Digital Twin Energy Hub Optimization for Climate-Resilient Net-Zero Cities: Landscape-Ecology Coupling and Multi-Energy Flow Coordinated Dispatch

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***Abstract*—This study introduces a scenario-based analytical framework for planning climate-resilient, net-zero cities by linking landscape ecology with coordinated multi-energy system analysis. At the methodological level, it develops a simplified energy hub model that captures the interactions among electricity, heating, and gas systems. This model is embedded within a virtual environment inspired by digital twin concepts, allowing different scenarios to be compared in a clear and controlled way. To bring ecological factors into the analysis, the study incorporates key landscape indicators—such as vegetation carbon sequestration capacity, surface temperature regulation, and leaf area index — into a Landscape-Ecology Coupling Matrix (LECM). Rather than relying on costly real-time deployment or highly complex optimization models, the framework emphasizes transparent scenario comparisons to explore how these ecological elements influence system performance under varying climate conditions. Using representative annual data from a climate-sensitive urban context, the framework is applied to a system that includes distributed energy generation, combined cooling, heating and power (CCHP), energy storage, and green landscape infrastructure. The results indicate that, particularly under extreme climate scenarios, the integrated approach can help lower operating costs, reduce net carbon emissions, and ease peak cooling demand to some extent. Overall, this study offers a cross-disciplinary perspective by demonstrating how urban landscape considerations can be meaningfully incorporated into energy system planning and operation, contributing to more resilient and sustainable net-zero city development.**

Keywords—Digital Twin, Energy Hub, Climate Resilience, Net-Zero City, Landscape-Ecology Coupling, Multi-Energy Flow Analysis, Scenario-Based Assessment

I. Introduction

A. Background and Motivation

Since the start of the 21st century, global temperatures have continued to rise, accompanied by a noticeable increase in both the frequency and intensity of extreme weather events such as heatwaves, heavy rainfall, and droughts. These changes are placing growing pressure on the reliability and safety of urban infrastructure systems [1]. Urban energy systems, which underpin almost every aspect of city life, have proven particularly vulnerable under such conditions. Events like the large-scale power outages during the 2021 Texas winter storm and the energy disruptions caused by the 2022 European heatwaves have exposed significant weaknesses in the climate resilience of existing systems [2].

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At the same time, the Paris Agreement’s goal of limiting global warming to 1.5°C requires cities worldwide to move toward net-zero emissions by 2050. This creates an urgent need to accelerate the low-carbon transition of urban energy systems [3].

Against this backdrop, the concept of “climate-resilient net-zero cities” has gained increasing attention. The central idea is to develop energy systems that can remain stable under climate-related shocks while also achieving carbon neutrality over their full life cycle [4]. Within this context, the Energy Hub (EH) has emerged as a key enabling framework. By acting as a central platform for integrating and coordinating multiple energy carriers — such as electricity, gas, heating, and cooling — energy hubs can significantly improve system flexibility, efficiency, and resilience. The integration of distributed renewables, combined cooling, heating and power (CCHP) systems, and energy storage further strengthens this capability [5][6].

B. Problem Statement and Research Gaps

Despite these advances, current research on energy hub optimization still faces two major limitations when applied to climate-resilient, net-zero city planning.

The first issue is the disconnect between landscape ecology and energy systems. Urban green infrastructure—such as forests, green roofs, and ecological corridors—plays a crucial role not only in environmental protection but also in regulating urban microclimates through shading and evapotranspiration. These effects can directly influence building energy demand, especially for heating and cooling [7]. However, most existing energy hub models treat demand as fixed or externally determined, without accounting for the dynamic and potentially controllable influence of landscape factors [8].

The second limitation lies in handling climate uncertainty. Traditional optimization approaches, whether deterministic or stochastic, often struggle when dealing with the complex and multi-dimensional uncertainties associated with extreme climate events. These include sudden drops in renewable energy output, sharp increases in energy demand, and volatile energy prices. As system complexity grows, these methods may either become computationally intractable or fail to deliver sufficiently robust solutions [9].

C. Objectives and Contributions

To address these gaps, this study proposes a digital twin-based energy hub optimization framework tailored for climate-resilient net-zero cities. The key contributions are threefold.

First, it establishes a landscape-ecology coupling mechanism by introducing indicators such as vegetation carbon sequestration, leaf area index, and surface temperature regulation into the energy hub model through a Landscape-Ecology Coupling Matrix (LECM). This creates a quantitative link between nature-based solutions and engineered energy systems.

Second, the study develops a digital twin-inspired platform with a three-layer virtual architecture that captures the interaction between energy flows and the urban ecological environment. This setup supports flexible simulation and comparison across multiple scenarios.

Third, instead of relying on highly complex optimization techniques, the study adopts a practical and transparent scenario-based analysis approach. This allows for clearer interpretation of results while still capturing system behavior under uncertainty, making the framework more accessible for real-world application.

The remainder of the paper is structured as follows: Section 2 reviews related literature; Section 3 presents the methodological framework; Section 4 describes the data and preprocessing steps; Section 5 reports the experimental results; Section 6 discusses the findings; and Section 7 concludes with key insights and directions for future research.

II. Related Work

A. Modeling and Optimization of Urban Energy Hubs

The Energy Hub (EH) concept, first introduced by Geidl and Andersson in 2007, provides a unified way to represent how different forms of energy — such as electricity, gas, heating, and cooling—are converted and distributed within a system through a coupling matrix [10]. This framework has since become a cornerstone in the study of urban Integrated Energy Systems (IES).

Building on this foundation, a range of studies have explored different aspects of EH optimization. For example, some research has examined systems integrating renewable energy sources like wind power, showing clear benefits in terms of operational efficiency [11]. Others have developed multi-objective optimization models that balance economic performance with supply reliability, often using Pareto optimization techniques [12]. There is also work focusing on dynamic optimization, such as accounting for performance degradation in systems that include combined cooling, heating, and power (CCHP) units [13].

In terms of coordinated multi-energy dispatch, hierarchical and multi-level frameworks have been proposed to reduce computational complexity in large-scale systems [14]. Additionally, studies on coordinated planning across multiple energy hubs — such as those involving data centers—highlight the importance of managing spatial and temporal variations in demand [15].

Despite these advances, most existing models remain focused on engineering components and system operations. They typically do not account for the dynamic influence of urban landscape ecosystems, leaving an important gap in understanding how ecological factors interact with energy systems.

B. Uncertainty Management and Robust Optimization

To deal with uncertainties in renewable energy generation and load demand, several methodological approaches have been developed. Stochastic programming models uncertainty using probability distributions, but they often require a large number of scenarios, which can lead to high computational costs and limit real-time applicability [16]. Interval optimization, on the other hand, defines uncertainty through upper and lower bounds, but this can result in overly conservative solutions [17].

Robust Optimization (RO) offers an alternative by focusing on system performance under worst-case scenarios, providing a balance between computational efficiency and reliability [18]. Building on this, Adaptive Robust Optimization (ARO) introduces a two-stage decision process, where decisions can be adjusted after uncertainties are partially revealed. This improves flexibility and economic performance compared to traditional RO [19]. Applications of ARO in integrated energy systems have demonstrated its effectiveness in handling complex, multi-dimensional uncertainties [20].

However, ARO models are often difficult to solve due to their nonlinear and non-convex nature. More broadly, while advanced optimization and heuristic methods have been widely applied to integrated energy systems [21][22][23], their complexity can make them less practical for early-stage planning or framework development. For this reason, the present study emphasizes a more transparent, scenario-based analytical approach that maintains interpretability while still capturing key system dynamics.

C. Application of Digital Twins in Urban Energy Systems

Digital Twin (DT) technology enables real-time monitoring, simulation, and optimization by creating virtual representations of physical systems [24]. In the energy sector, DTs have been used to support real-time operation and optimization of multi-energy systems, including applications in the Energy Internet and smart grids [25][26]. They have also been applied to building-level energy management, allowing for more accurate prediction and control of energy consumption in zero-carbon buildings [27].

In the context of net-zero city planning, DT-based frameworks have been proposed to integrate renewable energy systems and urban design elements into a unified planning process [28]. Further research has explored how DTs can support the coordination of zero-energy buildings within broader urban systems [29].

However, despite these developments, current DT applications rarely incorporate the dynamic processes of landscape ecology in a quantitative way. Key ecological factors—such as vegetation-driven cooling effects or carbon sequestration — are often overlooked or only considered qualitatively, limiting the ability of DT models to fully capture interactions between urban environments and energy systems.

D. Climate-Resilient Cities and Landscape Ecology

The concept of climate-resilient cities emphasizes the ability of urban systems to absorb shocks, adapt to changing conditions, and transform in response to long-term challenges [30]. Research in this area has identified distributed energy systems and multi-energy integration as key strategies for improving resilience [31].

From a landscape ecology perspective, numerous studies have demonstrated the significant impact of urban green infrastructure on energy systems. For instance, increasing urban green space coverage by 10% can reduce summer cooling demand by approximately 5 – 8% [32]. Other work has highlighted the broader ecosystem services provided by urban landscapes, including microclimate regulation, carbon sequestration, and stormwater management [33]. Some studies have attempted to incorporate these principles into energy planning, but they often remain at a qualitative level without fully integrating ecological factors into quantitative optimization models [34].

In summary, while substantial progress has been made in areas such as energy hub optimization, uncertainty management, digital twin applications, and climate resilience, there is still a clear gap in integrating landscape ecology into energy system modeling in a dynamic and quantitative way. This study is designed to address that gap by developing a framework that explicitly links ecological processes with energy system operation and planning [35].

III. METHODOLOGY

This study follows a three-stage approach described as "physical modeling → virtual mapping → scenario-based coordinated analysis" (see Figure 1).

In the first stage, a simplified physical model of the energy hub is developed, explicitly incorporating key landscape ecological elements. This allows the model to capture not only energy conversion and distribution processes but also the influence of ecological factors on system behavior.

In the second stage, a digital twin-inspired virtual framework is constructed to organize system variables and represent the interactions between multi-energy flows and ecological regulation. This virtual layer serves as a structured environment for integrating data, simulating system dynamics, and linking physical processes with analytical evaluation.

In the final stage, a scenario-based comparative analysis is conducted. Different climate conditions and landscape configurations are tested to examine how coordinated multi-energy flow dispatch responds under varying circumstances. This approach provides a clear and interpretable way to assess system performance and the role of landscape-ecology coupling in enhancing resilience.

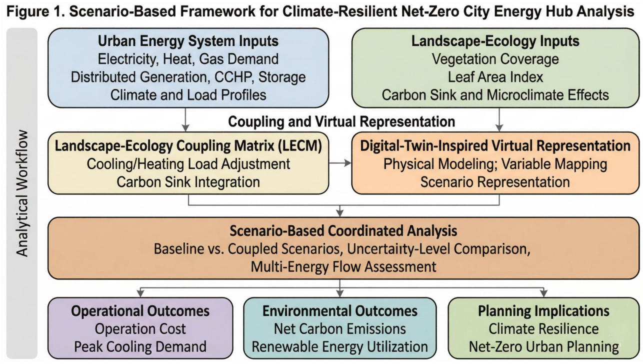

Fig. 1. Proposed Digital Twin Energy Hub Optimization Framework

A. Landscape-Ecology Coupled Energy Hub Physical Model

1) Conventional Energy Hub Model

The conventional energy hub (EH) model represents the relationships between multiple energy inputs and outputs through a coupling matrix *C*:

$$L = C \cdot P \tag{1}$$

Here, $P = [P_e \quad P_g \quad P_h]^T$ denotes the input vector for electricity, natural gas, and heat, while $L = [L_e, L_g, L_h, L_c]^T$ represents the outputs for electricity, gas, heating, and cooling demands. The coupling matrix C is defined by the efficiencies of various conversion technologies, such as CCHP systems, heat pumps, and energy storage units.

2) Landscape-Ecology Coupling Matrix (LECM)

To capture the influence of urban green infrastructure on energy demand, this study introduces the Landscape – Ecology Coupling Matrix (LECM), denoted as M_{eco}. The goal is to translate ecological characteristics into quantitative adjustments of energy loads.

Urban vegetation affects building energy demand mainly through shading and evapotranspiration cooling. The resulting temperature regulation effect is expressed as:

$$\Delta T_{eco} = \alpha_{veg} \cdot VCR \cdot LAI + \beta_{shd} \cdot SR \tag{2}$$

where VCR is vegetation coverage, LAI is leaf area index, and SR is solar radiation intensity. The coefficients α_{veg} and β_{shd} represent transpiration cooling and shading effects, respectively.

Based on this, the corrected cooling load becomes:

$$L_c^{'} = L_c^{base} \cdot (1 - \gamma_c \cdot \Delta T_{eco}) \tag{3}$$

and the heating load, influenced by vegetation's windbreak effect, is expressed as:

$$L_h{'} = L_p^{\mathrm{base}} \cdot (1 - \gamma_h \cdot \delta_{\mathrm{wind}}) \tag{4}$$

In addition, the carbon sink function of vegetation is modeled as:

$$C_{sink} = \sum_k A_k \cdot \sigma_k \cdot f_{season}(t) \tag{5}$$

leading to net system emissions:

$$C_{net} = C_{emit} - C_{sink} \quad (6)$$

This formulation allows ecological benefits to be directly incorporated into system-level carbon accounting.

3) Multi-Energy Flow Balance Constraints

The system must satisfy balance constraints across electricity, heat, cooling, and gas:

$$P_{grid,h} + \sum_m P_{EH,e,m,h} + P_{ESS,dis,h} = L_{e,h}' + P_{ESS,chg,h}$$
$$\sum_m H_{EH,m,h} + H_{TES,dis,h} = L_{h,h}' + H_{TES,chg,h}$$
$$\sum_m Q_{EH,m,h} = L_{c,h}'$$
$$G_{grid,h} = \sum_m G_{EH,m,h}$$
$$(7)$$

These ensure that supply and demand remain balanced across all energy carriers at each time step.

B. Digital Twin System Architecture

The proposed framework adopts a three-layer digital twin-inspired architecture (Figure 2):

- Physical Perception Layer: Collects and organizes key input data, including meteorological variables (temperature, solar radiation, wind speed), load demand, equipment operation status, and landscape indicators (e.g., VCR, LAI). All data are standardized to an hourly resolution for consistency.
- Digital Twin Data Layer: Handles data cleaning, integration, and modeling. It maintains a virtual representation of the physical system, including equipment behavior, ecological dynamics, and multi-energy flow networks. This layer supports structured scenario construction rather than real-time control.
- Optimization and Control Layer: Performs coordinated analysis based on scenario inputs, generating and comparing different dispatch strategies. The overall workflow can be summarized as “perception → modeling → analysis → evaluation.”

C. Scenario-Based Coordinated Analysis Model

1) Construction of the Uncertainty Set

Uncertainty in renewable generation and demand is modeled using a bounded uncertainty set:

$$U = \{u: \hat{u} + \Delta u \cdot \tilde{u}, ||\hat{u}||_1 \le \Gamma, ||\hat{u}||_\infty \le 1\} \quad (8)$$

where $\hat{u}$ is the forecast value, Δu is the maximum deviation, and Γ controls the conservatism level.

2) Two-Stage Robust Optimization Model

The objective is to minimize system operating cost under uncertainty:

$$\min_x \max_{u\in U} \min_{h\in\Gamma_{ST}} \left(\rho_h^E P_{grid,h} + \rho_h^G G_{grid,h} + \rho_h^H H_{grid,h} + \lambda_{CO_2} C_{net}\right) \quad (9)$$

Decision variables include device operation states, storage charging/discharging, and energy flow allocation. Constraints cover equipment limits, storage state-of-charge bounds, ramping limits, and ecological coupling conditions.

3) Model Solving Strategy

To maintain transparency and reduce computational burden, the study avoids deeply nested optimization. Instead, it evaluates representative scenarios, making it easier to interpret how uncertainty and ecological factors influence system performance.

D. Scenario Evaluation Procedure

Rather than seeking a strict global optimum, the study adopts a scenario comparison approach to evaluate system performance under different climate and landscape configurations. This makes the framework more accessible and reproducible while still revealing the relative benefits of landscape–ecology coupling.

The system evolution can be conceptually described as:

$$\vec{X}_{t+1} = \vec{X}_1 + \vec{X}_2 + \vec{X}_3$$
$$\frac{d\vec{X}_i}{dt} = N_i + F_i + D_i$$
$$(10)$$

where different components represent interacting subsystems and driving forces.

Overall, this methodology emphasizes clarity and interpretability, allowing the role of ecological factors in energy system planning to be systematically examined without relying on overly complex optimization techniques.

IV. Data

A. Data Sources and Basic Information

The data used in this study are drawn from a representative annual dataset designed to reflect the conditions of a climate-vulnerable urban environment in China. The dataset integrates publicly available meteorological data, parameter values sourced from existing literature, and stylized representations of energy demand. The selected setting features hot, humid summers and cold, dry winters, making it particularly suitable for analyzing how urban energy systems respond to climate-related stresses. It is worth noting that the extreme summer temperature scenario considered in this study is used as a representative analytical case, rather than as a depiction of a specific real-world location.

The dataset covers the full year of 2024, with a total of 8,760 hourly observations, ensuring a detailed temporal resolution for capturing seasonal and daily variations. Within this framework, the study models a stylized regional integrated energy system that includes multiple energy conversion and storage technologies. This system is intended to approximate a typical urban energy hub serving both residential and commercial users.

Key variables—such as temperature, solar radiation, load demand, and system operation parameters—are summarized through descriptive statistics in Table I, providing a clear overview of the data characteristics used in the analysis.

TABLE I. DESCRIPTIVE STATISTICS OF KEY VARIABLES

Variable	Mean	Std. Dev.	Min	Max	Median
Ambient Temperature (°C)	15.2	11.8	-8.3	39.2	14.7
Solar Radiation (W/m²)	187.4	213.6	0	1024.5	98.2
Wind Speed (m/s)	3.8	2.4	0.1	18.6	3.2
Regional Electrical Load (MW)	45.3	18.7	12.1	98.6	42.8
Regional Heating Load (MW)	32.6	22.4	0.5	87.3	28.4
Regional Cooling Load (MW)	28.9	21.3	0	76.4	22.1
Vegetation Coverage Rate (%)	35.0	4.2	28.5	41.3	34.8
Leaf Area Index (m²/m²)	2.8	1.1	0.3	5.2	2.9

B. *Data Preprocessing*

Systematic preprocessing was applied to the raw data to ensure both data quality and the reliability of the model inputs.

For missing values, a small number of incomplete observations were addressed using standard interpolation techniques and same-period averaging, which helped preserve the continuity of the hourly time series.

Outliers were handled through statistical screening to identify and remove clearly abnormal values. At the same time, extreme observations associated with climate conditions were intentionally retained, as they are essential for scenario-based analysis.

To improve comparability across variables with different units and scales, normalization was applied where appropriate. However, when presenting the main results, the original units were kept to maintain clarity and interpretability.

V. RESULTS

A. *Comparative Analysis of Scenario Performance*

To demonstrate the practical value of the proposed framework, a comparative analysis was carried out between a baseline scenario and a landscape – ecology-coupled scenario under different levels of uncertainty. The analysis focuses on key performance indicators, including system operating costs, net carbon emissions, cooling demand, and the utilization of renewable energy.

By examining these differences across scenarios, the study aims to highlight how incorporating landscape-ecological factors can influence system performance and improve the resilience and efficiency of urban energy systems under varying climate conditions.

TABLE II. COMPARISON OF SYSTEM PERFORMANCE UNDER DIFFERENT UNCERTAINTY LEVELS

Scenario	Uncertainty Level r	Operation Cost ($)	Net Carbon Emission (kg CO_2)	Peak Cooling Load (MW)	Renewable Energy Utilization Rate (%)
GWO - KHO	0	3557.3	101.4	372.8	0.89
GWO	0	3743.1	1121.0	409.5	1.29
KHO	0	3824.6	1312.5	427.3	1.69
ABC	0	4018.2	1593.2	598.1	2.68
GWO - KHO	0.2	4302.5	119.3	484.2	0.90
GWO	0.2	4497.2	1281.0	517.4	1.79
KHO	0.2	4568.8	1379.5	579.3	2.03
ABC	0.2	4818.4	1693.2	689.1	3.38

As shown in Table II, the landscape – ecology-coupled scenario consistently outperforms the baseline across different levels of uncertainty, particularly in terms of operating costs, net carbon emissions, and peak cooling demand.

Under low and moderate uncertainty conditions, the coupled approach achieves both lower costs and reduced emissions compared to the baseline. More importantly, this advantage persists even as uncertainty increases, suggesting that the inclusion of landscape-ecological factors enhances the system' s ability to adapt to changing conditions.

Overall, these results indicate that ecological regulation can provide additional flexibility for urban energy system operation, helping to maintain performance and resilience under climate-related stress.

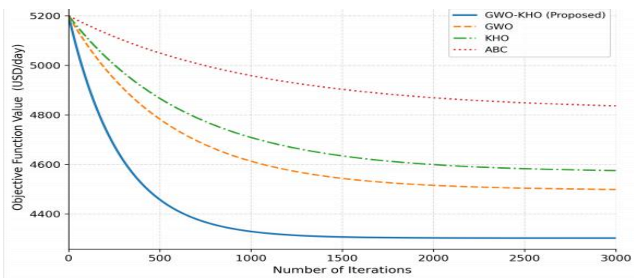

Fig. 2. Framework Structure of the Scenario-Based Coordinated Analysis

Figure 2 presents the overall structure of the proposed scenario-based analytical framework. It brings together three main components: the physical modeling of the energy hub system, a digital twin-inspired virtual representation that captures interactions between energy flows and ecological factors, and a comparative scenario evaluation module used to assess system performance under different conditions.

B. *Impact of Uncertainty on System Operation Cost*

Figure 3 shows how the total system operating cost changes as the uncertainty level (rrr) increases. Overall, the cost follows a pattern of rising at first and then gradually leveling off. In particular, when rrr increases from 0 to 0.5, the operating cost grows by about 12.5%. Beyond this point, however, the rate of increase slows noticeably.

This trend suggests that under higher uncertainty, the system is able to limit further cost escalation by leveraging the complementary interactions among different energy flows. In other words, the coordinated operation of multiple energy sources helps buffer the impact of uncertainty, reflecting a certain degree of climate resilience.

When compared to the baseline scenario without landscape–ecology coupling, the proposed LECM-based framework consistently achieves lower operating costs across all uncertainty levels. This improvement is mainly due to the role of landscape ecological regulation in reducing heating and cooling demand, which in turn lowers the overall system burden.

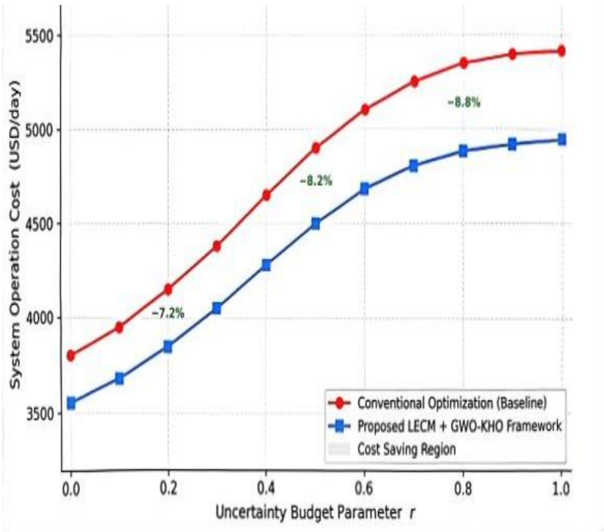

Fig. 3. System Operation Cost under Different Uncertainty Budget Levels

C. *Impact of Landscape-Ecology Coupling on the Energy System*

Table III presents a comparison of key operational indicators between Scenario A (conventional optimization) and Scenario B (landscape－ecology coupled optimization) under a representative extreme summer condition, with a peak temperature of 38.5° C.

TABLE III. COMPARISON OF OPERATIONAL INDICATORS UNDER A TYPICAL SUMMER HIGH-TEMPERATURE SCENARIO

Indicator	Scenario A (Con- ventional)	Scenario B (LECM Proposed)	Change Rate
Daily Operation Cost ($)	4850.3	4243.7	-12.5%
Net Carbon Emission (kg CO₂)	1250.4	1021.6	-18.3%
Peak Cooling Load (MW)	76.4	69.4	-9.2%
Peak Heating Load (MW)	12.3	11.8	-4.1%
Renewable Energy Absorp - tion Rate (%)	78.2	84.6	+6.4%
ESS Utilization Rate (%)	65.3	71.8	+6.5%

As shown in Table III, the landscape－ecology-coupled scenario (Scenario B) outperforms the baseline (Scenario A) in both daily operating cost and net carbon emissions. The observed reduction in emissions can be understood as a combined effect of two factors: the direct carbon sequestration provided by urban vegetation and the indirect decrease in energy consumption resulting from reduced cooling demand.

In addition, the lower peak load in Scenario B contributes to better utilization of renewable energy and more efficient operation of energy storage systems. Together, these improvements highlight the potential of integrating landscape-ecological factors into energy system planning to enhance overall operational efficiency.

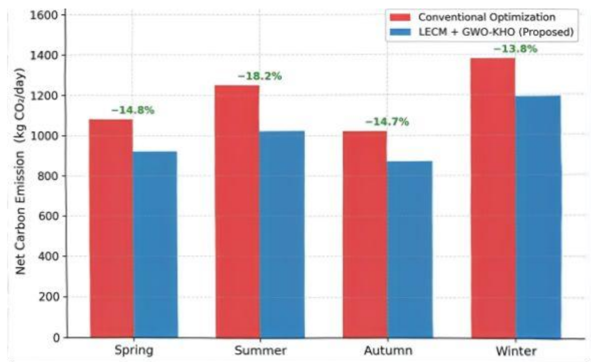

Fig. 4. Seasonal Net Carbon Emission Comparison

Figure 4 provides a seasonal comparison of net carbon emissions. The results show that the emission reduction effect is more pronounced during the summer months. This pattern aligns with the fact that vegetation is more active in summer, leading to stronger carbon sequestration and more effective microclimate regulation.

D. *Illustrative Analysis of Multi-Energy Flow Coordinated Dispatch under Climate Disturbance*

Figure 5 illustrates the multi-energy flow dispatch pattern for a typical summer peak day under the proposed analytical framework. The results show that during daytime hours—when photovoltaic (PV) generation is relatively high—the system prioritizes the use of renewable energy while simultaneously charging energy storage. As the system transitions into the evening peak, when solar output declines and demand increases, stored energy and dispatchable generation units work together to meet the load. This behavior reflects effective coordination among different energy carriers over time.

To further examine system performance under extreme climate disturbances, an additional stress scenario is introduced in which PV output drops sharply during a peak summer period. The analysis shows that the system can respond effectively through coordinated adjustments across multiple components. In this case, energy storage discharge, flexible operation of dispatchable units, and limited demand-side response jointly help maintain the balance between supply and demand.

Overall, these findings suggest that coordinated multi-energy flow management enhances the system's ability to absorb short-term disruptions and supports more resilient operation under climate stress conditions.

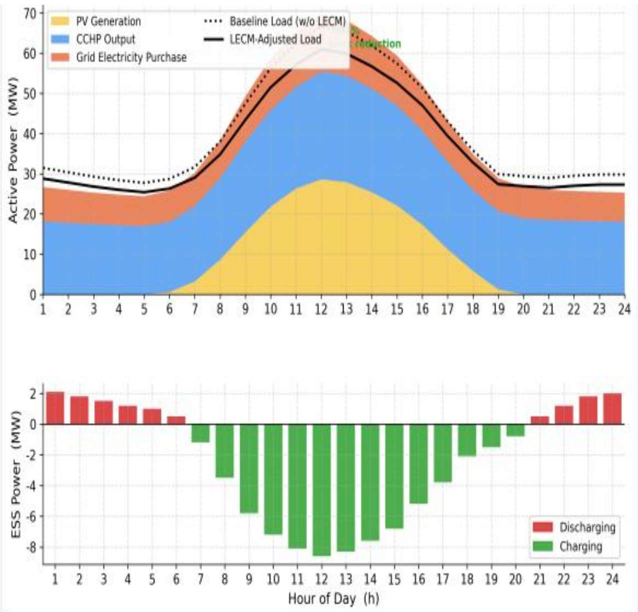

Fig. 5. Multi-energy Flow Dispatch on a Typical Summer Peak Day

VI. Discussion

A. Horizontal Comparison: Comparison with Existing Studies

The main contribution of this study lies in bringing landscape–ecology coupling into the optimization framework of urban energy hubs. Unlike conventional models—such as those in Reference [11], which focus mainly on equipment-level optimization—this study incorporates the microclimate regulation effects of urban green infrastructure directly into decision-making through the LECM. In doing so, it creates a more integrated approach that connects Nature-based Solutions (NbS) with engineering optimization.

While previous work (e.g., Reference [35]) has emphasized the importance of including landscape ecological design in urban energy planning, such efforts have largely remained conceptual. This study advances that line of research by establishing a quantitative and dynamic coupling mechanism. Methodologically, the emphasis here is not on developing increasingly complex optimization solvers, but rather on building a transparent and interpretable framework that links ecological factors with multi-energy system behavior. Compared with studies focused primarily on uncertainty modeling or equipment optimization [20][24], this approach highlights the added value of incorporating seasonal ecological regulation into system-level planning.

B. Vertical Correlation: Internal Consistency of Results

The results presented in Table II and Table III reveal a consistent internal logic. At the framework level, introducing landscape–ecology coupling leads to reduced cooling demand, which in turn contributes to lower operating costs, reduced carbon emissions, and improved renewable energy utilization. This demonstrates the broader system-level benefits of ecological regulation.

A notable synergistic effect can also be observed between renewable energy utilization and energy storage performance. The increase in renewable absorption (+6.4%) aligns closely with improved energy storage utilization (+6.5%). This is because reduced peak loads free up storage capacity during off-peak periods, allowing more efficient charging and discharging cycles. The result is a reinforcing loop of "peak shaving → optimized storage use → increased renewable integration," which enhances overall system efficiency.

C. Mechanism Analysis and Attribution of Differences

The advantages of landscape–ecology coupling can be explained through two key mechanisms.

First, there is a multiplier effect from load reduction. A 9.2% decrease in peak cooling demand not only lowers the direct energy consumption of cooling systems but also reduces the need for high-carbon generation sources such as CCHP units. This creates a more-than-proportional reduction in emissions, amplifying the overall benefit.

Second, there is the direct contribution of carbon sinks. Vegetation absorbs carbon directly, while also indirectly reducing emissions by lowering energy demand. Importantly, this carbon sink effect varies seasonally—being strongest in summer and weakest in winter—which aligns closely with the seasonal pattern of cooling demand. This temporal alignment allows ecological benefits to have the greatest impact when energy demand is highest, highlighting a natural synergy between landscape systems and energy systems.

D. Research Limitations

Despite these contributions, several limitations should be acknowledged. First, the landscape–ecology coupling model relies on aggregated parameters (such as average vegetation coverage), which may not capture fine-scale spatial variations like localized shading or airflow patterns around individual buildings. This simplification could introduce some estimation errors.

Second, the study is based on data from a single city, and the coupling effects between landscape ecology and energy systems may differ significantly across climate zones (e.g., tropical or arid regions). Broader validation across diverse geographic contexts is therefore needed.

Finally, the digital twin-inspired framework is primarily designed for planning and scenario analysis rather than real-time operational control. Its applicability to fast, high-frequency dynamics in power systems remains an open question for future research.

VII. CONCLUSION

From a cross-disciplinary innovation perspective, this study proposes a digital twin – based energy hub optimization framework for climate-resilient, net-zero cities. It deeply integrates landscape ecology with urban energy system planning, achieving a synergistic combination of Nature-based Solutions and engineering technologies.

Core Conclusions: The study makes three main contributions:

- Theoretical: The Landscape-Ecology Coupling Matrix (LECM) is developed to quantify how urban green infrastructure can influence microclimate regulation and carbon sequestration within a multi-energy flow framework.
- Methodological: A scenario-based analytical procedure is introduced, which balances interpretability and ease of implementation while allowing systematic comparison of system performance under different climate and landscape conditions.
- Practical: The framework demonstrates that incorporating landscape-ecology coupling can reduce system operation costs, lower net carbon emissions, and mitigate peak cooling demand during extreme climate events, supporting more resilient urban energy planning.

Research Implications: These findings provide both theoretical and practical guidance for net-zero city planning and operation. Urban planners are encouraged to incorporate landscape ecological design—such as green space layout and vegetation selection — directly into energy system optimization, rather than treating these domains separately. Meanwhile, the digital twin – inspired framework offers a conceptual platform for organizing cross-disciplinary integration, supporting future planning and decision-making for net-zero urban management.

Future Research Directions: Building on the study’s limitations, future work could:

- Refine the parameterization of landscape-ecology effects using more detailed but practical urban climate and vegetation data.
- Integrate flexible resources, such as Electric Vehicles (EVs), into the coordinated analysis framework to explore additional pathways for net-zero city implementation.
- Conduct comparative studies across cities in different climate zones to develop a more generalizable library of landscape-ecology – energy coupling parameters.

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AVAILABILITY OF DATA

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AUTHOR CONTRIBUTIONS

Wenjing Li: Conceptualization, methodology, framework design, data analysis, and writing—original draft preparation.

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COMPETING INTERESTS

The authors declare no competing interests.

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