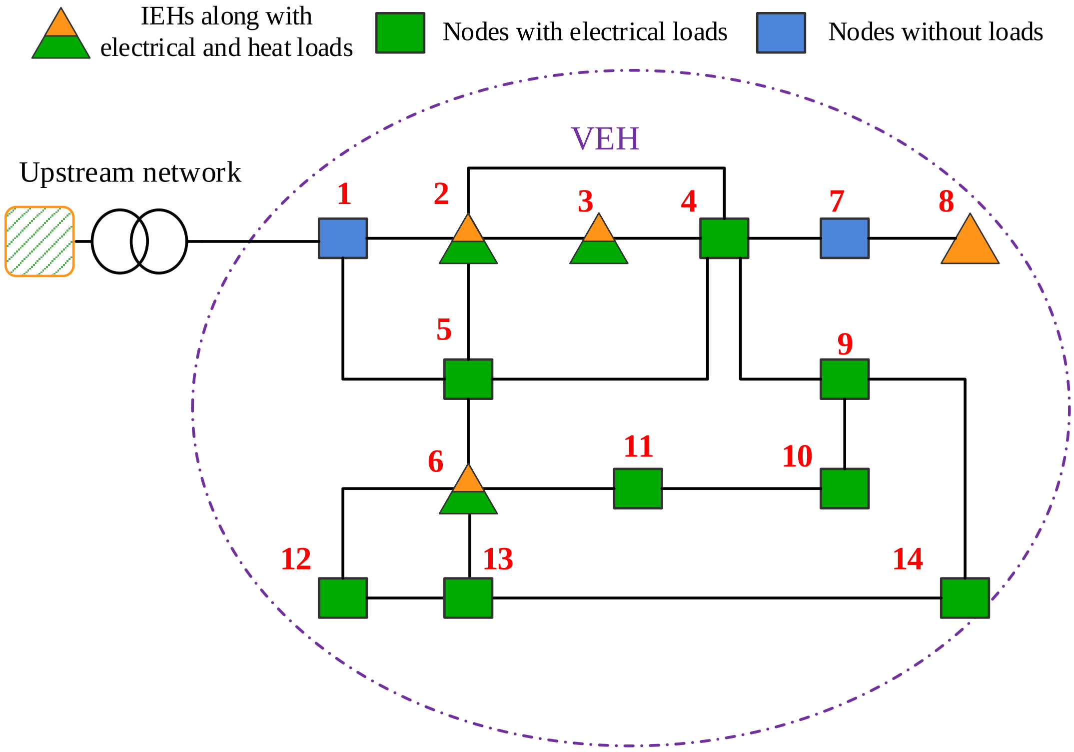


Figure 2. IEEE 14-Bus Test System Configuration.

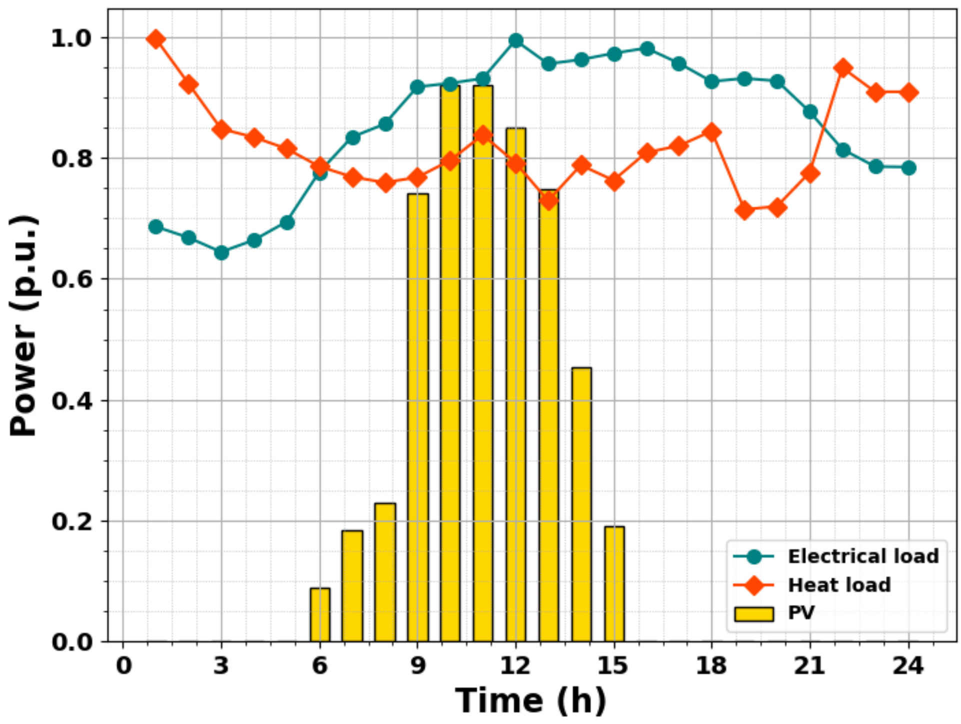


Figure 3. PV Power Generation and Load Projections, Shows estimated 15 MW PV power generation and the peak electrical (176 MW) and thermal loads (53 MW) with distribution across buses.

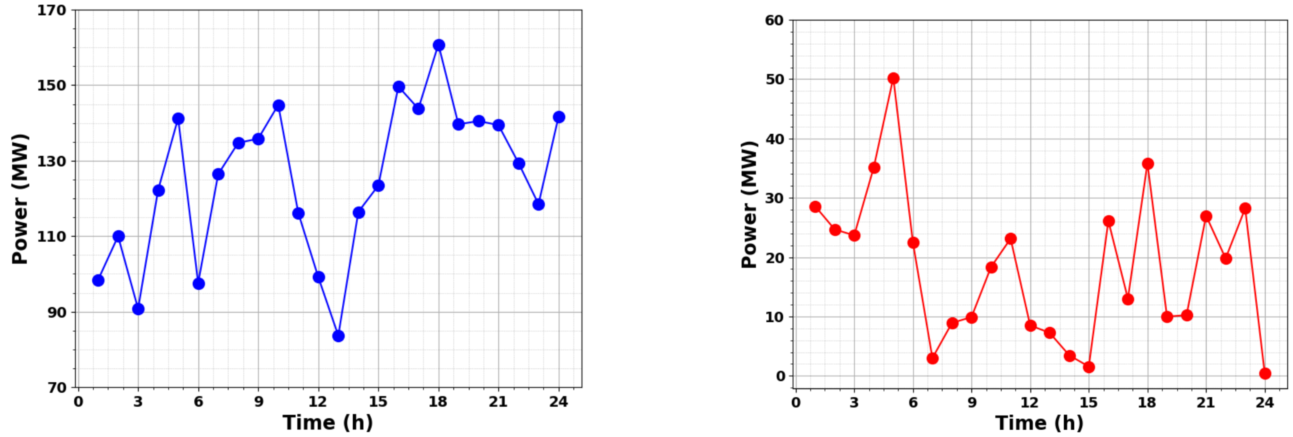
In this section, we begin a comprehensive evaluation of proposed market engagement strategy for VEH through 4 distinct scenarios:

1) Baseline scenario: At first, we investigate the performance of the VEH without integrating any side services in the framework of the presented stochastic-resilient two-stage problem.
2) The first scenario: based on the base scenario, we introduce the central role of the interactive EMM and evaluate its impact on the performance of the VEH.
3) The third scenario: Similar to the first scenario, but in this scenario, we include the direct load control program along with the interactive EMM and seek to understand how these elements collectively affect the performance of the VEH.
4) Third scenario: Similar to the second scenario, but we replace the ancillary service DRP with the direct load control program, allowing us to measure the relative merits of these two demand response services.

We employ the Monte Carlo method to make the created two-phase random optimization framework easier to implement. When making decisions on operation in real time, this method considers the inherent uncertainties related to photovoltaic systems and energy requirements. A normal probability distribution function with a 10% standard deviation and a 0 mean is used to generate a total of 2000 scenarios via Monte Carlo simulation. These scenarios are subsequently reduced to 5 representative scenarios using SCENRED tool in GAMS software. In addition, we use a robust optimization approach to address uncertainty related to the DAM price and introduce an uncertainty budget and different ranges for the maximum deviation between predicted and actual values.

To investigate the impact of ancillary services on operating costs, we keep the uncertainty budget and maximum deviation at fixed values of 4% and 15%, respectively. According to the performed simulation and the obtained results, the basic scenario appears as the most unfavorable scenario in terms of energy hub operation costs. In general, the operating costs of energy hubs are reduced by 9.25% in the first scenario, by 12.41% in the second scenario, and by 55.38% in the third scenario. These reductions reflect the synergistic contributions of the diverse mix of ancillary services integrated into the proposed market engagement strategy. The third scenario, characterized by the coordinated use of the interactive EMM and the ancillary service DRP, emerges as the prominent scenario. It generates the most income ($163.21k), has the cheapest operating costs ($143.31k), and incurs the smallest unbalance cost. To clarify the dynamics of VEH electricity trade in the day-to-day and local markets for the third scenario, we consider the data in Fig. 4. It is obvious that in accordance with the commitment of the VEH operator to implement the program to meet the demand for ancillary services in connection with the distribution system operator, power exchange between VEH and market saw a significant decrease from 146.2 MW at 10:00 to 81.5 MW the other day. It is at 13:00. This change in real-time trading dynamics is a major driver behind VEH's pursuit of increased power diversions in R-TM, offering prospect of increased profitability.

The involvement of the Virtual Energy Hub (VEH) in the Real-Time Market (R-TM), coupled with strategic power demand reduction and the implementation of ancillary service programs, significantly influences power exchange dynamics in the local electricity market. Specifically, the reduction in power demand during critical time frames—07:00 to 09:00 and 12:00 to 15:00—facilitates a notable decrease in power exchange with the local market. This reduction is achieved through an interactive Energy Market Management (EMM) system, which optimally coordinates energy resources across various Integrated Energy Hubs (IEHs) distributed throughout the industrial park. The strategic placement of multiple supply points within the industrial park has a profound impact on local energy exchange, particularly during peak load periods. As depicted in Figure 5, the hourly scheduling of Combined Heat and Power (CHP) units, Compressed Air Energy Storage (CAES) systems, and Power-to-Heat (P2H) storage units is crucial for distributing consumer demand efficiently. This scheduling highlights the VEH's capability to balance and manage energy supply from different sources, enhancing flexibility and resilience against uncertainties and potential cyber-attacks.



(a) Day-ahead market (b) Local market

Figure 4. Power Exchange in DAM and local market for the third Scenario, illustrates power exchanged in the DAM and local market under the third scenario, highlighting the variations in power trading and its impact on market costs.

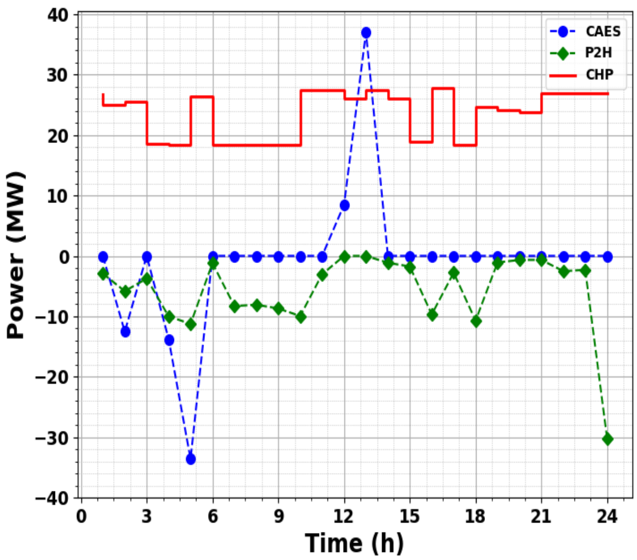


Figure 5. Optimal Thermal Dispatch for the System in the Third Scenario

Figure 6 illustrates the complementary benefits of integrating ancillary demand management and explicit load management initiatives, facilitated by the interactive EMM. The data demonstrate that the VEH operator's active participation in the ancillary service Demand Response Program (DRP) from 11:00 to 14:00 significantly optimizes electrical demand. In addition, the expansion of participation in the direct load control program further aligns with individual consumer activity plans. The overall impact on operating costs is substantial. Analysis shows that the implementation of the direct load control program results in a 6.02% reduction in operating costs for IEHs. Similarly, leveraging the ancillary service DRP contributes to a 2.29% reduction in costs. These results underscore the effectiveness of integrated demand response strategies in reducing operational expenses and optimizing energy management within the VEH framework.

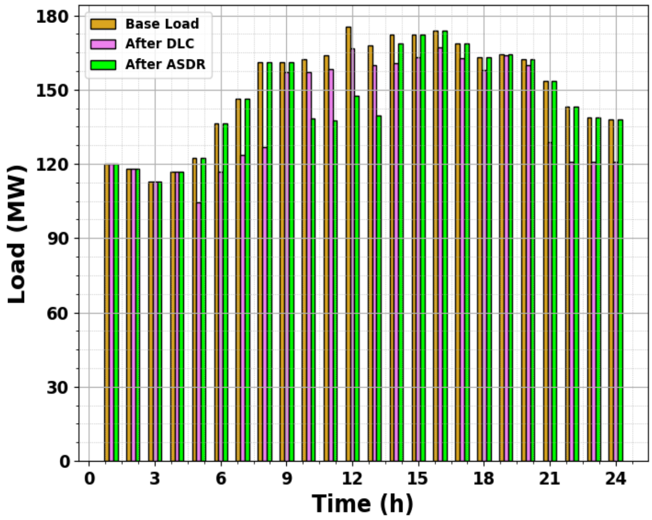


Figure 6. Effect of Interactive Energy Market Management (EMM) on System Loads

5.1. Sensitivity analysis

In this section, we turn to sensitivity analyses to clarify the impact of critical input parameters on the overall performance of virtual energy centers. These analyses serve as an important stepping stone for the VEH operator to capitalize on opportunities in various energy markets. It is important to note that all assumptions are consistent with those used in the third scenario.

I. Sensitivity to price differences

Our first sensitivity analysis revolves around understanding how the cost of operating entire VEH responds to relative differences in DAM prices and R-TM prices, especially in increasing regulations (σ_+) and decreasing regulations (σ_-). We systematically varied σ_+ and σ_- in seven equal steps ranging from 0.05 to 0.35. As shown in Table. 2, the results reveal a linear relationship between the energy hub operation cost and the σ_+ and σ_- values. This finding emphasizes the obvious impact of price differences between DAM and R-TM and highlights the essential need for a robust strategy to manage the inherent volatility in uncertainty of DAM price.

II. Sensitivity to strength parameters

Then, we investigate how changes in the robustness parameters affect the volume of power traded in DAM and performance of compressed air ESS. Economically, the energy hub operator's goal is to minimize energy exchanges with DAM during peak pricing periods while maximizing reliance on internal VEH resources, such as the compressed air ESS, to meet electrical needs. This strategy gains traction as the degree of robustness, denoted by $(\lambda^{Da}(t), \Gamma)$ on the previous day's market price rise. To investigate this scenario in detail, we chose four different combinations of $(\lambda^{Da}(t),\Gamma)$, namely (4, 15%), (24, 15%), (5, 15%) and (12, 25 "). Subsequently, we performed simulations reflecting the third scenario setup. Fig. 7 shows the change in power exchanged between the VEH and the previous day's market in different combinations $(\Gamma \text{،} \lambda^{Da}(t))$ Surprisingly, the exception of high and off-load times, exchanged power displays a steady range for various combinations for entire duration.

In Fig. 8, we deepen performance of compressed air storage system in response to different levels of strength. Here, we observe an increase in compressed air storage system engagement during off-peak and off-load periods in straight ratio to power swapped in DAM, underscoring the effectiveness of this approach in the strategic use of compressed air storage capabilities. Furthermore, compared to Γ, it is shown that λ^{Da} (t) has a stronger influence on variations of exchanged power during peak load and off-load times. Notably, the highest and lowest power exchanged between the energy hub and the market the other day during the low load peak period, along with the highest percentage of compressed air storage systems participating in the proposed strategy, are attributed to the highest range of λ^{Da} (t), or 25%. These findings prove the flexibility and efficacy of our suggested market involvement approach in resolving higher degrees of resilience in DAM price uncertainty.

Table. 2. System operating cost sensitivity to σ_+ and σ_-

	(σ_-, σ_+)						
	(1.05,0.95)	(1.1,0.9)	(1.15,0.85)	(1.2,0.8)	(1.25,0.75)	(1.3,0.7)	(1.35,0.65)
Operation cost ($)	115542	124826	134249	143394	152401	161408	170.277

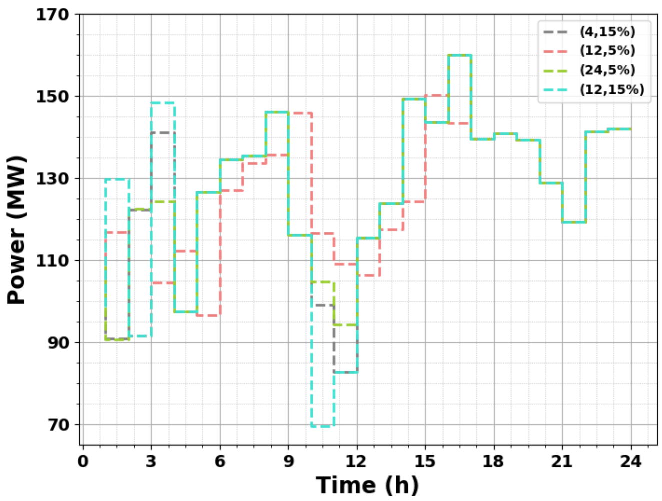


Fig. 7. The sensitivity of the power exchanged in the market the other day on the robust optimization parameters.

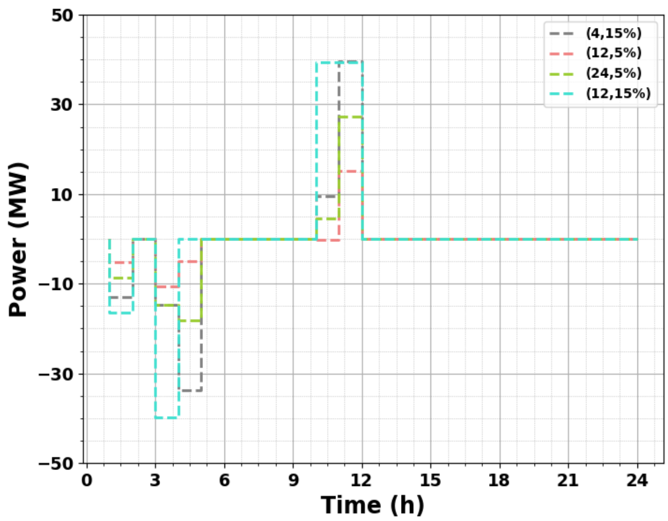


Fig. 8. The sensitivity of compressed air storage planning on robust optimization parameters.

The sensitivity analysis of system operating costs in Table 2 provides crucial insights into how variations in the parameters σ_+ and σ_-—which represent the multipliers for price increases and decreases, respectively—affect overall expenditure. These parameters are critical in understanding how fluctuations in Day-Ahead Market (DAM) prices influence the cost efficiency of the energy system. The analysis reveals a clear inverse relationship between the values of σ_+ and σ_- and the system's operating costs. As shown in Table 2, when the values of σ_+ and σ_- decrease, indicating a reduction in the extent of price variability, the operating costs exhibit a notable decrease. For instance, with σ_+ set at 0.65 and σ_- at 1.35, the operating cost is \$170,277. In contrast, when σ_+ increases to 0.95 and σ_- decreases to 1.05, the operating cost drops to \$115,542. This reduction of approximately 32% underscores that less volatile pricing conditions result in lower operational expenses. This trend highlights the financial advantage of maintaining a more predictable price environment.

The findings emphasize the importance of effective price management strategies. Energy systems that can minimize exposure to high price volatility can achieve significant cost savings. This underscores the value of incorporating advanced forecasting techniques and strategic pricing to reduce the impact of market fluctuations. By stabilizing price expectations, energy systems can better control their operational costs. Additionally, the sensitivity analysis illustrates the role of operational flexibility and risk management in cost efficiency. Systems capable of adapting to lower volatility and managing price uncertainties effectively will benefit from reduced operational expenses. This suggests that enhancing operational flexibility and adopting robust risk management practices are essential for achieving cost efficiency. These results also have implications for policymakers and market designers. Understanding the cost impact of price volatility can inform the design of regulations and market structures that aim to reduce price fluctuations and provide more stable market conditions. Such measures could lead to lower costs for energy systems and contribute to a more stable and predictable energy market. In summary, the sensitivity analysis demonstrates that managing price volatility and reducing the parameters σ_+ and σ_- can significantly lower operating costs. This highlights the importance of stable pricing environments, effective risk management, and strategic price planning in achieving cost efficiency in energy systems.

5.3. Discussion and analysis

The power purchase cost from the Day-Ahead Market (DAM) shows slight variations across the different cases. In the base case, the cost is \$178.12k. Case 1 sees an increase to \$182.44k, which is approximately 2.4% higher than the base case. Case 2, however, shows a decrease to \$175.64k, which is around 1.4% lower than the base case. Case 3 has a similar cost to Case 1 at \$182.19k, indicating a negligible difference of about -0.1% from Case 1 but still higher than the base case by 2.3%. The power purchase cost from the Real-Time Market (RTM) also varies significantly. The base case has a cost of \$0.291k. Case 1 reduces this slightly to \$0.243k, representing a decrease of about 16.5%. Case 2 increases significantly to \$4.93k, a dramatic rise of approximately 1594.5% compared to the base case. Case 3 completely eliminates this cost, bringing it to \$0k, a 100% reduction from the base case. The gas purchase cost from the Natural Gas Market (NGM) is highest in the base case at \$124.90k. Case 1 reduces this cost significantly to \$98.56k, a decrease of about 21.1%. Case 2 further reduces the cost to \$92.35k, which is approximately 26.1% lower than the base case. Case 3 has a slight increase from Case 2 but remains low at \$99.64k, a reduction of about 20.2% from the base case. Revenue from power sales to RTM shows significant differences among the cases. The base case generates \$11.51k. Case 1 remains almost the same at \$11.47k, a negligible difference of -0.3%. Case 2 sees a decrease to \$7.20k, which is about 37.4% lower than the base case. Case 3, however, shows a substantial increase to \$141.68k, representing an increase of approximately 1131.2%. Revenue from Demand Response Programs (DRPs) is not applicable in the base case and Case 1. Case 2 generates \$4.57k, while Case 3 significantly increases this revenue to \$17.43k, indicating a substantial growth of approximately 281.5% from Case 2 to Case 3. The comparison of these cases highlights the effectiveness of different strategies in reducing operational costs and increasing revenues. Case 3 emerges as the most efficient scenario, showing the highest revenue from power sales to RTM and DRPs, and the lowest total operation cost. The significant cost reductions in Cases 1 and 2, along with the remarkable results in Case 3, underscore the importance of integrating advanced market engagement strategies and demand response programs in optimizing energy hub operations.

6. Conclusion

In this study, we have presented a pioneering approach to optimize the market participation of a VEH that includes both the IEH and a diverse range of multiple energy industrial consumers. Our strategy is designed to navigate the complex landscape of energy trading in day-ahead, real-time, local electricity and NGMs. We design our technique as a novel two-stage resilient probabilistic optimization challenge to solve the complex problems in this industry. We leverage enhanced auxiliary services to guide R-TM exploitation decisions. A distinctive feature of our approach is its comprehensive consideration of uncertainties arising from a diverse set of sources. These uncertainties include variables such as day-to-day market pricing dynamics, fluctuating energy demand, and the inherent uncertainty of photovoltaic systems. We incorporate these uncertainties into a realistic power system model, carefully accounting for all operating constraints. This comprehensive approach is designed to meet the specific needs and concerns of the VEH user. Our simulations emphasize the effectiveness of the proposed strategy when combined with a transformative EMM and market-based DRPs. These synergistic elements collectively help to optimize the behavior of the VEH, leading to a significant reduction of 56.72% in total operating costs. This result emphasizes the tangible benefits of integrating advanced ancillary services in the framework of a VEH, providing cost-effective and sustainable solutions to determine optimal exploitation plans. As we chart the course for future research, our focus will shift to examining the role of VEHs in price formation in the evolving landscape of peer-to-peer energy trading mechanisms. This discovery promises to illuminate the potential of the VEH as an important player in shaping energy pricing dynamics, ultimately contributing to a more comprehensive understanding of its role in the broader energy system.

The future trends in the field of energy management, particularly focusing on the application of virtual energy hubs (VEHs), indicate several key directions:

- **Enhanced Integration of Renewable Energy Sources (RES)**: VEHs will increasingly integrate various renewable energy sources, such as photovoltaic systems and wind power, to ensure a sustainable and reliable energy supply. The ability to manage and balance these intermittent energy sources will be crucial.
- **Advanced Ancillary Services**: The development and implementation of advanced ancillary services, including market-driven demand response programs (DRPs) and interactive energy management mechanisms (EMMs), will be essential. These services will help optimize system performance, reduce operational costs, and enhance system reliability.
- **Stochastic Optimization Models**: The adoption of robust stochastic optimization models to handle uncertainties in energy markets, such as fluctuating energy prices and variable energy demand, will become more prevalent. These models will help VEHs effectively participate in diverse electricity markets, including day-ahead and real-time markets.
- **Energy Storage Solutions**: The integration of various energy storage options, such as compressed air energy storage and power-to-heat storage, will play a significant role in enhancing the flexibility and resilience of VEHs. These storage solutions will help manage energy supply and demand more effectively.
- **Collaborative Optimization in Distributed Energy Networks (DENs)**: Future trends will emphasize the collaborative optimization of multiple energy stations within distributed energy networks. This approach will enhance energy sharing, improve economic and environmental performance, and increase the overall efficiency of the energy system.
- **Electric Vehicle (EV) Integration**: The impact of electric vehicles on power systems will continue to be a significant area of research. Strategies to manage the increased power demand and maintain the performance of distribution components will be critical, especially as EV penetration increases.
- **Peer-to-Peer Energy Trading Mechanisms**: The exploration of peer-to-peer energy trading mechanisms will gain momentum. VEHs will play a pivotal role in shaping energy pricing dynamics and facilitating direct energy exchanges between consumers, further

decentralizing the energy market.

- **Sustainable Multi-Energy Systems (MESs)**: The development of sustainable multi-energy systems that integrate electricity, heat, and gas networks will be a key trend. These systems will require sophisticated management strategies to optimize their operation and achieve environmental and economic benefits.
- **Smart Grid and Digital Technologies**: The implementation of smart grid technologies and digital solutions, such as blockchain for transactive energy exchanges, will enhance the efficiency, transparency, and security of energy management systems.
- **Regulatory and Policy Support**: Supportive regulatory frameworks and policies will be essential to facilitate the deployment and operation of VEHs. Policymakers will need to address the technical, economic, and regulatory challenges to enable a smooth transition to advanced energy management systems.

These trends highlight the need for innovative solutions and collaborative efforts to address the challenges and leverage the opportunities in the evolving landscape of energy management. Innovative solutions will involve the development and deployment of advanced technologies, such as sophisticated energy storage systems, smart grid infrastructure, and integrated renewable energy sources. Collaborative efforts will be essential among various stakeholders, including government entities, industry leaders, academic researchers, and energy consumers, to create synergies and share best practices. Addressing challenges such as grid stability, energy storage, and market integration will require coordinated actions and shared resources. Leveraging opportunities like enhanced energy efficiency, cost reduction, and increased reliability of energy systems will depend on the effective collaboration of these diverse groups. The evolving landscape of energy management demands a dynamic approach that combines technological innovation with strategic partnerships to achieve sustainable and resilient energy systems for the future.

Future work will focus on enhancing uncertainty modeling by integrating advanced machine learning techniques to improve demand and generation forecasts. Additionally, expanding the model to include a broader range of renewable energy sources and storage technologies will be explored. Real-time optimization algorithms will be developed to improve the responsiveness and efficiency of the VEH in dynamic market conditions. Finally, case studies involving different industrial and residential scenarios will be conducted to validate the model's applicability and performance in diverse real-world settings.

Funding:

This work was supported by the general project of the National Natural Science Foundation of China, "Research on Elastic Energy Management and Operation Strategy of Comprehensive Energy Efficient Power Plants Based on Information Driven" (51977032), and the Smart Grid funding project of the National Natural Science Foundation of China, "Research on Operation Mechanism and Key Technologies of Comprehensive Energy Systems Based on Institutional Effectiveness Theory" (U1966204).

Reference

1. Siano P, De Marco G, Rolán A, Loia V. A survey and evaluation of the potentials of distributed ledger technology for peer-to-peer transactive energy exchanges in local energy markets. IEEE Syst J 2019;13:3454–66. https://doi.org/10.1109/JSYST.2019.2903172
2. Mir M, Ghadimi N, Abedinia O, Shokrani SAR. Robust Optimization-Based Energy Procurement. Robust Energy Procurement of Large Electricity Consumers 2019:67–85. https://doi.org/10.1007/978-3-030-03229-6_4
3. Moazeni S, Miragha AH, Defourny B. A risk-averse stochastic dynamic programming approach to energy hub optimal dispatch. IEEE Transactions on Power Systems 2018;34:2169–78. https://doi.org/10.1109/TPWRS.2018.2882549
4. Oskouei, M. Z., Mohammadi-Ivatloo, B., Abapour, M., Shafiee, M., & Anvari-Moghaddam, A. (2021). Strategic operation of a virtual energy hub with the provision of advanced ancillary services in industrial parks. IEEE Transactions on Sustainable Energy, 12(4), 2062-2073. https://doi.org/10.1109/TSTE.2021.3079256
5. Jadidbonab M, Mohammadi-Ivatloo B, Marzband M, Siano P. Short-term self-scheduling of virtual energy hub plant within thermal energy market. IEEE Transactions on Industrial Electronics 2020;68:3124–36. https://doi.org/10.1109/TIE.2020.2978707
6. Li R, Wei W, Mei S, Hu Q, Wu Q. Participation of an energy hub in electricity and heat distribution markets: An MPEC approach. IEEE

Trans Smart Grid 2018;10:3641–53. https://doi.org/10.1109/TSG.2018.2833279
7. Marsyukov V, Zhuldassov N, Bagheri M, Lu M, Naderi MS, Abedinia O, et al. Simulation of Dynamic Inductive Wireless Charging Using Overhead Line. 2018 8th IEEE India International Conference on Power Electronics (IICPE), IEEE; 2018, p. 1–6. https://doi.org/10.1109/IICPE.2018.8709337
8. Zhang G, Wang J, Ren F, Liu Y, Dong F. Collaborative optimization for multiple energy stations in distributed energy network based on electricity and heat interchanges. Energy 2021;222:119987.
9. Kuspan B, Bagheri M, Abedinia O, Naderi MS, Jamshidpour E. The influence of electric vehicle penetration on distribution transformer ageing rate and performance. 2018 7th International Conference on Renewable Energy Research and Applications (ICRERA), IEEE; 2018, p. 313–8. https://doi.org/10.1109/ICRERA.2018.8566966
10. Mohammadi M, Talebpour F, Safaee E, Ghadimi N, Abedinia O. Small-scale building load forecast based on hybrid forecast engine. Neural Process Lett 2018;48:329–51. https://doi.org/10.1007/s11063-017-9723-2
11. Javadi MS, Lotfi M, Nezhad AE, Anvari-Moghaddam A, Guerrero JM, Catalão JPS. Optimal operation of energy hubs considering uncertainties and different time resolutions. IEEE Trans Ind Appl 2020;56:5543–52. https://doi.org/10.1109/TIA.2020.3000707
12. Oskouei MZ, Mirzaei MA, Mohammadi-Ivatloo B, Shafiee M, Marzband M, Anvari-Moghaddam A. A hybrid robust-stochastic approach to evaluate the profit of a multi-energy retailer in tri-layer energy markets. Energy 2021;214:118948.
13. Sobhani SO, Sheykhha S, Madlener R. An integrated two-level demand-side management game applied to smart energy hubs with storage. Energy 2020;206:118017.
14. Zhao N, Wang B, Bai L, Li F. Quantitative model of the electricity-shifting curve in an energy hub based on aggregated utility curve of multi-energy demands. IEEE Trans Smart Grid 2020;12:1329–45. https://doi.org/10.1109/TSG.2020.3023389
15. Eladl AA, El-Afifi MI, El-Saadawi MM, Sedhom BE. A review on energy hubs: Models, methods, classification, applications, and future trends. Alexandria Engineering Journal 2023;68:315–42. https://doi.org/10.1016/j.aej.2023.01.021
16. Mansouri SA, Ahmarinejad A, Javadi MS, Catalão JPS. Two-stage stochastic framework for energy hubs planning considering demand response programs. Energy 2020;206:118124.
17. Wang R, Cheng S, Zuo X, Liu Y. Optimal management of multi stakeholder integrated energy system considering dual incentive demand response and carbon trading mechanism. Int J Energy Res 2022;46:6246–63. https://doi.org/10.1002/er.7561
18. Nezhad AE, Rahimnejad A, Gadsden SA. Home energy management system for smart buildings with inverter-based air conditioning system. International Journal of Electrical Power & Energy Systems 2021;133:107230.
19. Shams MH, Shahabi M, MansourLakouraj M, Shafie-khah M, Catalão JPS. Adjustable robust optimization approach for two-stage operation of energy hub-based microgrids. Energy 2021;222:119894. https://doi.org/https://doi.org/10.1016/j.energy.2021.119894.
20. He C, Wu L, Liu T, Shahidehpour M. Robust co-optimization scheduling of electricity and natural gas systems via ADMM. IEEE Trans Sustain Energy 2016;8:658–70. https://doi.org/10.1109/TSTE.2016.2615104
21. Oskouei MZ, Mohammadi-Ivatloo B, Abapour M, Shafiee M, Anvari-Moghaddam A. Privacy-preserving mechanism for collaborative operation of high-renewable power systems and industrial energy hubs. Appl Energy 2021;283:116338.
22. Wang R, Cheng S, Zuo X, Liu Y. Optimal management of multi stakeholder integrated energy system considering dual incentive demand response and carbon trading mechanism. Int J Energy Res 2022;46:6246–63. https://doi.org/10.1002/er.7561
23. Abdolrasol MGM, Hannan MA, Mohamed A, Amiruldin UAU, Abidin IBZ, Uddin MN. An optimal scheduling controller for virtual power plant and microgrid integration using the binary backtracking search algorithm. IEEE Trans Ind Appl 2018;54:2834–44. https://doi.org/10.1109/TIA.2018.2797121

Nomenclature

AC	Air Conditioner
CG	Constraint Column
DEN	Distributed Energy Network
DRP	Demand Response Programs
EEM	Exchange Energy Management
EES	Electrical Energy Storage
EGDR	Electrical-Gas Demand Response

EH	Energy Hub
EMD	Empirical Mode Decomposition
EMM	Energy Management Mechanism
ESC	Electrical Shifting Curve
ESS	Energy Storage System
EV	Electrical Vehicles
HEMS	Home Energy Management System
HER	Heating to Electricity Ratio
HVPL	High Voltage Power Line
IEH	Industrial Energy Hub
IES	Integrated Energy System
MES	Multi Energy System
MILP	Mixed Integrated Linear Programming
MINLP	Mixed Integrated Non-Linear Programming
MPEC	Mathematical Program with Equilibrium Constraint
NGM	Natural Gas Market
PSO	Particle Swarm Optimization
PV	Photovoltaic
RES	Renewable Energy Source
STLF	Short Term Load Forecasting
TOU	Time of Use
VEH	Virtual Energy Hub
WPT	Wireless Power Transfer
Parameters	
$KN(i)$	Bus incidence matrices
$KN(h)$	Hub incidence matrices
$x(i,j)$	Reactance of transmission line
$PF(ij,t)^{Max}$	Maximum transmission line power flow
$\lambda^{Da}(t)$	Day ahead market price
$\lambda^{G}(t)$	Natural gas market price
$\rho(k)$	Maintenance cost coefficients of CHP unit
$\rho(q)$	Maintenance cost coefficients of P2H unit
$\rho^{Voc}(e)$	Operating and maintenance cost coefficients of compressor
$\rho^{Voe}(e)$	Operating and maintenance cost coefficients of expander
π_a	Probability of each scenario
$\lambda^{Re}(t)$	Real time market price
$PT^{Max}(h)$	Maximum amount of power transmitted from/to local energy market to/from industrial energy hub
Variables	
$P^{Da}(t)$	Scheduled power exchange between the virtual energy hub and day ahead market
$P(h,t)$	Power generated or consumed by industrial energy hub
$PF(ij,t)$	Power flow on transmission line
$\delta(i,t)$	Bus voltage angle
$\Delta P^{Re}(s,t)$	Adjusted power exchange between the virtual energy hub and real time market
$P^{Dis}(e,t)$	Scheduled power production by compressed air energy storage system in discharging mode
$P^{Si}(e,t)$	Scheduled power production by compressed air energy storage system in simple cycle
$P^{Ch}(e,t)$	Scheduled power production by compressed air energy storage system in charging mode
$PT^{In}(h,t)$	The amount of power transmitted from local energy market to industrial energy hub
$PT^{Out}(h,t)$	The amount of power transmitted to local energy market from industrial energy hub
$H^{Dis}(q,t)$	Scheduled heat production by P2H storage in discharging mode
$H^{Ch}(q,t)$	Scheduled heat production by P2H storage in charging mode
$H^{Dir}(q,t)$	Scheduled heat production by P2H storage in direct mode
$H(k,t)$	Scheduled heat production by CHP unit
$G^{CAES}(e,t)$	Natural gas consumed by CAES unit
$G^{CHP}(k,t)$	Natural gas consumed by CHP unit
$GC^{Wh}(t)$	Scheduled gas consumption by industrial energy hubs
$\Delta P(k,s,t)$	Adjusted power production by CHP unit

$\Delta H^{Dis}(q,s,t)$	Adjusted heat production by P2H storage in discharging mode
$\Delta H^{Ch}(q,s,t)$	Adjusted heat production by P2H storage in charging mode
$\Delta H^{Dir}(q,s,t)$	Adjusted heat production by P2H storage in direct mode
$R^{DLC}(t)$	The revenue from participation in direct load control program
$R^{ASDR}(t)$	The revenue from participation in ancillary service demand response program
$\beta(s,t)$	Dual variable in the robust optimization model
$u^{In}(h,t)$	Binary variables to indicate the status of industrial energy hub in transactive energy management
$u^{Out}(h,t)$	Binary variables to indicate the status of industrial energy hub in transactive energy management