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Optimization of Campus Distributed Energy Systems Using a Hybrid AHP–TOPSIS Approach: A Case Study of Kitakyushu Science and Research Park

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Abstract

Universities are key actors in the global pathway to carbon neutrality due to their diverse energy demands and innovation capacity. Based on the author's previous study using twenty years of operational data (2002–2021), the distributed energy system (DES) at Kitakyushu Science and Research Park (KSRP), Japan, was found to exhibit a significant increase in carbon emission intensity from 0.12 to 0.25 tCO_2/GJ (+108%), primarily driven by equipment degradation and declining renewable penetration. Building on this diagnosis, this study aims to identify optimal improvement pathways by applying a hybrid multi-criteria decision-making (MCDM) framework combining Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Four criteria—emission reduction, economic efficiency, technological maturity, and policy compatibility— are used to evaluate multiple technologies and their combinations. The results show that photovoltaic (PV) systems rank highest among single technologies, while PV +storage achieves the best performance among two-technology systems, and a three-technology integration of PV + Storage + Smart Microgrid demonstrates the highest overall effectiveness, highlighting the importance of system-level coordination. Based on these findings, a phased roadmap is proposed, including short-term deployment of PV + Storage, medium-term integration of GSHP and microgrids, and long-term adoption of bioenergy and hydrogen. This study provides a transparent and reproducible AHP–TOPSIS framework with synergy evaluation and offers practical guidance for campus decarbonization.

Keywords

Distributed Energy System (DES) **;** *Multi-Criteria Decision Making; AHP–TOPSIS* **;** *Campus Carbon Neutrality* **;** *University*

1. Introduction

1.1. Background and Motivation

The global effort to achieve carbon neutrality by mid-century has placed university campuses at the forefront of the energy transition. Campuses are microcosms of urban systems: they host diverse building types (classrooms, laboratories, dormitories, libraries), have dynamic energy demands across electricity, heating, and cooling, and operate with centralized governance that can enable systemic interventions. As such, they offer ideal platforms to pioneer distributed energy systems (DES) that can later be replicated at community and municipal scales. (Ai et al., 2019; Guerrieri et al., 2019).

Japan, in particular, faces unique challenges and opportunities. Its 2050 carbon neutrality pledge is accompanied by ambitious intermediate goals under the “Green Growth Strategy.” (Ministry of Economy, Trade and Industry(METI), 2021). Yet, the nation’s high reliance on fossil fuels, the gradual retirement of nuclear capacity, and limited domestic renewable potential create pressing needs for efficient DES models. (Xie et al., 2018). Within this context, Kitakyushu Science and Research Park (KSRP) provides a valuable case study. Designed in the early 2000s with city-gas-based combined cooling, heating, and power (CCHP), it initially demonstrated significant carbon savings. However, twenty years of operation have revealed severe performance degradation, with carbon intensity more than doubling. (Yu et al., 2025).

1.2. Research Gaps

Existing studies on campus energy systems have evolved from single-technology analysis toward integrated multi-energy system optimization. Early research primarily focused on the performance of individual technologies, such as photovoltaic (PV) systems, combined heat and power (CHP), or ground-source heat pumps (GSHP), emphasizing energy efficiency and carbon reduction potential. (Wen et al., 2020).

More recent studies have highlighted the importance of integrated energy systems that combine renewable generation, energy storage, and intelligent control. (Shen et al., 2026). Campus microgrids, in particular, have emerged as a key solution for enhancing energy flexibility, resilience, and decarbonization performance. Studies from the United States and Europe demonstrate that PV–storage–microgrid integration can significantly improve system efficiency and reliability, while research in China emphasizes the coupling of PV, GSHP, and waste-to-energy systems under regional resource conditions. (Judge et al., 2024; Li et al., 2026; Yang et al., 2026; Zhou et al., 2025).

In parallel, multi-criteria decision-making (MCDM) methods, such as AHP, TOPSIS, and their hybrid forms, have been widely applied to evaluate energy technologies by considering economic, environmental, and technical factors. (Mesa Estrada et al., 2026). However, most existing studies focus on ranking individual technologies and rarely consider the interaction effects among technologies in integrated systems. (Demir et al., 2026).

Moreover, few studies incorporate long-term operational data into decision-making frameworks, limiting their applicability in real-world scenarios where system degradation and dynamic performance play a critical role.(Sayed et al., 2026).

Therefore, a comprehensive evaluation approach that integrates long-term empirical data, multi-criteria decision-making, and system-level synergy analysis remains lacking. This study aims to address this gap by proposing a hybrid AHP–TOPSIS framework combined with synergy evaluation for campus distributed energy systems.

1.3. Objectives

This study aims to fill these gaps through three contributions:

- Long-term diagnosis of KSRP’s DES, quantifying efficiency degradation and emission rebound using real operational data (2002–2021).
- Development of a hybrid AHP–TOPSIS framework that systematically ranks alternative technologies and their combinations under four weighted criteria.
- Proposal of a phased roadmap for campus energy transition, incorporating short-term feasibility, medium-term expansion, and long-term innovation, and situating these within Japan’s policy context and global best practices.

1.4. Structure of the Paper

The remainder of the paper is structured as follows. Section 2 presents the methodology, including data sources, the AHP–TOPSIS framework, and the incorporation of synergy coefficients. Section 3 reports the results for single technologies, two-technology combinations, and three-technology integrated systems. Section 4 extends the discussion by comparing international cases, analyzing policy implications, and exploring emerging digital optimization tools. Section 5 concludes with strategic recommendations and broader insights for sustainable campus development.

2. Methodology

2.1. Data Sources and Problem Context

The long-term operational characteristics of the DES are informed by the author's previous study based on 20 years of data (2002–2021) (Yu et al., 2025). The results indicate a clear trend of performance degradation, reflected in an increase in carbon emission intensity (CEI) and a decline in renewable energy contribution over time. Specifically, CEI increased from 0.12 tCO_2/GJ in the early operational phase to 0.25 tCO_2/GJ in the later phase, representing a 108% increase.

These observations are used in this study as contextual baseline information to support the subsequent optimization analysis, rather than being re-evaluated. The degradation trend is primarily associated with equipment aging, the gradual decommissioning of on-site generation units, and increased reliance on grid electricity.

To characterize system performance, two indicators are adopted: carbon emission intensity (CEI, tCO_2/GJ) and renewable energy ratio (RER, %), defined as follows. Table 1 summarizes their variations across different operational phases, while Equations (1)–(2) describe their calculation methods.

Electricity purchased by the system is assumed to be supplied by the Kyushu Electric Power grid mix, and emission factors are based on Japan-specific data corresponding to the respective operational periods. Although detailed annual data are not fully presented in this study, the long-term trends derived from previous research provide a consistent basis for evaluating system performance changes. Uncertainty related to operational variability and emission factors is acknowledged qualitatively.

$$CEI = \frac{C_{annual\ emissions}}{E_{energy\ supply}} \quad (1)$$

$$RER = \frac{E_{renewable}}{E_{total\ consumption}} \quad (2)$$

Where Cannual emissions $C_{annual\ emissions}$ means the annual total CO_2 emissions (tCO_2), $E_{energy\ supply}$ means the corresponding total supplied energy (GJ), $E_{renewable}$ means the renewable energy contribution (GJ) and $E_{total\ consumption}$ means the total final energy demand (GJ).

Table 1.DES Operational Characteristics by Phase (Source: Authors)

Years	Main Equipment Status	CEI (tCO_2/GJ)	RER (%)
2002-2011	Fuel cell + Gas engine + Solar + Urban power grid + Abs + Boiler	0.12	0.8
2012-2016	Gas engine + Solar + Urban power grid + Abs + Boiler	0.19	0.5
2017-2021	Urban power grid + Abs + Boiler	0.25	0

2.2. Multi-Criteria Decision-Making (MCDM) Framework

Multi-criteria decision-making (MCDM) integrates systematic evaluation techniques into conventional decision-making frameworks to address complexity, uncertainty, and trade-offs among multiple criteria (Pei et al., 2025). In practical energy system assessment, certain criteria—such as technological maturity and policy compatibility—are difficult to quantify precisely and are often interpreted based on structured knowledge derived from literature and policy reports rather than direct measurement. By organizing these heterogeneous indicators into a unified evaluation framework, MCDM provides a robust and transparent basis for assessing complex energy systems. (Battal Şal et al., 2025).

The overall MCDM framework employed in this study is illustrated in Figure 1, which integrates data collection, criteria weighting, and alternative ranking into a structured workflow. As shown in Figure 1, the process consists of five stages: (1) data collection based on long-term operational data (2002–2021) and literature sources; (2) establishment of the evaluation criteria system using IPCC, NEDO, and METI data; (3) determination of criteria weights through AHP pairwise comparison; (4) ranking of alternatives using TOPSIS; and (5) integration and interpretation of results for system optimization.

To further identify optimal improvement pathways, candidate technologies were screened through a structured literature review using the keyword combination "energy system AND university" in the Web of Science database, as summarized in Figure 2. The matrix presented in Figure 2 (page 4) classifies various energy technologies (e.g., PV, GSHP, bioenergy, storage) across different campus application scenarios, providing a systematic basis for selecting evaluation alternatives.

Based on this screening, the selected technologies were incorporated into a hybrid AHP–TOPSIS model. The Analytic Hierarchy Process (AHP), a structured technique based on pairwise comparisons, was employed to determine the relative weights of evaluation criteria using a literature-informed approach. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), which evaluates alternatives by measuring their distance from the ideal and anti-ideal solutions, was then applied to rank potential technology options. This combined approach enables a systematic, transparent, and reproducible comparison between current system performance and potential upgrade pathways, while ensuring consistency with widely accepted MCDM practices in energy system evaluation. (Mousavi et al., 2024).

2.3. Evaluation Criteria System

Based on literature [3, 11-13] and Japanese policy objectives, four core criteria were established (Table 2).

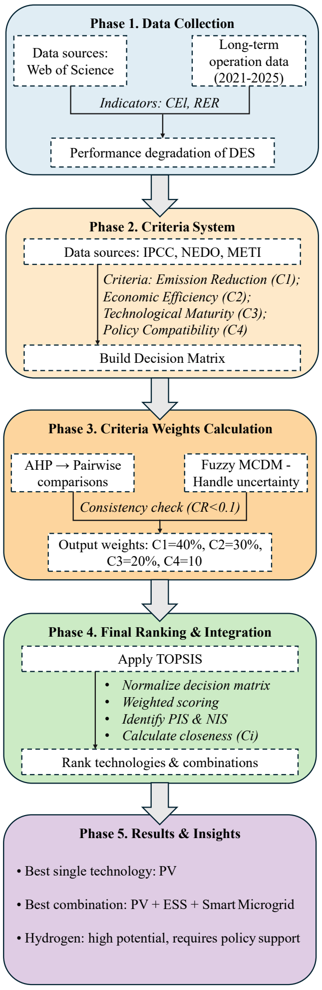

Figure 1 AHP-TOPSIS Hybrid Framework for DES Optimization (Source: Authors)

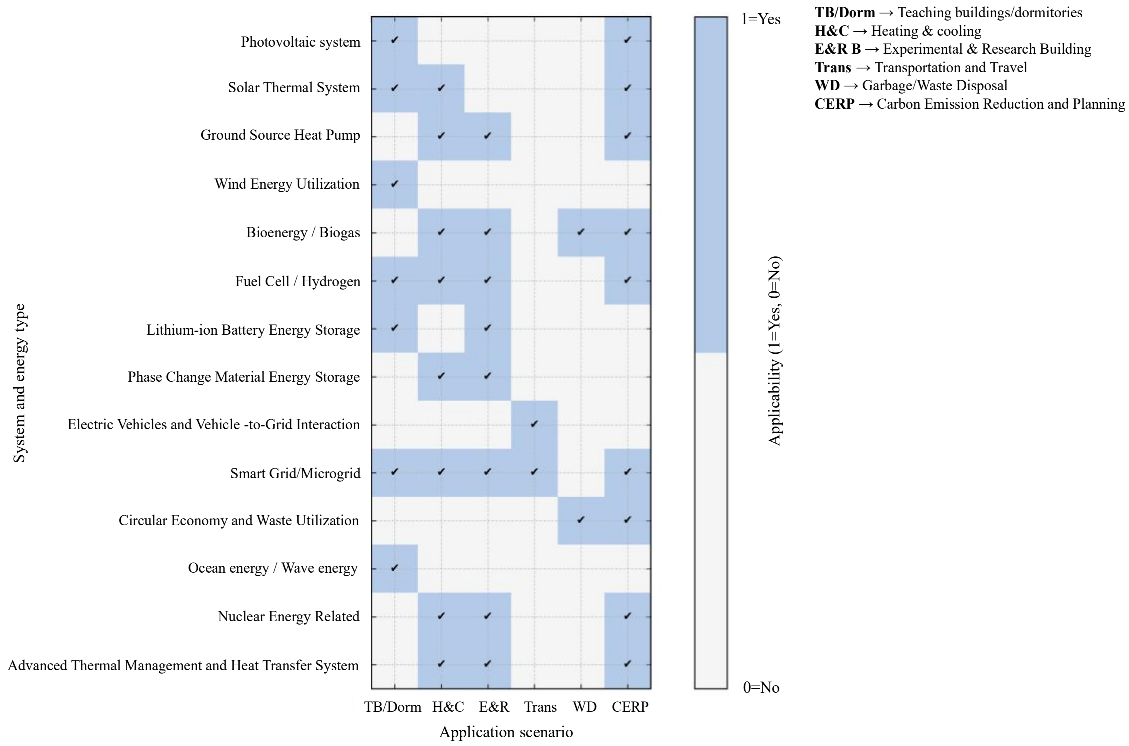

Figure 2 Matrix of University Energy Systems and Application Scenarios (Source: Authors)

Table 2. MCDM Evaluation Criteria System (Source: Authors)

Criterion	Symbol	Weight(AHP)	Type	Quantitative Indicator	Data Source
Emission Reduction Effect	C1	40%	Benefit	CO_2 reduction (tCO_2/year)	IPCC AR6 Methodology Report (Intergovernmental Panel on Climate Change, 2023)
Economic Efficiency	C2	30%	Cost	Payback period (years)	NEDO Techno-Economic Report (New Energy and Industrial Technology Development Organization (NEDO), 2024)
Technological Maturity	C3	20%	Benefit	TRL level (1-9)	Japan Energy Agency Technology Assessment (JAEA, 2024)
Policy Compatibility	C4	10%	Benefit	Subsidy coverage rate (%)	METI Green Growth Strategy (METI, 2021)

2.4. Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is a structured multi-criteria decision-making method that combines qualitative judgment with quantitative analysis. In this study, AHP was employed to derive the weights of the evaluation criteria

Step 1: Construct hierarchy

— Goal: Select optimal DES alternative for KSRP.

— Criteria: C1–C4.

— Alternatives: PV, storage, GSHP, hydrogen, etc.

Step 2: Construct the pairwise comparison matrix.

The pairwise comparison matrix A is constructed to represent the relative importance of the evaluation criteria with respect to the overall objective. In this study, pairwise comparisons were performed based on a combination of literature review, policy reports (IPCC, NEDO, METI), and expert-informed judgment. The Saaty 1–9 scale (Table 3) was adopted to ensure methodological rigor, consistency, and interpretability.

To enhance transparency and reproducibility, the complete pairwise comparison matrix used in this study is provided in Table 4. The geometric mean method was applied to derive the weight vector. The resulting consistency ratio (CR = 0.022) is below the acceptable threshold (CR < 0.10), indicating that the matrix satisfies the consistency requirement. The geometric mean method was applied to derive the weight vector. The consistency ratio (CR = 0.022) is below the acceptable threshold (CR < 0.10), indicating that the pairwise comparison matrix has satisfactory consistency.

Table 3. Saaty 1-9 Scoring Scale and Its Meanings (Source: Authors)

Scale	Meaning
1	Indicates that one factor is of equal importance compared to the other factor
3	Indicates that one factor is slightly more important than the other factor
5	Indicates that one factor is significantly more important than the other factor
7	Indicates that one factor is strongly more important than the other factor
9	Indicates that one factor is extremely more important than the other factor
2, 4, 6, 8	Intermediate values between the above adjacent judgments

Table 2.Table 4. AHP Pairwise Comparison Matrix for Evaluation Criteria (Source: Authors)

Criteria	C1 (Emission)	C2 (Economic)	C3 (Tech)	C4 (Policy)
C1	1	4/3	2	4
C2	3/4	1	3/2	3
C3	1/2	2/3	1	2
C4	1/4	1/3	1/2	1

Step 3: Weight vector calculation

The geometric mean method was applied:

$$GM_i = \sqrt[n]{\prod_{j=1}^{n} a_{ij}} \quad (4)$$

$$w_i = \frac{GM_i}{\sum_{i=1}^{n} GM_i} \quad (5)$$

$$W = (w_1, w_2, w_3, w_4)^T \quad (6)$$

Step 4: Consistency check

The maximum eigenvalue was obtained as λ_{max}. The consistency index (CI) and consistency ratio (CR) were calculated as:

$$\lambda_{max} = \frac{1}{n}\sum_{i=1}^{n}\frac{(AW)_i}{w_i} \quad (7)$$

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (8)$$

$$CR = \frac{CI}{RI} \quad (9)$$

Results: λ_{max}=4.060, CI =0.020, CR =0.022<0.10.

Final weights: C1 = 0.40, C2 = 0.30, C3 = 0.20, C4 = 0.10.

2.5. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

Following the determination of criterion weights by AHP, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was applied to rank all candidate alternatives. The principle of TOPSIS is that an optimal alternative should be closest to the positive ideal solution (PIS) and farthest from the negative ideal solution (NIS). To ensure transparency and reproducibility, the complete decision matrix, including data sources, units, and criterion attributes, is provided in Table 5.

Step 1: Construct a decision matrix

For m alternatives and nn criteria, the decision matrix is defined as:

$$X = [X_{ij}],\ i = 1, \ldots, m;\ j = 1, \ldots, n \quad (10)$$

where X_{ij} means the performance value of alternative i under criterion j. Each row of the matrix corresponds to a candidate technology (e.g., PV, wind, GSHP, hydrogen), and each column corresponds to an evaluation criterion (C1–C4).

Table 5. Decision Matrix for TOPSIS (Source: Authors)

Technology	C1 (tCO_2/year)	C2 (years)	C3 (TRL 1–9)	C4 (%)
PV	85	6	9	40
Wind	60	7	8	35
Li-ion	70	8	8	30
Bioenergy	75	12	6	45
GSHP	55	10	7	40
Hydrogen	50	15	5	20

In this study, the evaluation criteria are defined as follows:

— C1 (Emission reduction effect): measured in tCO_2/year (benefit criterion)

— C2 (Economic efficiency): measured as payback period in years (cost criterion)

— C3 (Technological maturity): expressed as TRL level (1–9) (benefit criterion)

— C4 (Policy compatibility): expressed as subsidy coverage rate (%) (benefit criterion)

The data were derived from IPCC AR6 reports, NEDO techno-economic assessments, JAEA technology readiness evaluations, and METI policy documents. The results obtained are in Table 5.

Step 2: Normalize

To eliminate dimensional effects, normalization is performed as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (11)$$

Step 3: Weighted normalization

Using the AHP-derived weights W=(0.4,0.3,0.2,0.1), the weighted matrix is obtained:

$$v_{ij} = w_j \times r_{ij} \quad (12)$$

Step 4: Determine ideal solutions

For benefit criteria:

$$V_j^+ = max(v_{1j}, \dots, v_{mj}), \quad V_j^- = min(v_{1j}, \dots, v_{mj}) \quad (13)$$

For cost criteria (payback):

$$V_j^+ = min(v_{1j}, \dots, v_{mj}), \quad V_j^- = max(v_{1j}, \dots, v_{mj}) \quad (14)$$

Step 5: Distance to ideal solutions

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - V_j^+\right)^2}, \quad S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - V_j^-\right)^2} \quad (15)$$

Step 6: Closeness coefficient

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}, \ 0 \leq C_i \leq 1 \quad (16)$$

Step 7: Ranking

Alternatives are ranked in descending order of C_i, where a higher value indicates stronger overall performance.

2.6. Synergy Coefficient

While the AHP–TOPSIS framework provides a systematic ranking of individual technologies, real-world campus energy systems are inherently integrated and rely on the interaction among multiple technologies. Therefore, an additional parameter—the synergy coefficient (σ)—is introduced to capture the interaction effects among combined technologies.

The overall performance of a technology combination is calculated as:

$$Score_{comb} = (\sum_{k=1}^{m} w_k \times C_k) \times \sigma \quad (17)$$

where w_k means the weight of each criterion derived from AHP, C_k means the TOPSIS closeness coefficient, and σreflects the degree of synergy between technologies.

(1) Conceptual basis of synergy

Unlike simple additive evaluation, the synergy coefficient captures the "1 + 1 > 2" system effect, which is widely observed in integrated energy systems. These effects arise from:

— Intermittency mitigation (e.g., PV + Storage)

— Demand–supply coupling (e.g., GSHP + PV)

— System coordination and optimization (e.g., Smart Microgrid integration)

This formulation allows the model to reflect real operational advantages of hybrid systems rather than treating technologies as independent units.

(2) Determination of coefficient range

The coefficient range $\sigma = 1.0\text{–}1.3$is defined based on a combination of:

— Empirical findings from integrated energy system studies (e.g., PV–storage performance improvements)

— Engineering practice benchmarks for hybrid renewable systems

— Reported performance gains in campus microgrid projects

(3) Classification of synergy levels

Based on the degree of functional complementarity, the synergy coefficient is categorized in Table 6.

(4) Methodological implication

By incorporating σ, the evaluation framework extends from single-technology ranking to system-level assessment, enabling:

— More realistic representation of campus DES configurations

— Identification of optimal technology portfolios rather than isolated solutions

— Enhanced decision support for phased deployment strategies

Table 6. Classification of Synergy Levels and Corresponding Coefficients for Technology Combinations (Source: Authors)

Synergy Level	σ Range	Description	Typical Examples	C4 (%)
Strong	1.25–1.30	High complementarity and system enhancement	PV + Storage, GSHP + PV	40
Moderate	1.15–1.20	Partial functional complementarity	Wind + Storage, Bioenergy + Waste	35
Weak	1.05–1.10	Limited interaction effects	Loosely coupled systems	30
None	1.00	Redundant or overlapping functions	PV + Solar Thermal	45

(5) Limitations and future work

Although the synergy coefficient is grounded in literature and engineering practice, it still contains a degree of controlled subjectivity, as it is not directly derived from simulation or operational datasets.

Future research may improve this approach by:

— Calibrating σ using HOMER simulations or digital twin models

— Applying Monte Carlo sensitivity analysis

— Incorporating real-world operational data from integrated campus systems

2.7. Research Workflow

The complete workflow integrates diagnosis, weighting, ranking, and synergy evaluation (Figure description for paper):

— Diagnosis: Identify performance gaps in current DES (CI trends, efficiency loss).

— Criteria weighting (AHP): Derive reliable weights (C1–C4).

— Single-tech ranking (TOPSIS): Evaluate individual alternatives.

— Combination evaluation: Apply synergy coefficients to derive scores for two- and three-technology systems.

— Roadmap design: Translate rankings into phased deployment strategies.

3. Results and Discussion

3.1. Performance of Single Technologies

The TOPSIS evaluation reveals that photovoltaic (PV) systems achieve the highest performance (C_i = 0.748), followed by wind energy (C_i = 0.643) and lithium-ion storage (C_i = 0.601). Technologies such as hydrogen fuel cells (C_i = 0.382) and nuclear-related systems (C_i = 0.441) rank lower due to high costs and lower maturity levels.

The ranking of single technologies demonstrates that while emission reduction potential is critical, economic feasibility and policy support strongly influence near-term applicability. The dominance of PV and storage confirms global trends in campus energy transition, where mature renewables form the backbone of decarbonization strategies.

The dominance of PV can be attributed to its high technological maturity (TRL 9), strong policy support in Japan, and rapidly declining costs. In contrast, hydrogen systems remain limited by high capital cost and infrastructure dependency, despite their long-term potential.

Furthermore, the results highlight that economic feasibility (C2) significantly influences rankings, particularly under current subsidy frameworks. This explains why mature technologies outperform emerging options even when the emission reduction potential is comparable.

3.2. Evaluation of Two-Technology Combinations

Recognizing that real-world campus energy systems rarely rely on single technologies, this study introduced a synergy coefficient (1.0–1.3) to evaluate two-technology systems. The results show that PV + Storage integration scored highest (final score = 0.903), demonstrating strong complementarity in addressing intermittency and maximizing self-consumption. PV + Smart Microgrid (0.786) and GSHP + PV (0.767) also achieved high rankings, highlighting the value of digital intelligence and renewable-driven clean heating/cooling (Table 7).

Other combinations, such as Bioenergy + Waste Utilization (0.695), revealed significant potential in campuses with agricultural or dining waste, while Wind + PV (0.691) offered diurnal complementarity but required additional storage to achieve stability. Redundant pairings such as PV + Solar Thermal ranked lowest (0.614), suggesting that duplication without complementarity reduces system-wide efficiency.

The analysis confirms that functional diversity and integration—rather than simple addition of capacity—drive system-level benefits in campus DES. This finding highlights that system integration, rather than individual technology performance, is the key driver of energy system optimization.

3.3. Evaluation of Three-Technology Combinations

Three representative three-technology systems were further assessed to capture higher-order synergies (Table 8). The PV + Storage + Smart Microgrid (Y) combination achieved the highest overall score (0.879), underscoring the transformative role of intelligent management platforms. Here, the microgrid functions as a "brain," coordinating PV generation and storage dispatch to achieve real-time optimization.

The PV + Storage + GSHP (X) pathway ranked second (0.857), offering a closed-loop solution for campuses with high HVAC demand by replacing fossil-based boilers with renewable-powered GSHPs. Meanwhile, Bioenergy + Waste + Storage (Z) achieved a moderate score (0.731), delivering strong co-benefits in waste reduction and circular economy branding, though its feasibility is highly context-dependent.

This tiered analysis shows that the addition of a third element—particularly digital control or efficient end-use technologies—significantly improves system-level outcomes beyond what two-technology pairings can achieve.

3.4. International Benchmarking

The results align closely with global experiences (Table 9). In Europe, universities such as Cambridge and TU Delft prioritize PV + Storage + GSHP, supported by strong policy frameworks under the EU Green Deal. In the United States, DOE-funded projects such as UC San Diego's microgrid demonstrate the resilience and efficiency gains of multi-technology integration, especially with fuel cells and EV charging. In China, near-zero energy campus pilots emphasize PV, GSHP, and waste-to-energy, reflecting local resource availability.

This benchmarking confirms that PV and storage form the universal core, while complementary technologies differ by region based on climate, policy, and resource context.

3.5. Policy Adaptation for Japan

Interpreting the results in Japan's policy context highlights both strengths and gaps. Current subsidies strongly favor PV and storage, which aligns with the short-term recommendations of this study. However, GSHP and bioenergy receive limited support, despite their demonstrated potential in integrated systems. Hydrogen fuel cells are promoted under the Green Growth Strategy, yet their immaturity at the campus scale limits near-term applicability.

Policy adaptation should therefore focus on:

— Expanding incentives for integrated systems (e.g., PV + Storage + GSHP) rather than isolated technologies.

— Supporting hydrogen and bioenergy demonstrations in universities as testbeds for long-term innovation.

— Recognizing digital infrastructure (AI optimization, digital twins, microgrids) as critical enablers of carbon neutrality.

The results demonstrate a clear transition from technology-centered optimization to system-level integration. While mature technologies such as PV dominate in the short term, future energy systems will increasingly depend on intelligent coordination and multi-energy coupling.

This aligns with global trends in campus energy systems, where digital platforms, microgrids, and hybrid energy solutions are becoming central to achieving carbon neutrality.

3.6. Phased Roadmap for Campus Decarbonization

Based on the findings, a phased strategy of "Core–Expansion–Feature" is proposed:

— Core (2025–2030): Deploy PV + Storage for immediate carbon reduction and grid stability.

— Expansion (2030–2040): Integrate GSHP and Smart Microgrids to enhance systemic efficiency and resiliency

— Feature (2040–2050): Incorporate bioenergy, waste utilization, and hydrogen as distinctive, context-driven innovations.

This roadmap ensures both short-term feasibility and long-term innovation, aligning campus actions with Japan's 2050 carbon neutrality pledge and international zero-carbon campus initiatives.

Table 7.TOPSIS evaluation results of single technologies (Source: Authors)

Technical Options	C1: Emission Reduction Effect (0.4)	C2: Economic Efficiency (0.3)	C3: Technological Maturity (0.2)	C4: Policy Compatibility (0.1)	Closeness (Ci)	Ranking
Photovoltaic system (PV)	0.155	0.054	0.180	0.060	0.748	1
Wind energy utilization	0.073	0.077	0.160	0.075	0.643	2
Lithium-ion battery storage	0.107	0.064	0.120	0.065	0.601	3
Solar thermal system	0.121	0.057	0.140	0.040	0.587	4
Bioenergy / Biogas	0.145	0.036	0.120	0.085	0.563	5
Electric vehicle and vehicle-grid	0.131	0.057	0.100	0.045	0.512	6
Smart grid / Microgrid	0.136	0.032	0.160	0.055	0.509	7
Circular economy and waste utilization	0.087	0.045	0.160	0.050	0.481	8
Ground source heat pump (GSHP)	0.058	0.050	0.140	0.080	0.469	9
Nuclear energy related	0.170	0.026	0.100	0.070	0.441	10
Fuel cell / Hydrogen energy	0.078	0.054	0.120	0.025	0.382	11
Advanced thermal management	0.092	0.018	0.060	0.035	0.291	12
Phase change material (PCM) storage	0.039	0.022	0.080	0.030	0.273	13
Ocean energy / Wave energy	0.194	0.011	0.040	0.020	0.241	14

Table 8. Evaluation of two-technology combinations (Source: Authors)

Ranking	Combination	Avg. Score	Synergy Coeff.	Final Score	Notes
1	PV + Storage (Solar-Storage)	0.695	1.30	0.903	Solves intermittency, stabilizes grid
2	PV + Smart Microgrid	0.655	1.20	0.786	Digital integration, flexible control
3	GSHP + PV	0.667	1.15	0.767	Clean heating/cooling + renewable power
4	Wind + PV (Hybrid Renewables)	0.628	1.10	0.691	Diurnal complementarity, but storage needed
5	Bioenergy + Waste Utilization	0.556	1.25	0.695	Strong circular economy synergies
6	Hydrogen + Smart Microgrid	0.502	1.15	0.577	Future-oriented, low near-term economics
7	PV + Solar Thermal	0.614	1.00	0.614	Redundant functions, weak complementarity

Table 9. Evaluation of three-technology combinations (Source: Authors)

Rank	Combination (Code)	Avg. Score	Synergy Coeff.	Final Score	Highlights
1	PV + Storage + Smart Microgrid (Y)	0.651	1.35	0.879	Strongest integration; “brain + hand” analogy
2	PV + Storage + GSHP (X)	0.659	1.30	0.857	Clean supply-demand loop for HVAC
3	Bioenergy + Waste + Storage (Z)	0.585	1.25	0.731	Circular economy, but context-dependent

4. Conclusion

This study evaluates the optimization pathways of the distributed energy system (DES) at Kitakyushu Science and Research Park (KSRP), Japan, using a hybrid AHP–TOPSIS framework combined with synergy analysis.

The long-term performance degradation of the existing DES is characterized by a 108% increase in carbon emission intensity over the past two decades. These findings are used as the baseline condition for subsequent optimization analysis. The deterioration is mainly attributed to equipment aging, reduced renewable energy contribution, and increased reliance on grid electricity.

Building upon this baseline, the multi-criteria evaluation identifies effective pathways to address system performance decline. The results indicate that photovoltaic (PV) systems represent the most suitable single technology under current economic and policy conditions, followed by wind energy and lithium-ion storage. More importantly, the findings demonstrate that system-level integration, rather than isolated technology deployment, is essential for restoring energy efficiency and achieving meaningful carbon reduction. Among the evaluated configurations, PV + storage emerges as the most effective two-technology solution, while PV + storage + smart microgrid achieves the highest overall performance, highlighting the critical role of intelligent energy management in future campus energy systems.

Based on these findings, a phased roadmap is proposed, emphasizing short-term deployment of mature technologies, medium-term system integration, and long-term innovation through emerging solutions such as hydrogen and bioenergy.

Methodologically, this study contributes by integrating long-term operational insights with a transparent and reproducible AHP–TOPSIS framework, while introducing a synergy-based evaluation of technology combinations. Practically, it provides an adaptable decision-support framework for campus-level carbon neutrality, with potential applicability to broader urban energy systems.

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Conflict of interest

The author(s) declare(s) that there is no competing interest

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