

Digital Computational Knowledge-Based Expert System for Multi-Energy Community Coordination with Carbon Accounting and Risk Chance Inference-aware Decision Intelligence

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Urban multi-energy communities face coupled carbon regulations, volatile markets, and uncertain renewable generation, creating a need for decision systems that adapt beyond static optimization. This study develops an adaptive computational knowledge-based expert system for coordinating electricity, heat, gas, hydrogen, and carbon flows under uncertainty. The architecture combines carbon accounting and tiered carbon trading with a joint conditional value-at-risk and chance-constrained decision structure. It comprises three intelligent cores: an adaptive knowledge-updating layer for dynamic parameter refinement, a digital-twin-based state inference engine for interconnected energy hubs, and a synchronization core that aligns operational decisions with observed system conditions. Distributed coordination is implemented through a decentralized alternating direction method of multipliers framework, supporting scalable reasoning while preserving modularity. Carbon trading is treated as a policy-sensitive decision component, enabling reward–penalty signals to influence operational inference rather than acting as a simple linear cost. The integrated risk-aware engine evaluates feasible schedules under renewable uncertainty and market volatility. Simulations for an energy-intensive industrial community show that the system reduces total operating cost by nearly 20% relative to a carbon-trading-only configuration, lowers carbon emissions by more than 51% through coordinated carbon reuse, and cuts carbon-trading expenditures by approximately 80%. Renewable energy is fully absorbed under adaptive coordination. Sensitivity analysis further indicates that higher carbon prices activate risk-aware responses that simultaneously reduce emissions and improve operating economics.

Keywords: Multi-energy energy hubs, Carbon accounting mechanism, Digital twin, Chance-constrained programming, Conditional value-at-risk

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Nomenclature

t	Index representing discrete time intervals within the scheduling horizon	a_{MR}	Unit cost of methane production in the methanation reactor
s	Index of stochastic scenarios used in risk evaluation	a_{P2G}	Operating cost coefficient of the power-to-gas unit
i	Index for energy hubs or subsystems	a_{CCS}	Cost coefficient associated with carbon capture operation
a_{PV}	Unit operating cost coefficient of photovoltaic generation	$a_{grid, buy}$	Electricity purchasing price from the external grid
a_{WT}	Unit operating cost coefficient of wind generation	$a_{grid, sell}$	Electricity selling price to the external grid
a_{GT}	Linear fuel cost coefficient of the gas turbine	$a_{gas, buy}$	Natural gas purchasing price from gas network
b_{GT}	Quadratic fuel cost coefficient of the gas turbine	$a_{gas, sell}$	Natural gas selling price to gas network
a_{WHB}	Operating cost coefficient of the waste heat boiler	θ_g	Emission factor of industrial gas consumption

θ_e	Emission factor associated with GT electricity output
θ_h	Emission factor associated with WHB thermal output
α	Conversion or capture efficiency parameter
π_s	Probability weight of scenario s
λ	Weighting coefficient of CVaR term in the objective
η	Welfare or policy adjustment coefficient
σ_{PV}	Standard deviation of photovoltaic forecast error
σ_{WT}	Standard deviation of wind power forecast error
$\Phi^{-1}(\cdot)$	Inverse cumulative distribution function of standard normal
ρ	Penalty parameter in ADMM augmented Lagrangian
ϵ_{pri}	Primal feasibility tolerance in ADMM convergence
ϵ_{dual}	Dual feasibility tolerance in ADMM convergence
D_{SUEC}	Total carbon emission allowance of the energy community
$D_{d,g}$	Carbon allowance attributed to industrial gas demand
D_{CHP}	Carbon allowance allocated to CHP operation
κ	Tier-dependent reward or penalty coefficient in carbon trading
$P_{PV}(t)$	Scheduled photovoltaic power output at time t
$P_{WT}(t)$	Scheduled wind turbine power output at time t
$P_{GT}(t)$	Electrical output of the gas turbine at time t
$Q_{WHB}(t)$	Thermal output of the waste heat boiler at time t
$P_{P2G}(t)$	Electrical power consumed by the power-to-gas unit
$P_{CCS}(t)$	Electrical power consumed by the carbon capture system
$G_{MR}(t)$	Methane production rate of the methanation reactor
$P_{grid,buy}(t)$	Electricity purchased from the external grid
$P_{grid,sell}(t)$	Electricity sold to the external grid
$G_{gas,buy}(t)$	Natural gas purchased from the gas network
$G_{gas,sell}(t)$	Natural gas sold to the gas network
$\Delta P_d(t)$	Adjustable electrical load deviation under demand response
$\Delta Q_d(t)$	Adjustable thermal load deviation under demand response
$\Delta G_d(t)$	Adjustable gas load deviation under demand response
E_{SUEC}	Net actual carbon emissions of the energy community
ΔE	Deviation between actual emissions and carbon allowance
CVaR	Conditional value-at-risk of total operating cost

$\mathbf{x}_i$	Local decision vector of hub i in ADMM
$\mathbf{z}$	Consensus variable shared among hubs
λ_i	Dual variable associated with consensus constraint
$\mathbf{e}(t)$	Digital-twin tracking error at time t

1. Introduction

1.1. Background and Challenges

Energy-intensive urban communities are evolving toward integrated multi-energy structures in which electricity, heat, natural gas, hydrogen, and carbon flows are jointly managed. Decarbonization policies and carbon trading schemes have transformed operational environments from cost-centered dispatch to regulation-aware management. In parallel, digital monitoring platforms and supervisory systems have increased data availability across distributed assets. These developments require coordinated decision processes that extend beyond conventional optimization and move toward structured expert system management of interconnected energy infrastructures. Within such communities, sector coupling technologies, including combined heat and power, power-to-gas conversion, and carbon capture, create tightly linked operational states [1]. Carbon accounting mechanisms introduce allowance constraints and incentive signals that must be interpreted consistently across energy carriers [2]. Renewable variability propagates through electricity networks and conversion pathways, influencing hydrogen production and gas utilization. Multi-energy demand response adds further coordination complexity by linking electrical, thermal, and gas loads under time-varying price signals. Real-time supervisory measurements generate continuous streams of state information, yet translating these observations into consistent operational actions demands scalable decision support architectures capable of structured risk assessment and distributed coordination. The convergence of carbon regulation, cross-carrier coupling, and real-time data integration has elevated multi-energy community management into a domain that requires adaptive knowledge-based reasoning and coherent expert system frameworks for reliable coordination under uncertainty [3], [4].

1.2. Literature Review and Related Works

Based on the above discussion, considerable literature has examined the coordinated operation of multi-carrier energy systems, particularly in the context of renewable variability, market volatility, and emerging carbon constraints. Despite substantial progress, the understanding of how risk control, demand-side flexibility, and carbon accounting can be co-managed within one operational model remains limited. This motivates a structured synthesis that compares prior work along a small set of lenses: system boundary, uncertainty representation, risk metric, carbon mechanism, validation realism, and computational scalability.

In their work, researchers [5] developed a stochastic energy hub scheduling framework incorporating Conditional Value at Risk (CVaR) and load shifting, emphasizing the sensitivity of risk outcomes to scenario construction. Similarly, authors [6] investigated the robust operation of electricity–gas–heat hubs with cross-carrier demand response, demonstrating how robustness tuning directly impacts conservatism and system self-consumption. Along these lines, researchers [7] formulated an integrated energy hub with electric vehicle demand and compared different risk-handling paradigms, highlighting their dependence on probabilistic behavior assumptions.

Meanwhile, authors [8] examined low-carbon integrated energy system planning using CVaR for hydrogen production pathways, while researchers [9] extended this approach to biomass-assisted systems, both showing the sensitivity of outcomes to risk confidence levels and resource assumptions. In comparison, researchers in [10]

Table 1. Taxonomy of Innovation-Oriented Features in Recent Energy Community Studies

Ref	demand response	Chance-constrained	CVaR	Digital twin	Carbon accounting	P2G and CCUS	Decentralized ADMM	Policy welfare
[29]	✓	X	X	✓	X	X	✓	X
[6]	✓	X	✓	X	X	✓	X	X
[7]	✓	✓	X	X	✓	✓	X	✓
[8]	✓	✓	✓	✓	X	✓	✓	X
[9]	✓	✓	✓	✓	X	✓	X	X
[21]	✓	✓	✓	✓	✓	X	✓	✓
[11]	✓	✓	✓	✓	X	X	✓	✓
[12]	X	✓	✓	✓	✓	✓	✓	✓
[23]	✓	X	X	✓	✓	✓	✓	✓
[14]	X	X	✓	X	✓	✓	✓	✓
[25]	X	✓	X	X	✓	X	X	✓
[26]	✓	X	X	✓	X	X	✓	X
[16]	X	X	✓	X	X	✓	X	X
[20]	✓	✓	✓	✓	✓	✓	✓	✓
Present work	✓	✓	✓	✓	✓	✓	✓	✓

proposed a data-driven robust optimization model with polyhedral uncertainty sets and carbon footprint accounting, reducing conservatism, though still dependent on historical regimes.

Beyond risk modeling, authors [11] proposed a decentralized distributionally robust chance-constrained management approach for electricity–hydrogen systems, while researchers [12] applied a similar chance-constrained structure to electro-hydrogen microgrids, both illustrating the computational and modeling burdens associated with distributional ambiguity. In a related direction, researchers [13] developed a chance-constrained energy management framework for industrial microgrids under demand response, emphasizing the subjectivity of robustness calibration.

With respect to carbon-oriented mechanisms, authors [14] introduced tiered carbon trading within rolling dispatch across multiple time horizons, while researchers [15] further analyzed its intraday operational implications. In the meantime, researchers [16] proposed coordinated multi-energy trading with explicit carbon emission flow accounting, while authors [24] integrated power-to-gas with stepped carbon trading, both highlighting the influence of regulatory assumptions. At the community level, researchers [17] and authors [18] analyzed park-level integrated energy systems with ladder-type carbon trading and internal carbon reuse, showing their dependence on policy parameterization and feasible utilization rates.

From a digitalization perspective, authors [19] introduced a digital twin for interconnected energy hubs to support coordinated operation, while researchers [20] applied digital-twin-assisted real-time energy management at the building level, both highlighting the need for data integration. Expanding on data-driven approaches, researchers [21] developed stochastic robust scheduling for energy clusters, and finally, the authors [22] proposed transfer-learning-based multi-energy load forecasting, with performance closely tied to data quality and domain stability.

On market interaction and demand response, the authors [23] investigated regional integrated scheduling with multi-load demand [24] response to reduce carbon trading costs, while researchers [25] examined low-carbon demand response under dynamic pricing. In decentralized settings, researchers [26] proposed a distributed optimization for energy and carbon coordination among multiple communities, and the authors [27] formulated a bi-level framework for demand response participation under risk-adjusted behavior. Complementarily, researchers analyzed battery storage optimization for sustainable energy communities, and authors [28] focused on enterprise-oriented demand response, both demonstrating strong dependence on tariff design and participation rules.

Table 1 presents a comparative taxonomy of fifteen recent original research studies and the present work.

The reviewed studies collectively reveal that progress has been strong in isolated dimensions, but cross-dimension coupling remains incomplete. One gap concerns the joint treatment of feasibility risk and cost risk under uncertain renewables, especially when uncertainty is correlated and policy variables influence feasible operating regions; this gap is visible across distributionally robust chance constraints and CVaR-constrained scheduling studies [30]. A second gap involves carbon accounting fidelity: carbon mechanisms are often modeled through tiered pricing or trading constructs, while carbon traceability frameworks demand measurements and assumptions that are not yet integrated into operational risk models [31]. A third gap appears at the implementation boundary, where decentralized or multi-domain coordination methods require communication, interoperability, and governance arrangements that are typically outside the optimization model, limiting claims of operational scalability [32]. Finally, market-oriented community models capture strategic behavior and welfare allocation, yet they tend to abstract away multi-carrier physics and data constraints, leaving an unresolved tension between economic realism and operational feasibility [33]. This indicates a pressing need for an integrated approach that coordinates multi-carrier conversions, demand response, and carbon mechanisms under uncertainty, while remaining computationally scalable and grounded in assumptions about data availability.

1.3. Main Contributions

To fill the persistent gaps in the coordinated operation of multi-carrier urban energy systems under uncertainty, this study develops an adaptive computational knowledge-based expert system for coordinated management of multi-energy communities operating under carbon accounting and market uncertainty. The contribution moves beyond a conventional scheduling formulation by structuring the problem as an expert decision architecture in which energy coordination, carbon regulation, and risk inference are embedded within an integrated reasoning framework. The system is designed to support coordinated operational management across electricity, heat, gas, hydrogen, and carbon domains while maintaining consistency with regulatory constraints and real-time supervisory data.

The proposed framework organizes multi-carrier coordination through a knowledge-based representation of interconnected energy hubs. Within this architecture, carbon accounting is modeled as an internalized regulatory module based on a tiered reward–penalty trading mechanism. Risk-aware decision intelligence is established through a joint chance-constrained and Conditional Value-at-Risk structure that enables probabilistic feasibility control and downside

risk assessment under renewable variability and price fluctuations. Demand response is incorporated as a multi-domain flexibility component that captures adaptation of electrical, thermal, and gas loads within a unified reasoning environment.

A digital twin-enabled real-time state inference engine is embedded as an intelligent synchronization core, aligning supervisory measurements with the computational expert model. An adaptive knowledge-updating layer refines selected operational parameters in response to observed deviations, thereby enabling dynamic adjustment of decision rules. To ensure scalable coordination across distributed hubs, the expert system employs a decentralized solution structure based on the Alternating Direction Method of Multipliers, supporting distributed inference while preserving consistency of shared variables.

The main contributions of this research are outlined as follows:

(1) **Knowledge-Based Multi-Energy Demand Response Coordination:** A structured knowledge representation layer is developed to model electrical, thermal, and gas load flexibility within a unified expert decision environment. This module enables coordinated multi-carrier demand adaptation under dynamic price signals and carbon accounting constraints, supporting intelligent operational management rather than isolated load shifting.

(2) **Risk-Inference-Driven Chance-Constrained Decision Intelligence:** A probabilistic reasoning structure is established through the integration of chance constraints and Conditional Value-at-Risk within the expert system's inference engine. This component performs structured risk assessment under renewable variability and market uncertainty, enabling coherent decision intelligence across interconnected energy hubs.

(3) **Digital Twin-Enabled Real-Time State Inference and Carbon Coordination:** A digital twin layer functions as a real-time state inference engine that synchronizes supervisory measurements with the computational expert model. This intelligent synchronization core maintains consistency between carbon accounting, energy conversion states, and operational decisions across electricity, heat, gas, hydrogen, and carbon subsystems.

(4) **Distributed Computational Expert Coordination via ADMM:** A decentralized computational reasoning framework based on the Alternating Direction Method of Multipliers is implemented to support scalable expert system coordination. This distributed architecture aligns with the physical separation of energy hubs while preserving consensus across shared decision variables and carbon-regulated constraints.

The remainder of the paper is organized as follows. Section 2 presents the proposed model, Section 3 describes the risk-aware solution method, Section 4 discusses the results, and Section 5 concludes the study.

2. Methodology

2.1. Sustainable Urban Energy Community Framework

The proposed SUEC sustainable urban energy community is structured as an integrated energy hub architecture (see Figure 1), in which electricity, gas, heat, hydrogen, and carbon are coordinated through dedicated hubs rather than treated as isolated subsystems. The framework is designed for energy-intensive urban industries and jointly supplies electricity, heat, and natural gas through coupled conversion, storage, and exchange pathways.

At the upstream level, the renewable energy hub aggregates power generated from WT and PV units. Renewable electricity is delivered to the electrical hub or routed to the P2G unit, enabling cross-carrier flexibility. The electrical hub manages electricity exchanges among renewable sources, the CHP system, the external power grid, and end-use electrical loads, and supports electricity

flows to conversion units when required.

The gas hub coordinates natural gas interactions among the gas grid, the P2G, and gas loads. Methane produced through the hydrogen pathway is injected into this hub, reducing dependence on external gas supply. In parallel, the hydrogen hub serves as an intermediate energy-carrier platform, receiving hydrogen from the P2G unit and supplying it to the methanation reactor, thereby linking the electricity, hydrogen, and gas subsystems. Thermal energy is organized through the heat hub, which collects heat generated by the CHP system, including the GT and WHB, and distributes it to heat loads. This hub enables coordinated heat recovery and allocation across industrial processes. Carbon flows are centralized in the carbon hub, which receives captured carbon dioxide from the CCUS unit. Captured CO₂ is either routed to the methanation reactor for synthetic methane production or managed under the CET mechanism. The CET unit interfaces with the carbon hub to evaluate emissions and apply the tiered reward-penalty carbon trading scheme, directly linking operational decisions to carbon costs or benefits.

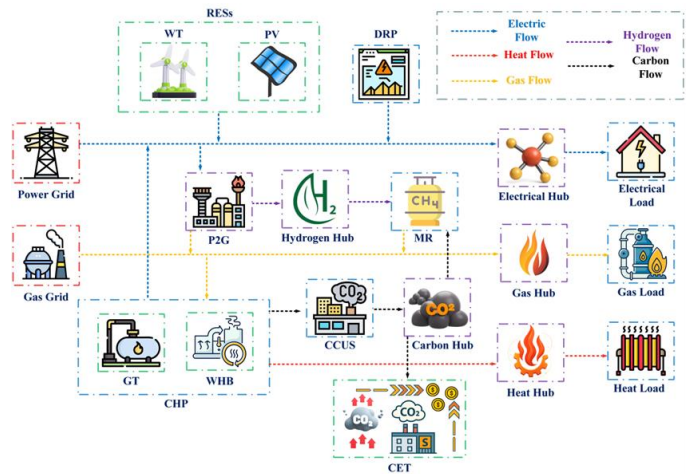


Fig. 1. Energy-hub-based framework of the SUEC considering a tiered reward-penalty carbon trading scheme.

2.2. Tiered Reward-Penalty Carbon Trading Model

The proposed carbon trading model is structured around three tightly connected components: the carbon allowance, the actual emission level, and a tiered reward-penalty mechanism. The carbon allowance is exogenously defined by the government. If the energy community's actual emissions are below its allocated allowance, surplus permits can be sold; if emissions exceed the allowance, additional permits must be purchased. The tiered structure is designed to decrease compliance costs under low-emission operation and to impose progressively higher penalties as emissions rise, which is consistent with the dual-carbon policy objective.

2.2.1. Carbon Allowance and Emission Accounting

Carbon dioxide emissions within the sustainable urban energy community primarily arise from industrial gas consumption and CHP operation, while electricity purchased from the external power grid is excluded from the accounting boundary. Accordingly, the total carbon allowance of the energy system, denoted as D_{SUEC} , is defined in Eq. (1) as the sum of the allowance associated with industrial gas consumption $D_{d,g}$ and the allowance related to CHP operation D_{CHP} .

$$D_{SUEC} = D_{d,g} + D_{CHP} \quad (1)$$

Equation (2) specifies the allowance attributed to industrial gas consumption. It aggregates over the scheduling horizon T , the product of the gas-related emission coefficient and the industrial gas demand $G_d(t)$.

$$D_{d,g} = \theta_g \sum_{t=1}^T G_d(t) \quad (2)$$

Eq. (3) describes the carbon allowance assigned to the CHP unit. The allowance is calculated as the sum of emissions associated with electricity production from the gas turbine $P_{GT}(t)$ and heat recovery from the waste heat boiler $Q_{WHB}(t)$, weighted by the corresponding emission coefficients. This equation links the CHP operating levels directly to its allocated carbon quota.

$$D_{CHP} = \theta_g \sum_{t=1}^T [\theta_e P_{GT}(t) + \theta_h Q_{WHB}(t)] \quad (3)$$

Actual emissions are then determined by considering both emission sources and emission mitigation technologies. Eq. (4) calculates the actual emissions from industrial gas consumption by applying a quadratic emission function to gas demand, capturing nonlinearity in emission behavior at different operating levels. Eq. (5) represents the actual emissions generated by the CHP system, expressed as a function of gas turbine power output and waste heat boiler heat production.

$$E_{SUEC} = E_{d,g} + E_{CHP} - E_{CO_2} \quad (4)$$

$$E_{d,g} = \sum_{t=1}^T (a_1 G_d(t)^2 + b_1 G_d(t) + c_1) \quad (5)$$

Carbon dioxide mitigation is incorporated through P2G, CCUS, and the methanation reactor. Eq. (6) quantifies the amount of carbon dioxide consumed by the P2G process, where captured CO_2 is reused as an input to synthetic fuel production.

$$E_{CHP} = \sum_{t=1}^T \alpha_{CHP} [P_{GT}(t) + a_2 Q_{WHB}(t) + b_2] \quad (6)$$

By combining the emission sources and the CO_2 consumption pathways, Eq. (7) defines the net actual carbon emissions of the energy community.

$$E_{CO_2} = \sum_{t=1}^T \alpha_{CSS} P_{P2G}(t) \quad (7)$$

2.2.2. Tiered reward–penalty mechanism

The deviation between actual emissions and the allocated carbon allowance is defined in Equation (8) as:

$$\Delta E = E_{SUEC} - D_{SUEC} \quad (8)$$

$$F_{CO_2} = \begin{cases} -u(\kappa_1 + f)d - u(\kappa_1 + \kappa_5 f)(-\Delta E - d), & -2d \leq \Delta E \leq -d, \\ -u(\kappa_1 + f)(-\Delta E), & -d \leq \Delta E \leq 0, \\ u\Delta E, & 0 \leq \Delta E \leq d, \\ ud + u(\kappa_1 + g)(\Delta E - d), & d \leq \Delta E \leq 2d, \\ u(\kappa_2 + g)d + u(\kappa_1 + \kappa_2 g)(\Delta E - \kappa_2 d), & 2d \leq \Delta E \leq 3d, \\ u(\kappa_3 + \kappa_3 g)d + u(\kappa_1 + \kappa_3 g)(\Delta E - \kappa_3 d), & 3d \leq \Delta E \leq 4d \end{cases}$$

where a positive value indicates excess emissions and a negative value indicates surplus allowance. Based on this deviation, the tiered reward–penalty function is formulated in Eq. (9). This piecewise function assigns different marginal reward or penalty rates depending on the magnitude of ΔE . When emissions are below the allowance, the system receives economic rewards that increase as

the emission reduction deepens over predefined intervals. Conversely, when emissions exceed the allowance, penalties are imposed and escalate stepwise as the excess grows.

Figure 2 provides a graphical illustration of the tiered reward–penalty mechanism. Negative deviations, where emissions remain below the allowance, result in negative costs, indicating economic rewards. As emissions exceed the allowance, the carbon trading cost becomes positive and increases in a stepwise manner across successive emission intervals.

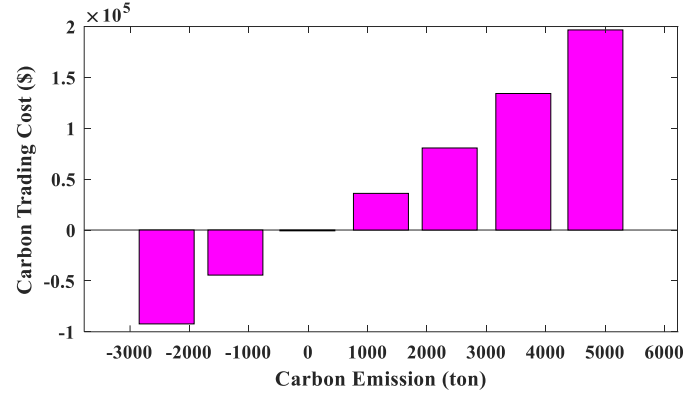


Fig. 2. Carbon trading cost as a function of emission deviation under the tiered reward–penalty mechanism.

2.3. Optimization Problem

The objective of the sustainable urban energy community is to minimize the total daily operating cost over the scheduling horizon T . This cost function aggregates all major economic components associated with energy production, conversion, curtailment, and external energy exchange, while internalizing carbon-related costs through the previously defined reward–penalty mechanism.

The first group of terms represents operation and maintenance costs of system components. Eqs. (10) and (11) define the operating costs of PV units and WT, respectively, calculated as the product of their unit cost coefficients and their corresponding power outputs over time. Eq. (12) captures the operating cost of the MR, which is proportional to its methane production level. Eq. (13) represents the cost associated with CCUS, linked directly to the amount of captured CO_2 . Eq. (14) accounts for the operating cost of the P2G unit as a function of its electricity input.

$$F_{PV} = \sum_{t=1}^T a_{PV} P_{PV}(t) \quad (10)$$

$$F_{WT} = \sum_{t=1}^T a_{WT} P_{WT}(t) \quad (11)$$

$$F_{MR} = \sum_{t=1}^T a_{MR} G_{MR}(t) \quad (12)$$

$$F_{CCS} = \sum_{t=1}^T a_{CCS} P_{CSS}(t) \quad (13)$$

$$F_{P2G} = \sum_{t=1}^T a_{P2G} P_{P2G}(t) \quad (14)$$

For the combined heat and power system, Eq. (15) models the fuel cost of the GT using a quadratic function of electrical output, reflecting nonlinear fuel consumption characteristics. Eq. (16)

specifies the operating cost of the WHB, proportional to its heat output.

$$F_{GT} = \sum_{t=1}^T (a_{GT} P_{GT}(t)^2 + b_{GT} P_{GT}(t)) \quad (15)$$

$$F_{WHB} = \sum_{t=1}^T a_{WHB} Q_{WHB}(t) \quad (16)$$

The second cost component addresses renewable energy curtailment penalties. Eqs. (17)-(18) define penalty costs for curtailed photovoltaic and wind power, respectively.

$$F_{c,PV} = \sum_{t=1}^T a_{c,PV} (P_{PV}(t) - P_{PV,u}(t)) \quad (17)$$

$$C^{curt} = \sum_{t \in T} \sum_{s \in S} \lambda_t^{curt} \left[\max(0, P_{t,s}^{ren} - P_{t,s}^{util}) \right] \quad (18)$$

The third component represents interaction costs with external energy networks. Eq. (19) models the net cost of electricity exchange with the power grid as the difference between electricity purchasing and selling revenues over time. Similarly, Eq. (20) defines the net cost of natural gas transactions with the gas grid, accounting for both purchases and sales.

$$F_{grid} = \sum_{t=1}^T (a_{grid,buy} P_{grid,buy}(t) - a_{grid,sell} P_{grid,sell}(t)) \quad (19)$$

$$F_{gas} = \sum_{t=1}^T (a_{gas,buy} G_{gas,buy}(t) - a_{gas,sell} G_{gas,sell}(t)) \quad (20)$$

Finally, all cost components are integrated in Eq. (21) to construct the unified objective function of the sustainable urban energy community. The formulation minimizes the expected total operating cost across all scenarios while explicitly accounting for downside risk through a Conditional Value-at-Risk (CVaR) term. This risk-aware structure penalizes unfavorable cost realizations beyond a specified confidence level, thereby enhancing the robustness of scheduling decisions under uncertainty. In parallel, a welfare-related component is incorporated to balance purely cost-driven optimization against broader system-level performance considerations. As a result, the objective function jointly captures operational expenditures, renewable curtailment effects, energy trading interactions with external networks, carbon-related costs, and risk-adjusted welfare outcomes within a single coherent optimization framework.

$$\begin{aligned} \min F_{SUEC}^{PW-CVaR} &= \sum_{s \in S} \pi_s F^{(s)} + \lambda_{CVaR} \\ &\left(\eta + \frac{1}{1-\alpha} \sum_{s \in S} \pi_s \xi_s \right) - \omega_{PW} \sum_{s \in S} \pi_s W_{PW}^{(s)} \\ \xi_s &\geq 0, \quad \forall s \in S \\ \xi_s &\geq 0, \quad \forall s \in S \\ F^{(s)} &= F_{c,PV}^{(s)} + F_{c,WT}^{(s)} + F_{grid}^{(s)} + F_{gas}^{(s)} + F_{PV}^{(s)} + F_{WT}^{(s)} + \\ &F_{MR}^{(s)} + F_{CCS}^{(s)} + F_{P2G}^{(s)} + F_{GT}^{(s)} + F_{WHB}^{(s)} + F_{CO_2}^{(s)} \end{aligned} \quad (21)$$

2.4. Constraints

The integrated energy system simultaneously supplies electricity, heat, and natural gas loads. Its operation therefore

requires a consistent representation of energy balance relations and clear limits on interactions with external electricity and gas networks.

The interaction constraints with the electricity grid and the gas network are defined first. Eqs (22)-(23) enforce mutually exclusive electricity buying and selling actions and restrict exchanged power within allowable limits. Similarly, Eqs. (24)-(25) impose the same conditions on natural gas transactions.

$$P_{grid,buy}(t) P_{grid,sell}(t) = 0 \quad (22)$$

$$P_{grid,min} \leq P_{grid}(t) \leq P_{grid,max} \quad (23)$$

$$G_{gas,buy}(t) G_{gas,sell}(t) = 0 \quad (24)$$

$$G_{gas,min} \leq G_{gas}(t) \leq G_{gas,max} \quad (25)$$

The electricity balance equation, given in Eq. (26), ensures that the total electricity supply from photovoltaic units, wind turbines, gas turbines, and grid purchases exactly meets electricity demand, including consumption by the power-to-gas unit, the carbon capture system, and electrical loads, as well as grid exports.

$$\begin{aligned} P_{PV}(t) + P_{WT,u}(t) + P_{GT}(t) + P_{grid,buy}(t) &= P_{P2G}(t) + \\ P_{CCS}(t) + (P_d(t) - \Delta P_d(t)) &+ P_{grid,sell}(t) \end{aligned} \quad (26)$$

To capture demand-side flexibility, the electrical load is modeled as an adjustable quantity through a demand response mechanism. This formulation allows partial load shifting over the scheduling horizon while preserving overall energy balance, thereby enhancing system flexibility without altering the carbon accounting structure.

The heat balance, formulated in Eq. (27), relates the thermal output of the waste heat boiler to an adjustable heat demand that incorporates demand response capability. Rather than assuming fully inelastic consumption, the formulation allows part of the thermal load to be reduced or temporally shifted, enabling flexible utilization of recovered heat while preserving overall thermal balance across the scheduling horizon. Similarly, the natural gas balance in Eq. (28) ensures consistency between gas supply and gas consumption while explicitly accounting for demand-side flexibility. Methane produced by the methanation reactor and gas procured from the external gas grid jointly meet gas sales to the grid, the gas turbine's fuel requirements, and an adjustable internal gas demand subject to demand response.

$$\begin{aligned} Q_{WHB}(t) &= Q_d(t) - \Delta Q_d(t), \quad \forall t \\ 0 &\leq \Delta Q_d(t) \leq \Delta Q_d^{max}, \quad \forall t \\ \sum_{t=1}^T \Delta Q_d(t) &= 0 \end{aligned} \quad (27)$$

$$\begin{aligned} G_{MR}(t) + G_{gas,buy}(t) &= G_{gas,sell}(t) + G_{GT}(t) + \\ (G_d(t) - \Delta G_d(t)), \quad \forall t \\ 0 &\leq \Delta G_d(t) \leq \Delta G_d^{max}, \quad \forall t \\ \sum_{t=1}^T \Delta G_d(t) &= 0 \end{aligned} \quad (28)$$

3. Integrated Risk-Aware and Data-Driven solution method

3.1. Digital-Twin Synchronization

This subsection adds a digital-twin layer to the proposed SUEC energy-hub architecture so that scheduling decisions remain consistent with the measured operation of the electrical hub, gas hub, heat hub, hydrogen hub, and carbon hub.

At each time step, the multi-carrier hub state is represented by a stacked state vector,

$$\mathbf{x}(t) = \begin{bmatrix} P_{PV}(t) & P_{WT,u}(t) & P_{GT}(t) & Q_{WHB}(t) & P_{P2G}(t) \\ P_{CCS}(t) & G_{MR}(t) & G_{gas,buy}(t) & G_{gas,sell}(t) \\ P_{grid,buy}(t) & P_{grid,sell}(t) \end{bmatrix} \quad (29)$$

The measurement stream (smart meters and supervisory signals) is mapped to the state through a linear observation model,

$$\mathbf{y}(t) = \mathbf{H}\mathbf{x}(t) + \mathbf{v}(t) \quad (30)$$

The digital twin propagates the virtual state using a linear time-step evolution model driven by the hub control vector,

$$\mathbf{x}(t+1) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{w}(t) \quad (31)$$

A measurement-update step corrects the predicted state using the innovation between $\mathbf{y}(t)$ and its virtual counterpart,

$$\mathbf{x}(t) = \mathbf{x}(t) + \mathbf{K}(t)(\mathbf{y}(t) - \mathbf{H}\mathbf{x}(t)) \quad (32)$$

The gain matrix is computed from the predicted error covariance and measurement covariance,

$$\mathbf{K}(t) = \mathbf{P}^-(t)\mathbf{H}^\top (\mathbf{H}\mathbf{P}^-(t)\mathbf{H}^\top + \mathbf{R})^{-1} \quad (33)$$

The covariance propagation is updated at each step to reflect process uncertainty and the applied controls,

$$\mathbf{P}^-(t+1) = \mathbf{A}\mathbf{P}(t)\mathbf{A}^\top + \mathbf{Q} \quad (34)$$

The synchronization mismatch that drives re-planning is defined as the innovation residual,

$$\mathbf{e}(t) = \mathbf{y}(t) - \mathbf{H}\mathbf{x}(t) \quad (35)$$

To embed digital-twin consistency into the daily scheduling problem, a tracking penalty is added to the cost function in Eq. (21), producing a digital-twin augmented objective,

$$\min F_{DT} = F + \lambda_{DT} \sum_{t=1}^T \mathbf{e}(t)^\top \mathbf{e}(t) \quad (36)$$

In parallel, the twin updates selected model parameters online through a recursive estimator,

$$\boldsymbol{\beta}(t) = \boldsymbol{\beta}(t-1) + \mathbf{L}(t)(\mathbf{z}(t) - \boldsymbol{\phi}(t)^\top \boldsymbol{\beta}(t-1)) \quad (37)$$

The adaptive gain is computed as,

$$\mathbf{L}(t) = \mathbf{S}(t-1)\boldsymbol{\phi}(t)(1 + \boldsymbol{\phi}(t)^\top \mathbf{S}(t-1)\boldsymbol{\phi}(t))^{-1} \quad (38)$$

3.2. Uncertainty Modeling via Chance-Constrained Programming

The operation of the SUEC is exposed to inherent uncertainty due to the stochastic nature of renewable energy generation, particularly photovoltaic and wind power. Forecast errors associated with solar irradiance and wind speed propagate through the electrical hub, affect conversion units, and influence both operational costs and carbon outcomes. To ensure robust and reliable scheduling decisions, uncertainty in renewable generation is addressed through a chance-constrained programming framework.

Let the actual available photovoltaic and wind power be represented as stochastic processes around their corresponding forecasts. Renewable output realizations are modeled as random

variables subject to probabilistic bounds, ensuring system feasibility is preserved at a predefined confidence level.

The uncertain available photovoltaic power is expressed as,

$$P_{PV,u}(t) = \bar{P}_{PV}(t) + \varepsilon_{PV}(t) \quad (39)$$

and the uncertain available wind power is given by,

$$P_{WT,u}(t) = \bar{P}_{WT}(t) + \varepsilon_{WT}(t) \quad (40)$$

To guarantee that the scheduled utilization of renewable generation does not exceed its uncertain availability, chance constraints are imposed. For photovoltaic generation, the probabilistic feasibility condition is defined as,

$$\mathbb{P}(P_{PV}(t) \leq P_{PV,u}(t)) \geq \alpha_{PV} \quad (41)$$

and similarly, for wind generation,

$$\mathbb{P}(P_{WT,u}(t) \leq P_{WT,u}(t)) \geq \alpha_{WT} \quad (42)$$

These probabilistic constraints are reformulated into deterministic equivalents using distributional properties of the forecast errors. Accordingly, the photovoltaic chance constraint is converted into,

$$P_{PV}(t) \leq \bar{P}_{PV}(t) - \Phi^{-1}(\alpha_{PV})\sigma_{PV}(t) \quad (43)$$

and the wind chance constraint becomes,

$$P_{WT,u}(t) \leq \bar{P}_{WT}(t) - \Phi^{-1}(\alpha_{WT})\sigma_{WT}(t) \quad (44)$$

Curtailment decisions are then implicitly governed by these bounds, ensuring that the scheduled renewable utilization respects uncertainty while minimizing expected curtailment penalties. The resulting feasible renewable power injected into the electrical hub satisfies,

$$P_{PV}(t) + P_{WT,u}(t) \leq P_{RES}^{\max}(t) \quad (45)$$

with the aggregate renewable uncertainty propagating to downstream conversion units. In particular, the electricity supplied to the power-to-gas unit under uncertainty is constrained by,

$$\mathbb{P}(P_{P2G}(t) \leq P_{PV,u}(t) + P_{WT,u}(t)) \geq \alpha_{RES} \quad (46)$$

The above constraint admits the following deterministic form,

$$P_{P2G}(t) \leq \bar{P}_{PV}(t) + \bar{P}_{WT}(t) - \Phi^{-1}(\alpha_{RES}) \sqrt{\sigma_{PV}^2(t) + \sigma_{WT}^2(t)} \quad (47)$$

To maintain consistency with the digital-twin synchronization layer, the uncertainty-aware renewable dispatch is further aligned with the corrected state estimate,

$$P_{PV}(t) + P_{WT,u}(t) \leq \hat{P}_{RES}(t) \quad (48)$$

Figure 3 illustrates the interval-based representation adopted for distributed renewable generation.

3.3. Solution Method via Alternating Direction Method of Multipliers

The SUEC scheduling problem couples multiple hubs through cross-carrier conversions and network interactions, which creates dense linking constraints and increases computational burden when solved in a monolithic form. To obtain a scalable solution structure consistent with the energy-hub architecture in Fig. 1 and the uncertainty-aware constraints, the optimization is reformulated into a consensus form and solved using the ADMM.

Let the decision vector be split into hub-specific blocks and a set of consensus variables that carry all coupling quantities (e.g.,

exchanges and shared injections). The decentralized formulation is expressed as

$$\min_{\{\mathbf{x}_i\}, \mathbf{z}} \sum_{i \in \mathcal{H}} f_i(\mathbf{x}_i) \quad \text{s.t.} \quad \mathbf{x}_i \in \mathcal{X}_i, \mathbf{A}_i \mathbf{x}_i = \mathbf{z}, \forall i \in \mathcal{H} \quad (49)$$

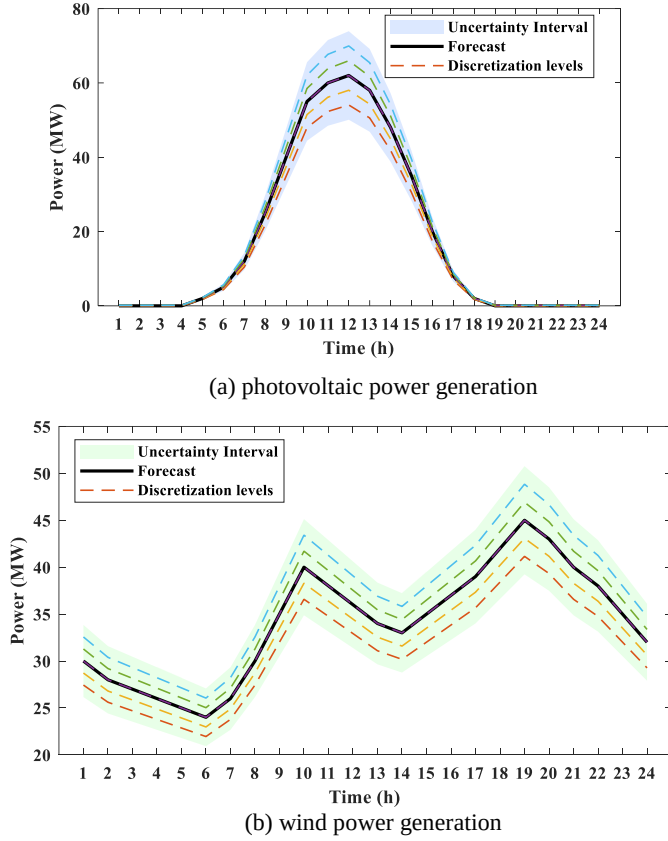


Fig. 3. Interval-based discretization of distributed renewable generation under uncertainty.

The augmented Lagrangian of Eq. (49) is written as

$$\mathcal{L}_\rho(\{\mathbf{x}_i\}, \mathbf{z}, \{\lambda_i\}) = \sum_{i \in \mathcal{H}} f_i(\mathbf{x}_i) + \sum_{i \in \mathcal{H}} \lambda_i^\top (\mathbf{A}_i \mathbf{x}_i - \mathbf{z}) + \frac{\rho}{2} \sum_{i \in \mathcal{H}} \|\mathbf{A}_i \mathbf{x}_i - \mathbf{z}\|_2^2 \quad (50)$$

At iteration $k+1$, each hub updates its local variables in parallel by solving

$$\mathbf{x}_i^{k+1} = \arg \min_{\mathbf{x}_i \in \mathcal{X}_i} \left\{ f_i(\mathbf{x}_i) + (\lambda_i^k)^\top (\mathbf{A}_i \mathbf{x}_i - \mathbf{z}^k) + \frac{\rho}{2} \|\mathbf{A}_i \mathbf{x}_i - \mathbf{z}^k\|_2^2 \right\}, \quad \forall i \in \mathcal{H} \quad (51)$$

The consensus update is then obtained from

$$\mathbf{z}^{k+1} = \arg \min_{\mathbf{z}} \sum_{i \in \mathcal{H}} \left\{ -(\lambda_i^k)^\top \mathbf{z} + \frac{\rho}{2} \|\mathbf{A}_i \mathbf{x}_i^{k+1} - \mathbf{z}\|_2^2 \right\} \quad (52)$$

which yields the closed-form averaging step

$$\mathbf{z}^{k+1} = \frac{1}{|\mathcal{H}|} \sum_{i \in \mathcal{H}} \left(\mathbf{A}_i \mathbf{x}_i^{k+1} + \frac{1}{\rho} \lambda_i^k \right) \quad (53)$$

The dual variables are updated by

$$\lambda_i^{k+1} = \lambda_i^k + \rho (\mathbf{A}_i \mathbf{x}_i^{k+1} - \mathbf{z}^{k+1}), \quad \forall i \in \mathcal{H} \quad (54)$$

Convergence is monitored using the primal and dual residuals,

$$\mathbf{r}^{k+1} = \{\mathbf{A}_i \mathbf{x}_i^{k+1} - \mathbf{z}^{k+1}\}_{i \in \mathcal{H}} \quad (55)$$

and iterations terminate when $\|\mathbf{r}^{k+1}\|_2 \leq \epsilon_{\text{pri}}$ and $\|\mathbf{s}^{k+1}\|_2 \leq \epsilon_{\text{dual}}$. In this structure, the local feasible sets $\mathcal{X}_i$ embed all hub-internal constraints (including the balance relations and interaction limits), while coupling is enforced only through $\mathbf{A}_i \mathbf{x}_i = \mathbf{z}$, which matches the physical coordination logic of the energy-hub architecture and the uncertainty-aware renewable dispatch constraints. Fig 4 shows a decentralized optimization procedure based on the ADMM.

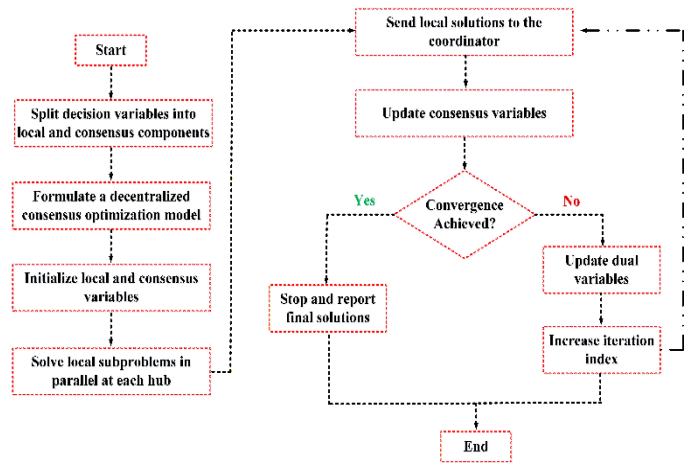


Fig. 4. Decentralized ADMM-Based Solution Procedure for Network-Coupled Energy Hubs

4. Results and Discussion

This study investigates an SUEC configured around a large-scale energy-intensive industrial complex, adapted from the benchmark system reported in [26]. The scheduling horizon is defined on an hourly basis over a representative daily cycle. The proposed optimization framework is implemented in Python using the Pyomo modeling environment and solved with the CPLEX solver.

To evaluate both the economic viability and environmental effectiveness of the proposed framework, a set of comparative scenarios is constructed as outlined in Table 2. These scenarios are designed to isolate the impacts of power-to-gas conversion, carbon capture and storage, carbon trading, and incentive-based policy mechanisms on system operation. Forecasted profiles of solar and wind power generation, together with electricity, heat, and gas demands of the industrial complex, are illustrated in Fig. 5. Input datasets and simulation configurations are documented in Tables A.1-A.6 in the Appendix. All remaining technical and economic parameters are reported in [34], [35], [36] and are therefore omitted here for brevity.

Based on Table 2, four scenarios are examined:

Scenario 1: Baseline case without power-to-gas conversion and carbon capture and storage.

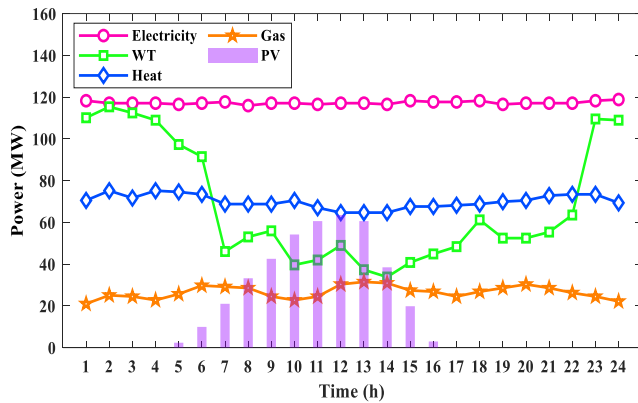
Scenario 2: Integration of power-to-gas and carbon capture and storage, without carbon trading.

Scenario 3: Inclusion of carbon trading, without an incentive-based reward-penalty mechanism.

Scenario 4: Full configuration incorporating all technologies and the reward-penalty mechanism.

Table 2. Scenario Definitions for Sustainable Energy System Scheduling

Feature / Scenario	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Power-to-Gas technology	No	Yes	Yes	Yes
Carbon capture and storage	No	Yes	Yes	Yes
Carbon trading mechanism	No	No	Yes	Yes
Incentive-based reward–penalty scheme	No	No	No	Yes

**Fig. 5.** Forecasted Renewable Generation and Energy Demand Profiles of the Industrial Complex

4.1. Economic and Environmental Performance Analysis

Figure 6 compares the photovoltaic utilization rate, wind utilization rate, carbon emissions, carbon trading costs, and total system costs across the four scenarios, providing a comprehensive assessment of renewable energy efficiency, environmental impacts, and economic performance.

As shown in Fig. 6, Scenario 1 exhibits limited utilization of renewable energy due to the absence of power-to-gas conversion. Excess solar and wind generation cannot be fully absorbed by the system, highlighting the role of power-to-gas technology in mitigating renewable curtailment and enhancing operational flexibility. Moreover, the lack of carbon capture and storage leads to the highest level of carbon emissions among all scenarios.

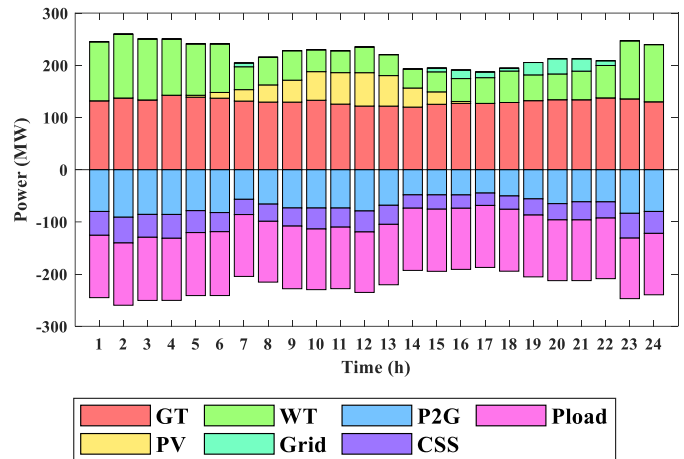
In Scenario 2, the deployment of carbon capture and storage substantially reduces carbon emissions compared to Scenario 1. However, because carbon trading is not implemented, the overall system cost remains relatively high, indicating that emission reduction alone does not guarantee economic efficiency.

Scenario 3 introduces carbon trading while maintaining similar emission levels to Scenario 2. The monetization of emission reductions through carbon trading results in a pronounced decrease in total system costs, demonstrating the financial effectiveness of market-based carbon mechanisms.

Scenario 4 delivers the most favorable performance across all evaluated indicators. Compared to Scenario 3, carbon emissions are reduced by more than 51%, carbon trading costs decline by approximately 80 percent, and total system costs are reduced by nearly 20 percent. These results indicate that the incentive-based reward–penalty mechanism significantly strengthens both environmental and economic outcomes when combined with carbon trading and conversion technologies.

Overall, Scenario 4 represents the most efficient and balanced operational strategy, achieving superior performance in renewable utilization, emission mitigation, and cost reduction.

PVUR (%)	91.83	100.00	100.00	100.00
WTUR (%)	85.39	100.00	100.00	100.00
CE (t)	2039.62	737.86	737.86	357.02
CTC (USD)	24562.78	0.00	-80269.40	-145165.36
Total Costs (USD)	168562.00	232082.00	151812.00	121551.00
	Scenario 1	Scenario 2	Scenario 3	Scenario 4

Fig. 6. Scenario-Based Evaluation of Renewable Utilization, Emissions, and System Costs**Fig. 7.** Electrical Dispatch Power-Load Balance

4.2. Energy Management and Optimal Allocation

The SUEC considered in this study is centered on an energy-intensive industrial unit characterized by relatively stable electrical demand over the scheduling horizon. Electricity supply is primarily provided by photovoltaic units, wind turbines, and the CHP system. In addition to end-use electrical loads, electricity consumption associated with the power-to-gas unit and the carbon capture and storage system is explicitly accounted for. The system also interacts with the external power grid to maintain overall balance under conditions of energy surplus or deficit, as illustrated in Fig. 7.

As shown in Fig. 7, renewable generation contributes substantially to meeting electrical demand throughout the day, while the CHP unit provides a stable base supply. Grid exchanges play a complementary role, absorbing excess power during periods of high renewable output and supplying electricity when internal generation is insufficient. This coordinated interaction enables the electrical hub to maintain balance while improving renewable utilization and operational flexibility.

Thermal energy demand within the energy community is predominantly satisfied by the waste heat boiler of the CHP system. By adopting a heat-led operational strategy, in which electrical generation is adjusted according to thermal demand, the heat balance is achieved in a simplified and consistent manner. This strategy is reflected in Fig. 8, where the thermal output closely follows the heat load profile, indicating effective recovery and utilization of waste heat without the need for auxiliary thermal sources.

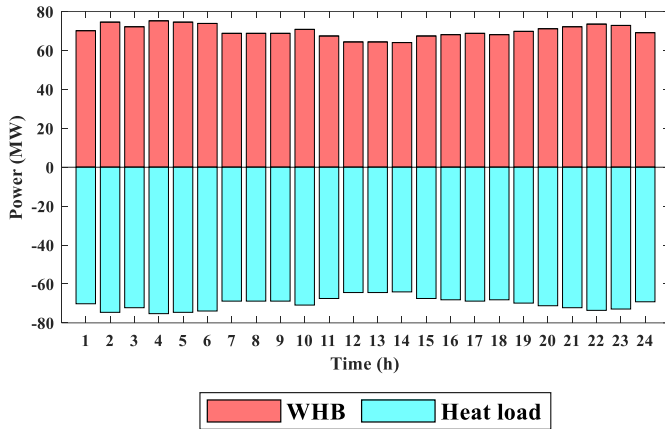


Fig. 8. Heat Dispatch Power-Load Balance

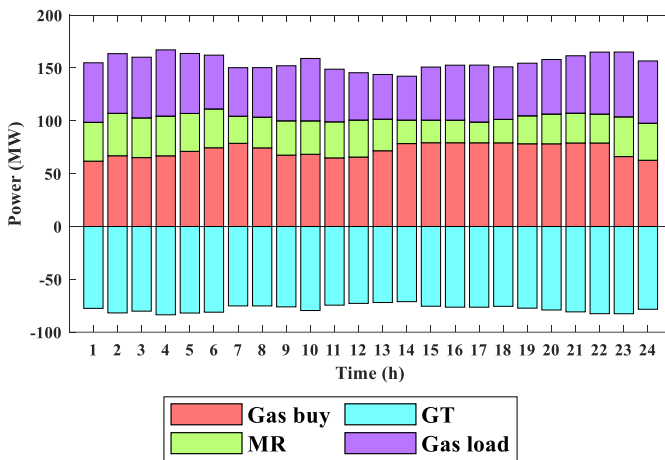


Fig. 9. Gas Dispatch's Power-Load Balance

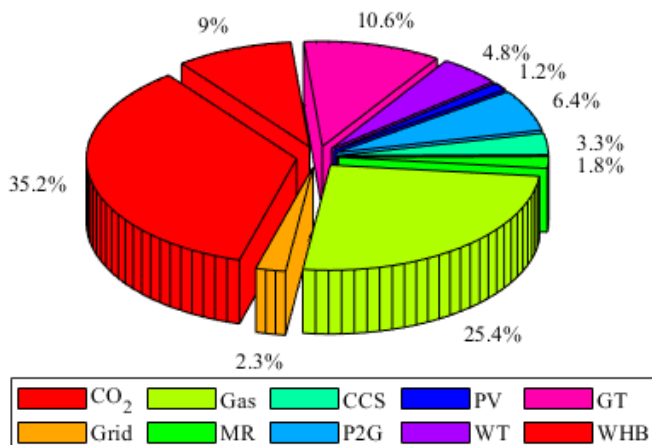


Fig. 10. Cost Breakdown of Energy Community Components

The CHP system consumes a significant volume of natural gas to simultaneously produce electricity and heat. The heat-led dispatch strategy facilitates coordinated balancing between electrical and thermal loads; however, gas supply remains subject to external procurement constraints. Natural gas deficits are compensated through transactions with external gas suppliers, which are limited by pipeline capacity and logistical considerations. Under these conditions, optimal scheduling is achieved through coordinated electricity and gas purchasing decisions. As shown in Fig. 9, when gas supply reaches its upper bound, additional

electricity is purchased from the power grid to preserve overall system balance and ensure uninterrupted operation.

The cost distribution among different components of the sustainable urban energy community is presented in Fig. 10. The results indicate that renewable energy units and the methanation reactor account for a relatively small share of total system costs. Consequently, internal gas production is limited, and the system relies more heavily on external gas purchases. A notable outcome is the significantly negative carbon trading cost, which reflects the economic benefits generated under the tiered reward–penalty carbon trading mechanism. This result demonstrates that the proposed policy framework not only incentivizes emission reduction but also contributes to lowering total system costs. Overall, the integrated coordination of energy management, conversion technologies, and carbon trading enables simultaneous achievement of emission mitigation, environmental protection, and improved economic performance.

4.3. Adaptive Analysis of Demand Response

To evaluate the demand-side flexibility of the studied sustainable urban energy community, a time-of-use (TOU) electricity tariff scheme is introduced in combination with flexible electrical, thermal, and gas loads. This framework enables a comparative assessment of system behavior before and after the implementation of demand response and highlights the interaction between price signals and multi-energy load adjustment.

Table 3 summarizes the adopted TOU tariff structure, which divides the scheduling horizon into off-peak, mid-peak, and peak-price periods. Low electricity prices during off-peak hours (00:00–08:00 and 22:00–24:00) encourage load recovery and energy-intensive operations, whereas significantly higher prices during peak intervals (11:00–15:00 and 18:00–22:00) provide a strong economic signal for load reduction. Intermediate price levels during transition periods (08:00–11:00 and 15:00–18:00) facilitate gradual load shifting rather than abrupt changes. This tiered price design establishes the economic basis for effective demand response without imposing artificial operational constraints.

Figures 11(a)–11(c) illustrate the comparative load profiles of the energy community before and after the activation of demand response. As shown in Fig. 11(a), the electrical load exhibits a clear peak-shaving and valley-filling behavior under the TOU tariff. Electricity consumption during high-price periods is noticeably reduced, while part of the deferred demand is shifted toward low-price hours. This redistribution alleviates peak demand pressure on the electrical hub and reduces reliance on costly grid electricity purchases.

Figure 11(b) demonstrates that thermal loads also respond to the demand response mechanism, despite being indirectly coupled to electricity through the CHP system. Heat demand is partially rescheduled in coordination with electricity price signals, reflecting the flexibility enabled by thermal inertia and heat storage effects. This coordinated adjustment supports the heat-led operation of the CHP unit while improving overall system efficiency.

Similarly, Fig. 11(c) shows that gas load profiles are influenced by demand response through their linkage with electricity-driven conversion processes and CHP operation. Gas consumption is reduced during peak electricity price periods and moderately increased during off-peak intervals, indicating an implicit cross-carrier demand response effect. This behavior enhances coordination between electricity and gas hubs and mitigates supply stress during constrained operating conditions.

Overall, the combined evidence from Table 3 and Fig. 11 confirms that the integration of time-of-use tariffs with flexible multi-energy loads enables effective demand response across electricity, heat, and gas domains. The comparative analysis demonstrates improved load

smoothing, enhanced scheduling flexibility, and more efficient utilization of system resources, reinforcing the role of demand response as a key operational lever in sustainable urban energy communities.

Table 3. Time-of-Use Electricity Tariff Structure for Demand Response Analysis

Time Period (h)	Electricity Selling Price (\$/MWh)	Electricity Purchasing Price (\$/MWh)
00:00 – 08:00	18.75	25
08:00 – 11:00	69.75	93
11:00 – 15:00	97.50	130
15:00 – 18:00	69.75	93
18:00 – 22:00	97.50	130
22:00 – 24:00	18.75	25

4.4. Sensitivity Analysis

To further assess the robustness of the proposed sustainable urban energy community, a sensitivity analysis is conducted on key economic, technical, and demand-side parameters.

The results in Table 4 indicate that the system exhibits differentiated sensitivity to economic, technical, and demand-side parameters. Electricity price variations have a direct and symmetric effect on total operating cost. A 20% increase in electricity price raises total cost by approximately 6.7% while reducing carbon emissions by nearly 11%, reflecting stronger demand response activation and reduced reliance on grid electricity during peak periods. Conversely, lower electricity prices weaken demand response incentives and lead to higher emissions.

Gas price sensitivity primarily affects the operation of the CHP system and internal gas consumption. An increase in gas price results in a 17.1% reduction in carbon emissions, driven by lower gas utilization and increased reliance on renewable electricity. However, this improvement comes at the expense of higher total costs. In contrast, reduced gas prices stimulate gas consumption, increasing emissions and slightly reducing renewable utilization due to higher CHP dispatch.

Carbon price variation emerges as one of the most influential policy parameters. A 20% increase in carbon price leads to a substantial 22.6% reduction in emissions while simultaneously reducing total system cost. This counterintuitive cost reduction is attributed to the reward–penalty mechanism, which generates significant economic benefits under low-emission operation. When

carbon prices are reduced, emission levels rise, and total costs increase, underscoring the effectiveness of the tiered carbon trading design.

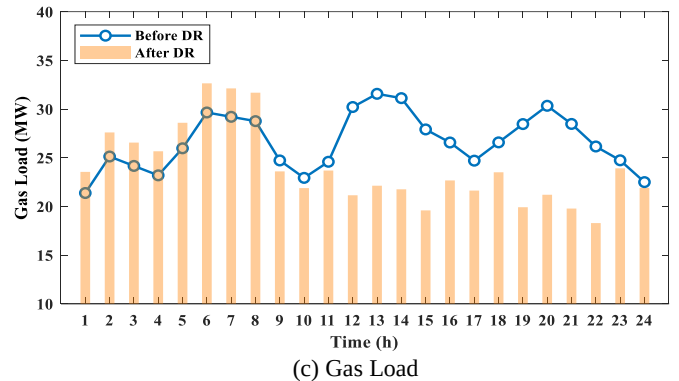
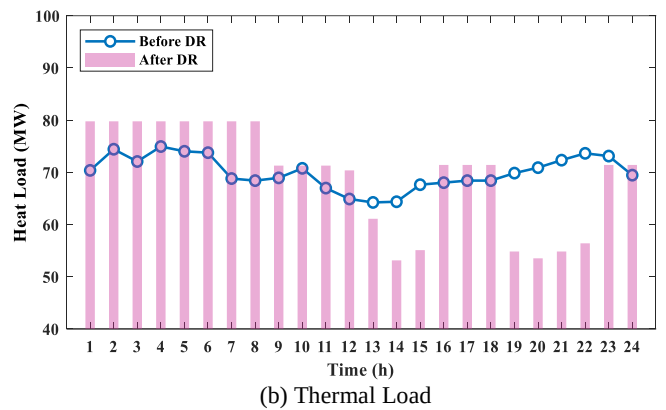
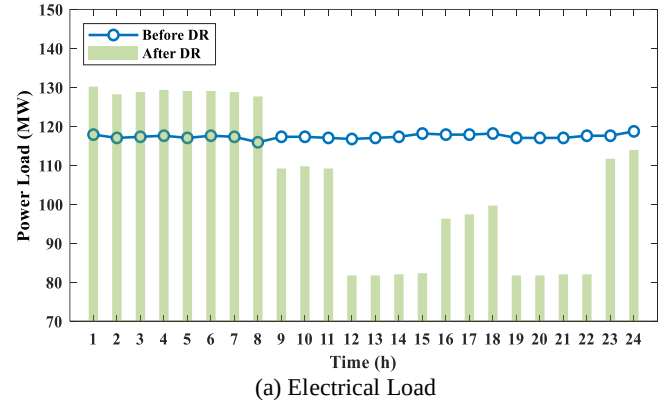


Fig. 11. Comparative Load Response under Time-of-Use Pricing

Table 4. Numerical Sensitivity Analysis of Key Parameters under the Full Configuration Scenario

Parameter Varied	Variation Level	Total Cost (\$)	Change (%)	Carbon Emissions (t)	Change (%)	Renewable Utilization (%)
Base case	Nominal	121,551	—	357.02	—	100.0
Electricity price	−20%	114,230	−6.02	382.15	+7.04	100.0
	+20%	129,684	+6.69	318.47	−10.81	100.0
Gas price	−20%	116,842	−3.87	401.26	+12.39	98.6
	+20%	128,975	+6.11	295.84	−17.13	100.0
Carbon price	−20%	126,403	+3.99	389.77	+9.17	100.0
	+20%	118,294	−2.68	276.42	−22.58	100.0
P2G efficiency	−15%	130,215	+7.12	341.08	−4.46	94.8
	+15%	112,764	−7.23	298.31	−16.44	100.0
Load flexibility	Low	128,906	+6.06	368.95	+3.33	97.4
	High	113,489	−6.61	284.76	−20.24	100.

Technical sensitivity analysis shows that power-to-gas efficiency plays a critical role in both economic and environmental performance. A decrease in efficiency increases total cost by more than 7% and reduces renewable utilization due to higher curtailment. Conversely, improved efficiency lowers system cost by 7.2% and reduces emissions by more than 16%, highlighting the strategic importance of conversion efficiency improvements.

Demand-side flexibility demonstrates a strong and consistent impact across all performance indicators. High flexibility reduces total cost by 6.6% and carbon emissions by over 20%, while ensuring full renewable utilization. Low flexibility, in contrast, leads to higher costs, increased emissions, and reduced renewable absorption.

4. Conclusions

This study addressed the operational and policy challenges of managing a sustainable urban energy community built around an energy-intensive industrial system, where multiple energy carriers, carbon constraints, and demand-side flexibility interact over a daily scheduling horizon. To respond to these challenges, an integrated optimization framework was developed that combines a multi-energy hub architecture with power-to-gas conversion, carbon capture and storage, a tiered reward–penalty carbon trading mechanism, demand response across electricity, heat, and gas, and a risk-aware objective function augmented by CVaR and digital-twin synchronization.

The results demonstrated clear and quantifiable improvements across economic and environmental dimensions. Under the full configuration scenario, renewable utilization reached 100 percent, while total system costs were reduced by nearly 20 percent compared with scenarios lacking incentive-based carbon trading. Carbon emissions declined by more than 51% relative to the baseline configuration, driven by coordinated operation of P2G, CCUS, and the reward–penalty mechanism. Demand response further enhanced system performance by smoothing multi-energy load profiles and reducing peak electricity demand, which lowered reliance on grid purchases and improved scheduling efficiency. Sensitivity analysis confirmed that electricity price, gas price, carbon price, conversion efficiency, and load flexibility exert differentiated yet systematic impacts on cost, emissions, and renewable absorption, with carbon price and demand flexibility emerging as the most influential parameters.

These findings align directly with the initial objectives of improving renewable integration, reducing carbon emissions, and enhancing economic performance within an urban industrial energy community. The outcomes confirm the hypothesis that coordinated multi-energy management, when coupled with market-based carbon incentives and flexible demand, can outperform conventional cost-driven scheduling strategies. From a practical perspective, the results highlight the importance of policy-consistent carbon pricing and demand-side participation as effective levers for operational improvement, while emphasizing the role of conversion efficiency in reducing curtailment and emissions.

The main contribution of this work lies in the unified treatment of multi-carrier energy flows, carbon trading incentives, demand response, uncertainty handling, and decentralized solution methods within a single, coherent framework. The approach provides a structured pathway for translating policy signals and technological options into operational decisions.

At the same time, the study is limited by its focus on a single representative industrial case and a daily scheduling horizon, which constrains the assessment of long-term investment dynamics and seasonal effects.

Future research will extend this framework to multi-site energy communities, longer planning horizons, and tighter coupling with real-time control. Further work is also planned to incorporate

predictive learning for demand and renewable forecasts, as well as adaptive policy parameters that evolve with market and regulatory conditions.

Appendix

Table A.1. Energy and power-related inputs

Parameter Name	Value	Unit
Nominal photovoltaic capacity	305.40	MW
Nominal wind turbine capacity	298.20	MW
Maximum gas turbine electrical output	145.60	MW
Maximum waste heat boiler thermal output	82.30	MW
Power-to-gas electrical intake limit	61.80	MW
Carbon capture system power demand	18.90	MW

Table A.2. Thermal and gas demand parameters

Parameter Name	Value	Unit
Average industrial heat demand	74.60	MW
Peak industrial heat demand	86.20	MW
Average industrial gas load	27.40	MW
Maximum allowable gas demand	34.10	MW
Methanation reactor gas output limit	41.80	MW

Table A.3. Economic and market-related parameters

Parameter Name	Value	Unit
Off-peak electricity selling tariff	19.90	\$/MWh
Off-peak electricity purchasing tariff	26.20	\$/MWh
Peak electricity selling tariff	102.30	\$/MWh
Peak electricity purchasing tariff	136.50	\$/MWh
Mid-peak electricity selling tariff	73.40	\$/MWh
Mid-peak electricity purchasing tariff	97.80	\$/MWh
Natural gas purchasing price	31.60	\$/MWh
Natural gas selling price	27.40	\$/MWh

Table A.4. Emission and carbon accounting parameters

Parameter Name	Value	Unit
Gas-related emission coefficient	0.214	tCO ₂ /MWh
CHP electrical emission factor	0.187	tCO ₂ /MWh
CHP thermal emission factor	0.162	tCO ₂ /MWh
Carbon allowance scaling factor	1.08	–
Carbon price base level	52.40	\$/tCO ₂
Upper-tier carbon penalty multiplier	1.32	–

Table A.5. Efficiency and conversion ratios

Parameter Name	Value	Unit
Gas turbine electrical efficiency	0.41	–
Waste heat recovery efficiency	0.83	–
Power-to-gas conversion efficiency	0.58	–
Carbon capture efficiency	0.91	–
Methanation conversion efficiency	0.76	–

Table A.6. Risk, uncertainty, and optimization settings

Parameter Name	Value	Unit
CVaR confidence level	0.95	–
Chance-constraint reliability level	0.90	–
Photovoltaic forecast error deviation	0.11	p.u.
Wind power forecast error deviation	0.14	p.u.
ADMM penalty coefficient	1.45	–
Digital-twin tracking weight	0.62	–

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this manuscript.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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