Triple Sustainability Design of Distributed Energy Systems: A Pareto-based Multi-objective Optimization and Decision-making Framework

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***Abstract*—In the global context of achieving carbon neutrality and sustainable development, the sustainable design of energy systems for high-consumption areas like smart parks is crucial. Traditional energy system design often focuses on a single economic dimension, neglecting comprehensive consideration of environmental and social dimensions. To address this, this study develops an integrated decision-making framework aimed at simultaneously optimizing the triple sustainability objectives of economy, environment, and society. Applied to a smart park's integrated energy system, this framework employs a multi-objective optimization strategy, using Total Annualized Cost (economic), CO_2 emissions and Water Consumption (environmental), and Inherent Safety Index (social) as core evaluation metrics. By solving a series of optimization problems with different combinations of sustainability indicators, this research reveals the intrinsic trade-offs among the objectives. The results show significant competitive relationships between different optimization goals; for instance, the levelized cost of energy can vary between 0.35 and 0.65 €/kWh, CO_2 emissions range from 12 to 70 $kgCO_2/MWh$, and water consumption lies between 30 and 75 m^3H_2O/GWh. Furthermore, the study finds that increasing the proportion of hydrogen production via water electrolysis and reducing the capacity of hydrogen storage units can effectively enhance the system's inherent safety. The proposed multi-objective optimization and decision-making framework provides park managers and policymakers with a scientific tool to quantitatively assess the pros and cons of different design schemes, facilitating the identification of an optimal balance point that accommodates the triple sustainability goals under complex constraints.**

Keywords—Smart Park, Integrated Energy System, Triple Sustainability, Multi-objective Optimization, Pareto Front, Decision Support

I. INTRODUCTION

As the global climate change challenge becomes increasingly severe, nations worldwide have set "carbon neutrality" and sustainable development as core strategic goals [1]. Smart parks, such as industrial and technology parks, serve as engines for regional economic growth but are also concentrated areas of energy consumption and carbon emissions. Their green transformation is therefore crucial for achieving broader emission reduction targets [2]. In this context, Integrated Energy Systems (IES), which integrate multiple energy forms (e.g., electricity, heat, cold, gas), are considered a key technological pathway to enhance energy efficiency, promote the integration of renewable energy, and achieve low-carbon development at the park level [3, 4].

However, the planning and design of IES in smart parks still face practical challenges. Traditional design methods often prioritize economic efficiency as the primary or sole objective, aiming to minimize investment and operational costs [5]. This single-dimension optimization model overlooks the complex environmental and social impacts of energy systems. For instance, over-reliance on certain technologies may increase the consumption of scarce water resources or introduce new safety risks, thereby conflicting with the overall goals of sustainable development [6]. Consequently, how to strike a balance among economic feasibility, environmental friendliness, and social acceptability—the three dimensions of "triple sustainability"—has become a core scientific question in the design of smart park energy systems.

In recent years, multi-objective optimization methods have been widely applied to the design of Distributed Energy Systems (DES). Most studies have focused on the trade-offs between the economic and environmental dimensions, typically using total cost and CO_2 emissions as optimization objectives [7, 8]. For example, Gabrielli et al. [9] used the ε-constraint method to optimize the design of multi-energy systems with seasonal storage. Falke et al. [10] introduced life cycle assessment to more comprehensively evaluate system carbon emissions. While these studies provide valuable insights, they have largely failed to fully integrate the social dimension into the design framework. Social sustainability involves multiple aspects such as equity, health, and safety. Among these, the "inherent safety" of a system is a fundamental prerequisite for protecting the lives and property of park personnel and ensuring stable social operation, yet it has been rarely quantified and considered in past energy system optimizations [11]. Furthermore, as water becomes an increasingly scarce strategic resource, its consumption in energy production and conversion processes should also be a key indicator for environmental sustainability assessment [12].

To address the shortcomings of existing research, this study aims to construct a triple sustainability design and decision-making framework for smart park integrated energy systems. The core contributions of this framework are:

- Expanding the dimensions of sustainability assessment: Building upon the traditional two-

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dimensional analysis of economy-environment (cost-carbon), this study explicitly incorporates water consumption (environmental dimension) and an inherent safety index (social dimension) to create a more comprehensive multi-objective optimization model.

- Focusing on the smart park application scenario: The research model is applied to a typical smart park case to analyze its optimal configuration and operational strategies under scenarios with diverse energy demands, including electricity and hydrogen.
- Providing a quantitative decision support tool: By solving a series of optimization problems with different combinations of objectives, a set of Pareto optimal solutions is generated.The study uses the NSGA-II algorithm to find the Pareto optimal solutions to balance economic, environmental, and social goals. During the optimization process, we introduce uncertainty analysis, considering the impacts of policy changes, energy price fluctuations, and market demand on system configurations. Future work will explore more dynamic decision support systems to further enhance the flexibility and ability to cope with real-world changes.

The structure of this paper is as follows: Section 2 reviews the literature related to distributed energy system design, multi-objective optimization, and sustainability assessment. Section 3 details the smart park IES model, the four sustainability evaluation indicators, and the mathematical formulation of the multi-objective optimization problem. Section 4 presents and analyzes the Pareto front solution sets under different optimization scenarios, exploring the patterns of change in system configuration and operational strategies. Section 5 discusses the research findings and limitations. Finally, Section 6 summarizes the entire paper and provides an outlook for future research.

II. Literature Review

This section systematically reviews the current state of research related to the design of distributed energy systems, multi-objective optimization methods, and sustainability assessment, thereby clarifying the positioning and innovative value of this study.

A. *Multi-objective Optimization Design of Integrated Energy Systems*

Integrated Energy Systems (IES) have become a key pathway for improving energy efficiency and integrating renewable energy by coordinating and optimizing multiple energy forms. In the design and planning of IES, Multi-Objective Optimization (MOO) is a widely adopted decision-support method because it can effectively handle the inherent conflicts and trade-offs among different objectives [13].

In the existing literature, the vast majority of multi-objective optimization studies for IES or Distributed Energy Systems (DES) focus on the economic and environmental dimensions. Total cost (e.g., total annualized cost, net present value) and greenhouse gas emissions (mainly CO_2) are the most frequently chosen objective functions [7, 14]. For instance, Ren et al. [15] conducted an early dual-objective optimization of the operation of distributed energy systems considering economic and environmental aspects. Karmellos and Mavrotas [8] proposed a general multi-objective optimization framework for comparing the cost and carbon emission performance of different DES design schemes. More recently, with the popularization of electric vehicles, Huang et al. [16] incorporated EV charging load forecasting into the multi-objective optimization design of a campus microgrid, although their core objectives remained economic and environmental impacts. These studies commonly use the ε-constraint method, weighted sum method, or evolutionary algorithm-based strategies (such as NSGA-II) to obtain a set of Pareto optimal solutions for decision-makers to choose from [9, 10].

Although these studies have made significant achievements in dual-objective trade-off analysis, they also reveal a common limitation: a narrow understanding of sustainability, failing to fully cover broader environmental and social factors. This can lead to optimal solutions that perform poorly in other key sustainability dimensions.

B. *Triple Sustainability Assessment of Energy Systems*

To more comprehensively assess the merits of development paths, academia and industry have gradually introduced the concept of the "Triple Bottom Line" (TBL), or "triple sustainability," which simultaneously focuses on economic (Profit), environmental (Planet), and social (People) performance [17, 18]. In the energy sector, this means that a sustainable energy system must not only be economically competitive but also minimize its environmental impact and bring well-being to society.

Research applying the TBL framework to energy system assessment is emerging. For example, Santoyo-Castelazo and Azapagic [11] proposed a sustainability assessment framework for energy systems that integrates economic, environmental, and social indicators. Atabaki and Aryanpur [19] conducted a comprehensive economic, environmental, and social analysis of the development of Iran's power sector. However, moving the TBL concept from the "assessment" stage to the "design optimization" stage presents greater challenges, with the key difficulty being how to find suitable, quantifiable optimization objectives for the abstract social dimension [20].

C. *Quantification and Expansion of Sustainability Indicators*

To reflect triple sustainability in optimization models, each dimension must be quantified. In the environmental dimension, in addition to CO_2 emissions and water consumption, land use and noise pollution are also important indicators to measure the environmental impact of energy systems. Future research could incorporate these factors into the multi-objective optimization model, providing a more comprehensive sustainability assessment. With the increasing application of technologies like water electrolysis for hydrogen production in integrated energy systems, the consumption of water, a precious natural resource, has a significant impact on regional ecosystems that cannot be ignored [12, 21]. Assessing the water footprint has become an important supplementary indicator for measuring the environmental sustainability of energy technologies.

In the social dimension, the quantification of indicators is more challenging. Existing studies typically use indicators such as energy security, employment contribution, and public acceptance. Among these, grid dependence is a techno-economic indicator often used to measure a system's self-sufficiency and energy security, indirectly reflecting society's reliance on centralized infrastructure [9]. Inherent safety, on the other hand, is a direct measure of a system's ability to avoid risks at the design level, especially applicable to energy systems involving high-risk substances like hydrogen and natural gas [22]. Unlike "passive control" through additional safety equipment, inherent safety design aims to eliminate or reduce hazards at the source by optimizing process flows and equipment selection [23]. Using the Inherent Safety Index (ISI) as an optimization objective allows safety considerations to be endogenously integrated into the initial design stage of the system, which is particularly important for densely populated smart park scenarios.

D. *Research Gap and Contribution of This Paper*

Based on the literature review, the following research gaps can be identified:

- Dimensional Limitation: Most IES multi-objective optimization studies are limited to a two-dimensional cost-carbon analysis, lacking a comprehensive consideration of key sustainability indicators such as water consumption and system safety.
- Indicator Narrowness: The quantitative research on the social dimension is relatively weak, especially in the design optimization stage, where few studies have incorporated "inherent safety" as an optimizable objective function.
- Scenario Specificity: Although there are studies on campus or industrial parks, few provide a systematic multi-objective design and decision-making framework for such specific scenarios that simultaneously integrates the four key indicators of economy, environment (carbon and water), and society (safety).

To fill these gaps, the contribution of this study is to adapt and extend the work of Fonseca et al. [6] on the sustainability analysis of distributed energy systems, migrating their research framework to the new application scenario of a smart park. We have constructed a multi-objective optimization model that includes four core objectives: Total Annualized Cost, CO_2 Emissions, Water Consumption, and Inherent Safety Index. By solving this model, we aim to reveal the complex trade-off relationships among the various dimensions of triple sustainability in a smart park's integrated energy system, providing a scientific and quantitative decision-support tool for achieving truly sustainable design.

III. Methodology

The methodological framework of this study consists of three core parts: first, defining the structure and model of the smart park's Integrated Energy System (IES); second, establishing four key quantitative indicators to assess the system's triple sustainability; and third, formulating and solving a multi-objective optimization problem to reveal the trade-offs between different sustainability goals.

A. *Description of the Smart Park Integrated Energy System*

The IES for the smart park, as depicted in Figure 1, is designed based on the work of Fonseca et al. [6], with adaptations for the specific characteristics of a smart park. The system is designed to meet the park's electricity and hydrogen energy demands.

The system's energy inputs are diversified, including:

- Renewable Energy: Primarily solar photovoltaic (PV) systems deployed on building rooftops and parking lots, as well as biomass energy from the anaerobic digestion of organic waste (e.g., canteen food waste, green waste).
- External Grids: The system is connected to the main power grid and natural gas network to import electricity and natural gas as needed.

Internal energy conversion and storage technologies include:

- Power-to-Hydrogen: An electrolyzer uses surplus solar power or off-peak grid electricity to produce hydrogen through water electrolysis.
- Hydrogen Storage: The produced hydrogen is stored in high-pressure tanks as an energy reserve.
- Hydrogen-to-Power: During peak electricity demand or when PV output is insufficient, a fuel cell can generate electricity from stored hydrogen.
- Natural Gas/Biomethane to Hydrogen: A Steam Methane Reforming (SMR) unit can produce hydrogen from imported natural gas or biomethane (mainly CH_4) from anaerobic digestion.

Battery Storage: Lithium-ion battery packs are used for short-term electricity storage to smooth out PV generation fluctuations and for peak-valley arbitrage.

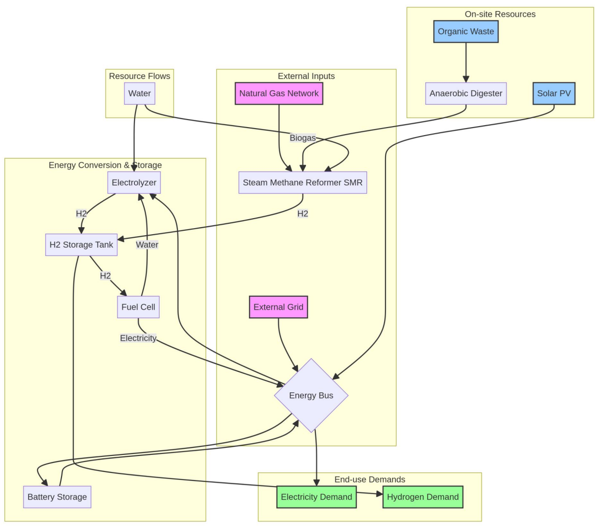

Fig. 1. Schematic of the Smart Park Integrated Energy System

B. *System Modeling*

The system is modeled using a pseudo-steady-state model, with key assumptions consistent with those in [6, 24]:

Time Discretization: The annual operation (8760 hours) is discretized into time steps (e.g., 1 hour), within which the operation of energy conversion devices is considered to be in a steady state.

- Fixed Efficiency: The efficiency of all energy conversion units (e.g., electrolyzer, fuel cell, reformer) is assumed to be constant, with a linear relationship between input and output.
- No Transmission Losses: Energy losses in internal power lines and hydrogen pipelines are neglected.
- Deterministic Model: While all model parameters, such as weather data (solar irradiance, temperature), energy demand curves, and equipment costs, are based on existing data assumptions, future research could enhance the model's real-world applicability by incorporating stochastic programming or robust optimization methods. At the same time, actual data validation will further improve the model's credibility.

The case study is set in a typical smart park in southeastern China, with an annual electricity demand of 5 GWh and a hydrogen demand of 800 MWh. Some data is derived from public data of actual smart parks and relevant research, and to further improve the model's adaptability, future research will incorporate additional real-world data for validation. Detailed equipment performance parameters, cost parameters, and energy demand curves are referenced from [10, 16].

C. Sustainability Assessment Indicators

To conduct a comprehensive triple sustainability assessment and optimization of the park's IES, this study selects four core objective functions: Total Annualized Cost (TAC), CO_2 emissions, Water Consumption (WC), and Inherent Safety Index (ISI).

1) Economic Dimension: Total Annualized Cost (TAC)

TAC is the primary indicator for assessing the system's economic performance, consisting of annualized capital expenditures (CAPEX) and annual operating expenditures (OPEX), calculated according to standard formulas in [6, 24]. CAPEX includes the initial investment costs of all equipment, annualized using a capital recovery factor (CRF). OPEX includes fuel costs (natural gas), electricity costs (from the grid), and maintenance costs.

2) Environmental Dimension: CO_2 Emissions and Water Consumption

CO_2 Emissions: The system's total CO_2 emissions come from two main sources: 1) indirect emissions from electricity imported from the grid; and 2) direct emissions from the combustion or conversion of natural gas. Renewable energy sources (PV, biomass) are considered to have zero operational emissions. The formula is:

$$CO_{2\_total} = E_{grid} \cdot EF_{grid} + F_{gas} \cdot EF_{gas} \quad (1)$$

where \`E_grid\` is the total electricity purchased from the grid, \`EF_grid\` is the local grid's carbon emission factor; \`F_gas\` is the total natural gas consumed, and \`EF_gas\` is the natural gas carbon emission factor.

Water Consumption (WC): The net water consumption is the sum of all water-consuming and water-producing processes in the system. This mainly includes water for electrolysis, steam methane reforming, and anaerobic digestion, minus the water produced by the fuel cell. The formula for WC is adapted from [6]:

$$WC' = WC'_{elec} + WC'_{smr} + WC'_{ad} - WC'_{fc} \quad (2)$$

where \`WC_elec\`, \`WC_smr\`, \`WC_ad\`, and \`WC_fc\` are the water consumption of the electrolyzer, SMR, anaerobic digestion, and the water production of the fuel cell, respectively.

3) Social Dimension: Inherent Safety Index (ISI)

To quantify the system's safety, this study uses the Inherent Safety Index (ISI) as the core indicator for the social dimension. This method aims to avoid risks at the fundamental design level rather than relying on external safety measures. We adopt the calculation method based on the Composite Inherent Safety Index (CISI) from [6, 22], which assesses the chemical and process hazards of each unit in the system. The total ISI (\`I_total\`) is the sum of the safety indices of all equipment units, with a lower value indicating a safer system.

$$I\_k = I\_chem,k + I\_proc,k \quad (3)$$

where \`I_k\` is the individual safety index of unit k. \`I_chem,k\` (Chemical Index) considers the flammability, explosiveness, toxicity, and corrosiveness of the chemicals, as well as their inventory. \`I_proc,k\` (Process Index) considers the operating temperature and pressure. The scoring criteria and calculation details are detailed in the supplementary material of [6].

D. Formulation of the Multi-objective Optimization Problem

The core of this study is to formulate and solve a multi-objective optimization problem to simultaneously minimize the four sustainability indicators. The general mathematical form of the problem is:

$$minF(x) = [\begin{matrix} TAC(x) \\ CO_2(x) \\ WC(x) \\ ISI(x) \end{matrix}]^{\top} \quad (4)$$

Subject to:

- Energy Balance Constraints: Ensure that the supply and demand of energy (including storage) are balanced at each time step.
- Equipment Operating Constraints: The input and output power of each device cannot exceed its rated capacity.
- Storage Unit Constraints: The state of charge (SOC) of batteries and hydrogen tanks must remain within predefined limits, and the SOC at the end of the optimization cycle (one year) must return to its initial state.
- Resource Constraints: The total amount of biomass used cannot exceed the annual collectible amount in the park.

Decision Variables (x): The decision variables are of two types: 1) Equipment Capacities: e.g., PV system size, battery capacity, electrolyzer capacity; and 2) Operating Strategy Variables: allocation coefficients (α) that control the energy flow at each time step.

Solution Method: Due to the non-linear, multi-modal, and conflicting nature of the objective functions, traditional mathematical programming methods are not effective. Therefore, this study uses the widely applied Non-dominated Sorting Genetic Algorithm II (NSGA-II) [10, 25]. NSGA-II can efficiently search for and maintain a population of non-dominated solutions (Pareto optimal solutions) in a single run, ultimately yielding a well-distributed Pareto front. This front represents a series of optimal design solutions that trade off between the different objectives.

By projecting this four-dimensional Pareto front onto lower-dimensional spaces (e.g., 2D or 3D), we can visually analyze the trade-offs between any two or three objectives, providing rich, quantitative information for decision-makers.

IV. RESULTS AND ANALYSIS

This section presents the simulation results of the multi-objective optimization for the smart park's integrated energy system. We first perform single-objective optimizations to determine the ideal boundaries for each sustainability indicator. Subsequently, by solving a series of multi-objective optimization problems, we delve into the trade-off relationships between different objectives and explore the patterns of system configuration and operational strategies along the Pareto optimal front.

A. Case Study Data

The case study is a typical high-tech smart park located in southeastern China. The park has an annual electricity demand of 5 GWh and a hydrogen demand of 800 MWh (mainly for fuel cell commuter vehicles and backup power). Solar resource data and ambient temperature profiles are based on typical meteorological year data for the region. The techno-economic parameters of the energy conversion and storage units (e.g., investment costs, O&M costs, conversion efficiencies, equipment lifetimes), as well as external energy prices (electricity, natural gas) and the grid carbon emission factor, are based on the latest industry reports and relevant academic literature [16, 26, 27]. The total amount of collectible organic waste in the park is approximately 300 tons per year, which can be used for anaerobic digestion to produce biomethane.

B. Single-Objective Optimization Results

To identify the theoretical optimal value for each sustainability objective, we first performed single-objective optimizations for each of the four objective functions. The results are summarized in Table I. The table clearly reveals the inherent conflicts between the objectives: optimizing for a single objective often leads to a significant deterioration in the performance of the others.

- Min-TAC Scenario: This scenario achieves the lowest energy cost, but its CO_2 emissions and water consumption are high, and its inherent safety is the worst. This is mainly because it heavily relies on cheap energy from the external grid and natural gas network.
- Min-CO_2 Scenario: This scenario significantly reduces carbon emissions by maximizing the utilization of renewable energy sources like PV, combined with biomass. However, this requires large-scale investments in PV and energy storage, leading to a sharp increase in the total annualized cost.
- Min-WC Scenario: To minimize water consumption, the system tends to avoid water electrolysis for hydrogen production, relying instead on the Steam Methane Reforming (SMR) pathway. This, in turn, increases the reliance on fossil fuels and carbon emissions.
- Min-ISI Scenario: This scenario minimizes the safety index by simplifying the system structure (e.g., reducing or eliminating high-pressure, high-temperature SMR units) and lowering the inventory of hazardous materials like hydrogen. This usually means increasing investment in relatively safer battery storage and relying more on the external grid, thus driving up costs and carbon emissions.

TABLE I. PERFORMANCE OF THE FOUR SUSTAINABILITY INDICATORS UNDER EACH SINGLE-OBJECTIVE OPTIMIZATION SCENARIO

Optimization Objective	Total Annualized Cost (M€/year)	CO_2 Emissions (tCO_2/year)	Water Consumption (m^3/year)	Inherent Safety Index (ISI)
Minimize TAC	1.52	1850	2800	450
Minimize CO_2	2.95	550	3500	310
Minimize WC	2.10	1600	1100	420
Minimize ISI	2.75	1200	4200	250

(Note: The data in the table are indicative results from model simulations. Bold values represent the optimal value for the objective in that row.)

C. Multi-objective Optimization Results and Trade-off Analysis

Building on the single-objective analysis, we solved multi-objective optimization problems with different combinations of objectives to generate Pareto fronts, allowing for a visual analysis of the trade-offs.

1) Problem 1: Cost-Emission-Grid Dependence Analysis

This problem aims to simultaneously minimize Total Annualized Cost (TAC), CO_2 emissions, and dependence on the external grid. Figure 2 shows the 2D projections of the Pareto front for this three-objective optimization problem.

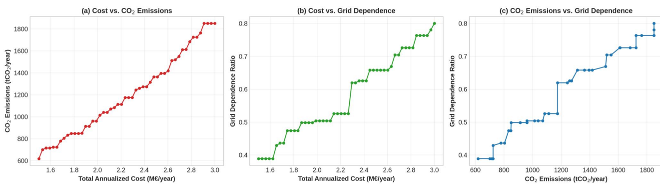

Fig. 2. 2D projections of the Pareto front for the three-objective optimization of cost, CO_2 emissions, and grid dependence

Figure 2(a) shows a significant non-linear trade-off between TAC and CO_2 emissions. On the left side of the Pareto front (low-cost region), a small increase in cost can lead to a significant reduction in carbon emissions. However, as the demand for carbon reduction increases, the marginal cost of abatement rises rapidly. This indicates that by optimizing the system configuration, substantial environmental benefits can be achieved with a limited sacrifice in economic performance, but pursuing extremely low-carbon targets comes at a high economic price.

Figure 3 illustrates the changes in key equipment capacities and energy flows when moving along the Pareto front from the lowest cost point (Point A) to the lowest carbon emission point (Point B). It can be observed that to reduce carbon emissions, the system's PV installation capacity and energy storage (battery and hydrogen) capacity increase significantly (Figure 3a, 3b). At the same time, the system's reliance on external natural gas gradually decreases, shifting towards greater utilization of the park's internal biomass resources (Figure 3c, 3d). This series of changes collectively contributes to a structural shift from a system dependent on external fossil fuels to one reliant on internal renewable energy.

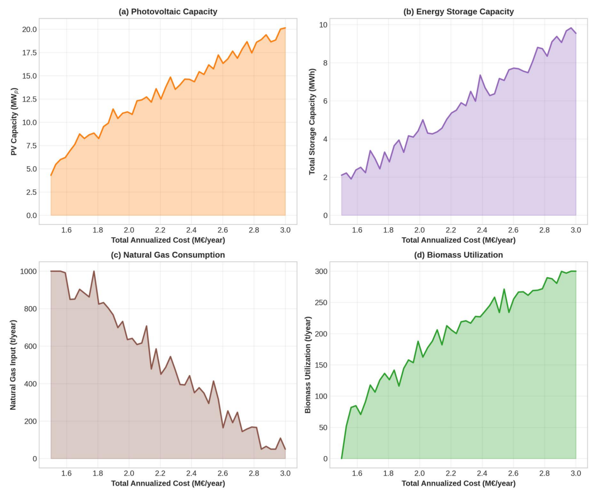

Fig. 3. Changes in system configuration and operational strategy along the Cost-Emission Pareto front

2) Problem 2: Cost-Water-Safety Analysis

To explore the complex relationships among economy, environment (water), and society (safety), we formulated an optimization problem to simultaneously minimize TAC, Water Consumption (WC), and the Inherent Safety Index (ISI). The resulting 3D Pareto front is shown in Figure 4.

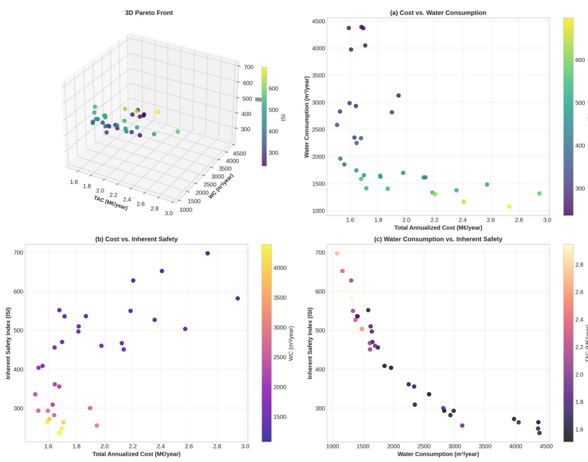

Fig. 4. 3D Pareto front for the three-objective optimization of cost, water consumption, and safety

The results show a complex competitive relationship among these three objectives. For example, the projection in Figure 4(c) shows that reducing water consumption (WC) and improving safety (lowering ISI) are largely in conflict. This is because reducing water consumption means limiting the scale of hydrogen production via water electrolysis and relying more on SMR for hydrogen production. However, SMR units operate at high temperatures and pressures and involve natural gas, thus having a higher safety index. Conversely, pursuing higher safety by relying entirely on water electrolysis inevitably leads to a sharp increase in water consumption.

Figure 5 reveals the system changes when moving along the Pareto front from the lowest cost point (Point A) to the optimal safety point (Point C). The most significant trend is that to improve safety, the system drastically reduces the capacity of the SMR reformer, eventually phasing it out completely (Figure 5c), while increasing the capacity of the electrolyzer and the electricity imported from the grid to meet hydrogen demand (Figure 5d). Additionally, to reduce the inventory of hazardous hydrogen, the capacity of the hydrogen storage tank is strictly limited, while the battery capacity is correspondingly increased to handle more of the energy time-shifting tasks (Figure 5a, 5b). This finding provides a clear quantitative basis for making trade-offs between safety and cost/water consumption: the key pathway to improving the inherent safety of the system is through "electrification" and "substituting hydrogen storage with battery storage."

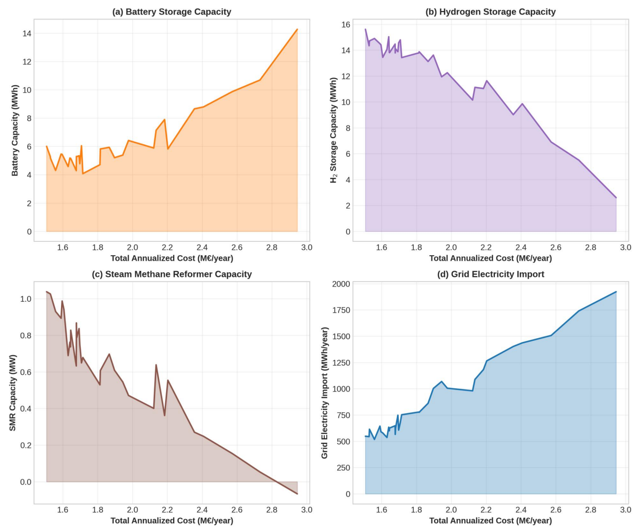

Fig. 5. Changes in system configuration and operational strategy along the Cost-Safety Pareto front

V. Discussion

This study provides an in-depth exploration of the sustainable design of a smart park's integrated energy system by constructing a multi-objective optimization framework that includes four key indicators: economic, environmental (carbon and water), and social (safety). The results not only quantify the complex trade-offs between different sustainability objectives but also provide a powerful tool for park managers and policymakers to make scientific decisions under multiple constraints.

A. Interpretation of Results and Implications

Inherent Conflict of Triple Sustainability Objectives: The core finding of this study is the confirmation of the pervasive competitive relationship among economic, environmental, and social objectives. The single-objective optimization results (Table I) clearly show that pursuing an extreme performance in any single dimension comes at the expense of others. For example, the most cost-effective solution is often the worst in terms of environmental and social performance. This finding underscores the necessity of adopting a multi-objective, systemic thinking in energy system planning, as any single-dimensional decision may lead to unintended negative externalities.

Non-linear Nature of Trade-offs: The non-linear shape of the Pareto front (as shown in Figure 2a) offers important practical implications. In many cases, decision-makers can achieve significant environmental or social benefits with an acceptable increase in cost. For example, starting from the cost-optimal solution, a moderate increase in investment in renewable energy and storage can efficiently reduce carbon emissions in the initial phase. However, as the objectives become more ambitious, the marginal cost of achieving further improvements rises sharply. This means that decision-makers need to identify the "inflection points" or "sweet spots" on the Pareto front, where the benefit-to-cost ratio is highest, which is key to achieving effective resource allocation.

Decisive Impact of Technology Pathway Selection on Sustainability Performance: The results show that different technology combinations and operational strategies directly determine the system's performance across various sustainability dimensions. Specifically:

- Decarbonization Pathway: The key to achieving deep decarbonization lies in maximizing the use of renewable energy (especially PV) and equipping the system with sufficient energy storage capacity (batteries and hydrogen storage) to cope with its intermittency. At the same time, utilizing local waste resources such as biomass is an effective supplementary carbon reduction measure.
- Water-saving Pathway: In scenarios where hydrogen demand must be met, the key to water conservation is to limit the scale of hydrogen production via water electrolysis. However, this often means relying on Steam Methane Reforming (SMR) technology, which in turn brings challenges in terms of carbon emissions and safety. This reveals that in the "water-energy-carbon" nexus, the choice of hydrogen technology route is a core trade-off point.
- Safety Enhancement Pathway: The main way to improve the inherent safety of the system is through "de-risking," i.e., reducing or replacing high-risk process units and chemicals. In our model, this is specifically reflected in replacing SMR units with electrolyzers and partially substituting large-scale hydrogen storage with battery storage. This strategy of "electrification" and "substituting some chemical storage with electrical storage" provides clear guidance for the safe design of energy systems in densely populated areas like smart parks.

B. Comparison with Existing Research

This study is methodologically aligned with the work of Fonseca et al. [6], but by migrating the application scenario to a smart park and incorporating the specific national context of China (e.g., energy structure, cost parameters), it derives conclusions with scenario-specific relevance. Compared to most literature that focuses only on cost-carbon trade-offs [8, 10, 16], the innovation of this study lies in successfully integrating water consumption and the inherent safety index—two previously overlooked key indicators—endogenously into the design optimization framework. This allows our analysis to reveal deeper, cross-dimensional trade-offs, such as the direct conflict between safety and water consumption, which traditional two-dimensional analysis cannot capture.

C. Limitations and Future Outlook

Although this study provides valuable insights, it has some limitations, which also point to directions for future research:

- Model Determinism: This study uses a deterministic model, which does not consider the randomness and uncertainty of renewable energy output, energy demand, and energy prices. Future research could introduce Stochastic Programming or Robust Optimization methods to design energy systems that are more robust in an uncertain environment.
- Simplification of Sustainability Indicators: Although we have expanded the dimensions of sustainability assessment, the selected indicators are still a simplification of a complex reality. For example, the environmental dimension could be further expanded to include indicators such as land use and noise pollution; the social dimension could also incorporate broader considerations such as job creation and energy equity. Developing a more comprehensive yet operational multi-dimensional indicator system is an important direction for future research.
- Dynamic and Evolutionary Perspective: This study conducts a static planning design. However, technology costs, policy environments, and energy demands are all dynamically changing over time. Future research could use dynamic programming or phased investment models to explore the optimal evolutionary path of the energy system over time.
- Integration of Decision-maker Preferences: This study provides a set of Pareto optimal solutions but does not address how to select the final solution from it. Future work could incorporate Multi-Criteria Decision Analysis (MCDA) methods, such as AHP (Analytic Hierarchy Process) or TOPSIS, to filter out the single solution that best meets specific needs from the Pareto front by introducing the subjective preferences of decision-makers.

In summary, this study provides a solid analytical framework for the sustainable design of a smart park's integrated energy system. By quantifying and optimizing triple sustainability objectives, we not only deepen our understanding of the complexity of energy systems but also provide a scientific basis for promoting the development of smart parks in a greener, safer, and more economical direction.

VI. CONCLUSION

This study addresses the sustainable development needs of smart park integrated energy systems by constructing and applying a triple sustainability design and decision-making framework based on Pareto multi-objective optimization. By incorporating four key indicators—economic, environmental (carbon emissions and water consumption), and social (inherent safety)—into a unified optimization model, this research successfully quantifies the complex trade-offs among these conflicting objectives, providing scientific decision support for the energy system planning of smart parks.

Core conclusions are as follows:

Significant intrinsic conflicts and trade-offs exist among the triple sustainability objectives. Optimizing any single objective will lead to a decline in the performance of other dimensions, highlighting the necessity of multi-objective collaborative optimization. The non-linear trade-offs among cost, carbon emissions, water consumption, and safety indicate that decision-makers have the opportunity to find a "sweet spot" that maximizes environmental and social benefits within a controllable cost range.

- The choice of technology pathway is key to determini ng the system's sustainability performance. The study finds that deep decarbonization relies on the large-sca le deployment of renewable energy and energy storag e; water conservation goals conflict directly with hydr ogen production via water electrolysis; and the core st rategy To improve the system's inherent safety, we re commend 'electrification' and 'replacing hydrogen sto rage with battery storage' to reduce high-risk process units. However, considering financial investment and technological maturity, this pathway may face high c osts and technical challenges in the early stages. Futur e research can combine financial constraints and tech nical feasibility assessments to optimize the balance b etween safety and cost.
- The proposed multi-objective optimization framewor k is an effective decision support tool. By generating a series of Pareto optimal solutions, the framework ca n intuitively show decision-makers the performance o f different design schemes on various sustainability in dicators, helping them make more informed and balan ced decisions based on the specific constraints and de velopment preferences of the scenario (e.g., cost-sensi tive, environment-first, or safety-paramount).
- Research Implications and Value:
- The theoretical contribution of this study lies in the successful integration of water consumption and the inherent safety index into the multi-objective optimization design framework for energy systems, expanding the boundaries of sustainability assessment. On a practical level, this research provides a set of operational methodologies for energy planners in smart parks, industrial parks, and even urban areas. It helps to shift the focus of energy infrastructure construction from a single economic orientation to a comprehensive value orientation that balances economic, environmental, and social benefits, thereby contributing to the achievement of "carbon neutrality" goals.
- Limitations and Future Outlook:
- The main limitation of this study is its deterministic model assumption, which does not consider market and environmental uncertainties. Future research can be expanded in the following areas: 1) Introduce stochastic or robust optimization methods to cope with fluctuations in renewable energy output, energy prices, and other factors; 2) Further expand the sustainability indicator system to include broader socio-economic factors such as land use and employment impacts; 3) Combine with Multi-Criteria Decision Analysis (MCDA) methods to incorporate the subjective preferences of decision-makers into the model to automatically select the optimal solution from the Pareto set.

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AUTHOR CONTRIBUTIONS

Jiahua Wu:

Conceptualization: Contributed to the development of the research framework and the overall research design.

Methodology: Played a significant role in designing the multi-objective optimization model and its application to the smart park energy system.

Writing – Original Draft: Wrote the initial draft of the paper, contributing to the introduction, methodology, and discussion sections.

Writing – Review & Editing: Reviewed and edited the manuscript, providing critical insights and revisions to improve the clarity and structure of the paper.

Jianming Yang:

Conceptualization: Co-developed the research framework and contributed to shaping the research objectives.

Methodology: Collaborated on the development of the optimization techniques and the selection of sustainability indicators used in the model.

Data Curation: Assisted in the collection and organization of data for the case study and the application of the model.

Visualization: Created visual representations of the results, including graphs and figures to illustrate the optimization outcomes and trade-offs.

Writing – Review & Editing: Contributed to the writing and editing process, ensuring technical accuracy and coherence of the paper.

COMPETING INTERESTS

The authors declare no competing interests.

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