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Engineering application of hybrid artificial intelligence for optimizing solar multigeneration systems in university buildings

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ABSTRACT

Built environments with diverse energy demands, such as university buildings, face challenges in meeting energy requirements with renewable sources. This study develops a hybrid artificial intelligence framework to optimize a solar-based multigeneration energy system designed for complex building energy demands. The framework integrates Response Surface Methodology for design space exploration and screening, Artificial Neural Networks for capturing nonlinear system behavior, and Genetic Algorithms for global optimization, improving accuracy, convergence, and computational efficiency. Baseline and optimized models were evaluated using the Building Energy Optimization (BEopt) software and Engineering Equation Solver (EES) to assess demand-side and supply-side performance. The optimized configuration reduced electricity, cooling, and heating demands by 16.3, 15.8, and 16.9 percent, and achieved a maximum exergy efficiency of 29.23 percent, representing a 14.18 percent improvement over the baseline. Although the cost rate increased to 14.12 dollars per hour, this increase reflects the incorporation of upgraded system components and additional photovoltaic generation capacity beyond peak demand, which improves operational robustness, resilience, and performance. The system also achieved substantial reductions in site energy use and Carbon Dioxide emissions while generating surplus energy. By integrating a compression chiller, the design effectively harnessed solar energy for simultaneous cooling and heating, demonstrating a practical engineering pathway toward zero-energy performance at the campus scale. The outcomes confirm that hybrid artificial intelligence-based optimization can improve energy efficiency and environmental performance in built environments. Future extensions will examine additional renewable integrations across building types and broader climatic conditions, further supporting the framework's adaptability.

1. Introduction

The built environment accounts for roughly 34% of global energy use and about 37% of greenhouse gas emissions (UNEP, 2023; IEA, 2024), making operational performance a major decarbonization lever (Fosas et al., 2025). Zero Energy Buildings (ZEBs) address this challenge by reducing operational demand and offsetting remaining consumption through on-site renewable energy generation (Jaysawal et al., 2022; Wang et al., 2024), thereby reducing fossil fuel dependence and

associated emissions (Maduta et al., 2025). In practice, ZEB outcomes depend on how boundaries are defined, for example, delivered versus primary energy, and on-site versus off-site offsets, and on whether performance is evaluated under typical operation or optimized schedules (Bilardo et al., 2024; Satola et al., 2021). ZEB targets are broadly applicable in diverse built environments; however, achieving these goals in complex, multifunctional buildings such as university campuses is particularly challenging due to climate sensitivity, high cooling dependence, and diverse building typologies within higher education estates

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(Davidson et al., 2024). University campuses include laboratories, teaching spaces, offices, residential, and recreational facilities with occupancy-dependent energy profiles, creating heterogeneous and time-varying loads that complicate energy optimization (Almasri et al., 2024; Quevedo et al., 2023).

Beyond this functional diversity, the scale and operational intensity of university campuses further complicate ZEB implementation. Educational buildings account for a substantial share of non-residential energy use, and performance is strongly shaped by occupancy patterns, control strategies, and system operation (Gul et al., 2015; Amaral et al., 2020; Gui et al., 2020). Demand-side measures, such as envelope retrofits, high-efficiency systems, and improved operational control, can significantly reduce consumption in educational buildings, although their effectiveness depends on the climate and usage patterns (Almasri et al., 2024; Emil et al., 2021). Achieving ZEB performance, therefore, also requires careful selection and sizing of renewable energy systems, such as Photovoltaic (PV) installations, to offset residual demand under local operating conditions (Sunny et al., 2024; Olivieri et al., 2020). As an example, a campus-scale study demonstrates that PV integration can deliver substantial economic and environmental benefits, with optimized systems supplying around 40% of campus electricity demand, achieving local self-consumption rates of approximately 77%, and reducing Carbon Dioxide (CO₂) emissions by up to 30% (Olivieri et al., 2020). However, such PV-focused integration studies rarely evaluate coordinated demand reduction and multigeneration system sizing within a unified optimization framework, limiting their transferability to heterogeneous campus loads and retrofit constraints. In contrast, isolated interventions tend to underperform (Olivieri et al., 2020; Aghamolaei et al., 2023). In this context, Artificial Intelligence (AI) techniques offer a practical means of addressing the nonlinear and multi-objective nature of campus energy systems by supporting data-driven optimization of efficiency, cost, and environmental performance (Manmatharasan et al., 2025; Elwy et al., 2024). Recent studies have similarly reported machine-learning-based solar farm optimization (Assareh et al., 2025a) and explainable-AI-enabled development of building energy management systems (González-Briones et al., 2025), highlighting the relevance of AI for building-scale energy planning and decision support. Most existing studies still report demand-side management and renewable system optimization as separate problem formulations, and many do not benchmark performance against well-established optimization baselines, underscoring the need for integrated frameworks tailored to university buildings (Amaral et al., 2020; Barber et al., 2022).

Achieving ZEB objectives in university campuses requires not only advanced optimization strategies but also modeling workflows that can represent retrofit impacts and operational variability (Ibrahim et al., 2024; Rajasekaran et al., 2024) and evaluate renewable supply options under realistic operational constraints (Barber et al., 2022). Building energy simulation translates system retrofit choices, such as envelope upgrades, Heating, Ventilation, and Air Conditioning (HVAC) system replacement, and lighting efficiency improvements, into hourly or sub-hourly load profiles that reflect operational schedules and internal gains (Pan et al., 2023). Dynamic simulation engines such as EnergyPlus support this process by enabling high-resolution representation of HVAC, lighting, and equipment loads and parametric exploration of demand-side design options (Ibrahim et al., 2024; Chiesa et al., 2021; Bamdad et al., 2023). Beyond descriptive simulation, coupling EnergyPlus with optimization has demonstrated measurable operational benefits; for example, EnergyPlus-based model predictive control achieved 49.7% daily peak-load reduction and 17.6% energy savings versus rule-based control in a case study (Bamdad et al., 2023). To operationalize demand-side analysis within a cost-performance optimization context, the Building Energy Optimization Tool (BEopt) has been applied as a wrapper around EnergyPlus to systematically compare retrofit packages and produce consistent demand profiles that can be carried forward into system sizing studies and multigeneration system

evaluation (Mobayen et al., 2025; Assareh et al., 2025b). The resulting demand profiles can then be linked to system-level thermodynamic models to quantify energy and exergy performance, cost, and emissions under site-specific constraints using Engineering Equation Solver (EES) (Klein, 1993; Saadmohammadi et al., 2024). Coupled workflows using the Building Energy Optimization Tool and Engineering Equation Solver (BEopt-EES) have been applied to renewable-driven ZEB and multi-generation systems, typically reporting energy efficiencies of 33–34% and exergy efficiencies of around 35% under optimized configurations (Mobayen et al., 2025; Assareh et al., 2025b).

Selecting appropriate renewable supply systems is equally critical for achieving ZEB targets in university campuses (Davidson et al., 2024; Medrano et al., 2018). University campus diagnostics show wide dispersion in building performance (reported ranges of 50–470 kWh/m².year), and average non-renewable primary energy use can be about four times higher than benchmark thresholds (45–55 kWh/m².year), indicating that deep retrofits and carefully sized renewable supply are typically required rather than incremental measures alone (Medrano et al., 2018). Consistent with this, a recent review of retrofit ZEB case studies found Photovoltaic (PV) systems were adopted in all cases, highlighting the centrality of PV sizing and boundary assumptions in retrofit-to-ZEB pathways (Ibrahim et al., 2024). On the supply side, EES integrated with Transient System Simulation Tool (TRNSYS), EnergyPlus, or BEopt enables component-level thermodynamic simulation and consistent performance accounting across changing environmental conditions and operating states (Klein, 1993; Saadmohammadi et al., 2024; Assareh et al., 2025c; Nikitin et al., 2023). For institutional-scale ZEB configurations, optimized hybrid renewable electrification and storage have been explored using explicit system sizing (Oğuz et al., 2024; Eisapour et al., 2021). For example, uncertainty-aware designs that account for correlated climate and demand variability and equipment degradation show that deterministic schemes can lose up to 28.2% of annual renewable supply and more than 50% of net energy balance and carbon reduction over a 20 year service life, with corresponding implications for sustained CO₂ mitigation, whereas robustly sized systems consistently meet ZEB targets with self-sufficiency ratios approaching 90% (Lu et al., 2024).

To search large design spaces efficiently, hybrid Artificial Intelligence (AI) optimization methods are increasingly used, most commonly combining Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs) to reduce computational burden while retaining multi-objective search capability (Barber et al., 2022; Allal et al., 2024; Naserabad et al., 2021). Hybrid ANN-GA optimization and related algorithmic frameworks have been shown to efficiently approximate thermodynamic objective spaces, as reported across several recent high-impact studies on renewable-driven multigeneration systems (Mohtasim et al., 2025; Yilmaz et al., 2024; Verma et al., 2024), with exergy efficiencies exceeding 60% and competitive cost and CO₂ emissions trade-offs in multigeneration energy systems (Naserabad et al., 2021). Response Surface Methodology (RSM) has also been used as a structured screening and response-surface approximation step in BEopt-EES workflows, yielding energy and exergy performance (33.05% and 34.02%) comparable to ANN-assisted optimization while reducing simulation burden (Allal et al., 2024). Recent comparative studies in building performance optimization have also shown that algorithm choice materially affects solution quality, with Particle Swarm Optimization (PSO) and Multi-Verse Optimizer (MVO) outperforming GAs in several daylighting and energy optimization problems (Vojdani et al., 2024). The literature shows that AI-based methods, including deep reinforcement learning and RSM-assisted predictive optimization, can improve the cost-effective and climate-sensitive design of hybrid renewable and multigeneration energy systems (Legrene et al., 2025; Assareh et al., 2025d). Likewise, recent studies using an ANN-GA method to optimize geothermal and solar multigeneration systems confirmed that hybrid AI optimization can improve thermoeconomic performance, but these studies did not combine structured RSM screening with integrated

demand-side and supply-side optimization under consistent building-level metrics (Yilmaz et al., 2024). A building-scale study has also shown that machine learning can guide optimization beyond surrogate prediction alone, yet such frameworks still do not integrate structured RSM screening with simultaneous demand-side and supply-side optimization under consistent building-level metrics (Asghari et al., 2026).

However, despite these promising results, most studies remain case-specific and are often evaluated under narrowly defined loads and boundary conditions, with limited benchmarking across well-established optimization approaches and limited evidence of transferability to heterogeneous campus portfolios (Medrano et al., 2018; Allal et al., 2024). Accordingly, comparative evidence is still limited on how common hybrid pipelines, including RSM-assisted sampling, ANN surrogate modeling, and GA-based multi-objective search, perform relative to established multi-objective baselines when evaluated using the same decision variables, constraints, and metrics (Elwy et al., 2024; Karbasforousha et al., 2024; Zorn et al., 2025). This gap motivates practical, reproducible frameworks that integrate calibrated demand modeling, thermodynamic evaluation, and hybrid AI optimization while remaining interpretable and useable under real operational and budget constraints and benchmarked against the most comparable best-performing methods in the literature.

To address this gap, a hybrid AI-driven optimization framework is developed and validated for achieving ZEB targets in multifunctional university environments, integrating supervised RSM-based screening with ANN and GA under consistent decision variables, constraints, and performance metrics. The proposed framework simultaneously optimizes demand-side retrofit decisions and supply-side sizing of a solar-based multigeneration energy system, addressing a key limitation of existing studies that typically treat these aspects as separate problems. The main novelty of this study is threefold: (1) an integrated RSM-ANN-GA framework that jointly optimizes demand-side retrofit decisions and supply-side sizing of a solar-based multigeneration system; (2) improved convergence, computational efficiency, and robustness through supervised RSM-based screening combined with AI-driven multi-objective optimization; and (3) systematic benchmarking using a real university case study under identical decision variables, constraints, and performance metrics. The study contributes a practical and reproducible hybrid AI-based methodology for integrated demand-supply energy optimization, demonstrates its effectiveness under realistic operational and budget constraints, and provides a scalable approach adaptable to different climates and building typologies for advancing intelligent ZEB implementation. By balancing energy efficiency, cost, and environmental objectives, the proposed framework bridges theory and practice under real operational constraints and is adaptable to other complex built environments. The remaining sections are organized as follows: Section 2 introduces the hybrid optimization framework and modeling methodology, Section 3 presents system configuration and optimization setup, Section 4 reports results and comparative analysis, Section 5 discusses limitations and future directions, and Section 6 concludes the paper.

2. Methodology

This study optimizes energy performance for ZEB implementation in a multifunctional university campus by addressing demand- and supply-side solutions through advanced modeling tools, optimization techniques, and a hybrid framework. The research is structured into two main components:

1. **Demand-Side Optimization:** Reduces energy consumption through building design and material optimization.
2. **Supply-Side Optimization:** Ensures efficient green energy production to meet the residual energy need using a hybrid optimization framework.

Fig. 1 illustrates the research framework.

2.1. Demand-side optimization

This optimization focuses on modeling and improving the case study building energy performance using BEopt and EES. These tools enable precise estimation of annual energy requirements and support material optimization to minimize energy use. The main steps include:

- **Energy Load Assessment:** Utilizing BEopt and EES to determine energy demand based on building dimensions, architecture, occupancy, and location.
- **Material Optimization:** Leveraging simulation outputs from BEopt to identify and select energy-efficient materials, minimizing cooling, heating, and electricity loads.
- **Performance Comparison:** Comparing the baseline and optimized designs through data derived from BEopt and EES to quantify efficiency improvements.

2.2. Supply-side optimization

This optimization involves modeling and refining the system to meet the required energy. Thermodynamic simulations were conducted using EES, incorporating weather data from Meteonorm. This approach integrates thermodynamic analysis with advanced optimization techniques to enhance system performance. The optimization process involves:

- 1 **System Modeling:** Developing a comprehensive thermodynamic model of the solar farm, including PV panels and a compression chiller to simultaneously generate heating, cooling, and electricity for the building.
- 2 **Optimization Framework:** Employing a hybrid optimization approach that combines Response Surface Methodology (RSM), Artificial Neural Networks (ANNs), and Genetic Algorithms (GAs):
 - RSM identifies trends and provides an initial approximation of the design space for optimization.
 - ANN refines the model by accurately capturing nonlinear relationships and improving prediction accuracy.
 - GA achieves global optimization by balancing trade-offs between performance and cost.
- 3 **Multi-Objective Optimization:** Two performance metrics are used. Exergy efficiency is defined as the ratio of useful exergy output, reflecting energy quality and effective utilization (Dincer et al., 2012). The cost rate represents the total hourly system cost, expressed in United States dollars per hour (\$/h), including capital recovery and operating expenses. These metrics jointly assess thermodynamic performance and economic feasibility.
- 4 **Validation and Benchmarking:** Benchmarking the optimized system against existing designs to validate performance improvements and ensure reliability.

Regarding system boundary and carbon accounting, CO₂ reductions are calculated within an operational boundary defined as the building's annual delivered electricity balance. The boundary includes annual building electricity demand after demand-side optimization and annual PV electricity generation from the solar farm. Thermal outputs (heating and cooling) are accounted for through their electricity requirement in the EES model; embodied emissions and lifecycle emissions are excluded.

Annual net grid electricity import is computed as follows:

$$E_{Grid,import} = E_{Load} - E_{PV,used} \quad (1)$$

where E_{Load} is the annual building electricity demand and $E_{PV,used}$ is the PV electricity self-consumed to serve the building load. If PV generation

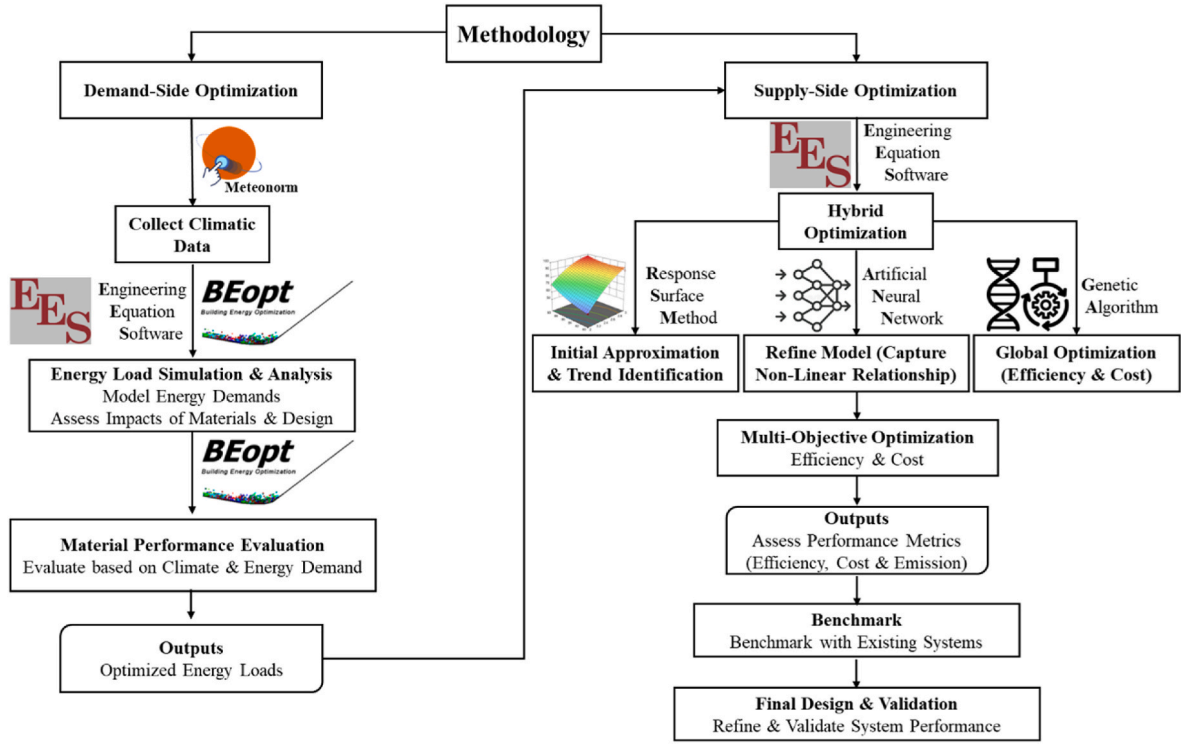


Fig. 1. Overview of the proposed methodology for integrated demand- and supply-side optimization.

exceeds demand, exported electricity is defined as:

$$E_{\text{Export}} = \max(0, E_{\text{PV}} - E_{\text{Load}}) \quad (2)$$

Operational CO₂ emissions are computed as:

$$CO_{2,\text{Operational}} = E_{\text{Grid,import}} \times EF_{\text{Grid}} \quad (3)$$

where $E_{\text{Grid,import}}$ is the annual net grid electricity import (kWh/year), and EF_{Grid} is the national grid emission factor (kgCO₂/kWh). The emission factor used in this study was selected from the International Energy Agency's Emissions Factors 2025 database for the case-study country, Iran (International Energy Agency (IEA), 2025). CO₂ reduction is reported as:

$$\Delta CO_2 = CO_{2,\text{Baseline}} - CO_{2,\text{Operational}} \quad (4)$$

Surplus energy generation (annual) is defined as exported electricity:

$$E_{\text{Surplus}} = \max(0, E_{\text{PV}} - E_{\text{Load}}) \quad (5)$$

This is reported together with the ZEB annual balance condition ($E_{\text{PV}} \geq E_{\text{Load}}$).

2.3. Integration of demand and supply-side results

The optimized results from demand-side and supply-side analyses are integrated to design an energy-efficient, renewable-powered system tailored to the case study building. The reduced energy demand from the demand side serves as a key input for system sizing and configuration in the supply-side optimization. The integration ensures:

- The system is properly scaled to meet the building's optimized energy demand.
- Exergy efficiency and cost are balanced to provide economic and environmental benefits.

In addition, the annual ZEB balance, surplus export (E_{Export}) and operational CO₂ reductions are all evaluated using the same operational

system boundary defined in Section 2.2 to ensure consistent accounting across baseline and optimized cases. This integrated approach facilitates achieving ZEB goals while maintaining optimal indoor comfort and minimizing operational costs.

2.4. Validation and benchmarking

To validate the optimized renewable energy system, its performance is benchmarked against existing renewable energy solutions and ZEB standards. Key performance metrics, including exergy efficiency, cost rate, and emission reduction, are assessed and compared using established benchmarks and data from similar studies. This validation confirms that the system aligns with practical energy performance requirements and environmental goals. While this study does not include full-scale experiments at the selected case study site due to resource constraints and time limitations, future research could focus on field testing the optimized design under real operational conditions. Such field tests would further improve the feasibility and practical implementation potential of this system across diverse building types and climatic regions.

3. System design and analysis

This part presents the design and evaluation of a solar-based renewable energy system developed to meet the building's energy requirements. It integrates building energy simulation with advanced optimization techniques to quantify energy demand, assess system improvements, and identify optimal configurations based on thermodynamic and economic performance.

3.1. Configuration and modeling

The faculty building consists of three floors, and its design parameters, including dimensions, architecture, occupancy, and location, were used as input for BEopt simulations to calculate its annual energy demand. The building is in Dezful City, which has a hot semi-arid climate

(BSh) under the Köppen classification, characterized by long, very hot summers, mild winters, and low annual rainfall. The hottest month is July, while the coldest is December, with temperatures fluctuating from 19.2 °C to 55.6 °C. These climatic and geographic characteristics significantly influence the energy demands of the building, which were thoroughly evaluated in its current state to identify areas for optimization.

Fig. 2 presents the actual view and floor maps of the faculty building, illustrating its layout and design characteristics. These visuals, along with Tables 1–3, define the geometric, functional, and construction inputs used for energy load simulation and demand-side optimization.

Table 1 lists the dimensions and construction characteristics, detailing the size and materials across floors to accommodate functional requirements, structural considerations, and energy efficiency goals.

BEopt was used to evaluate different material combinations and envelope configurations to identify the most energy-efficient design. The objective was to improve energy performance while maintaining structural integrity and functional usability. Table 2 summarizes the optimal materials and envelope features selected through the BEopt simulations, which significantly improved thermal insulation and reduced both cooling and heating demands.

One key feature is the use of high Solar Heat Gain Coefficient (SHGC)

windows on the back façade to enhance passive solar heating throughout cooler seasons. Window area distribution was also optimized. A total window-to-wall ratio of 15% was allocated as follows: 20% on the front facade, 40% on the back facade, and 20% on each of the left and right facades. This configuration balances daylight availability with thermal performance.

Beyond envelope optimization, the simulation framework also depends on clearly defined boundary conditions and performance assumptions. Key weather inputs, building operation parameters, technology performance assumptions, and economic inputs used in the simulations are summarized in Table 3 to improve transparency and reproducibility.

Advanced wall sheathing composed of Oriented Strand Board (OSB) combined with R-15 insulation enhances the thermal resistance of the envelope. Meanwhile, internal partitions incorporating R-13 fiberglass batt insulation at 16-inch spacing improve internal heat regulation. In addition, uninsulated 2 × 6 wood studs (24-inch spacing), double wood studs with R-45 fiberglass insulation, and steel studs insulated with R-19 fiberglass batts are strategically applied to minimize conductive heat transfer. Internal shading coefficients of 0.7 for both summer and winter seasons maintain stable indoor thermal conditions by controlling solar heat gain throughout the year. The design further integrates energy-



1st Floor

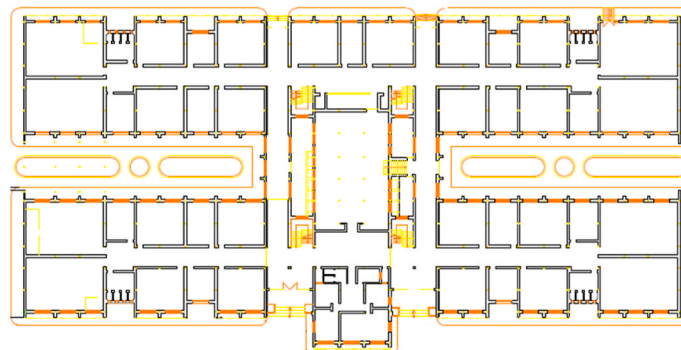
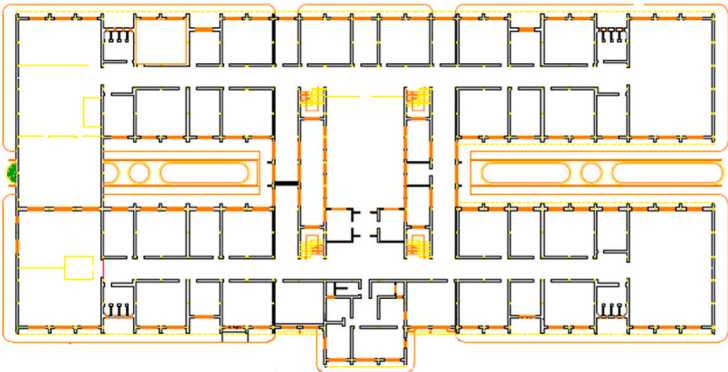


Fig. 2. Architectural floor plans of the case study building: First, second, and roof Levels

2nd Floor



3rd Floor

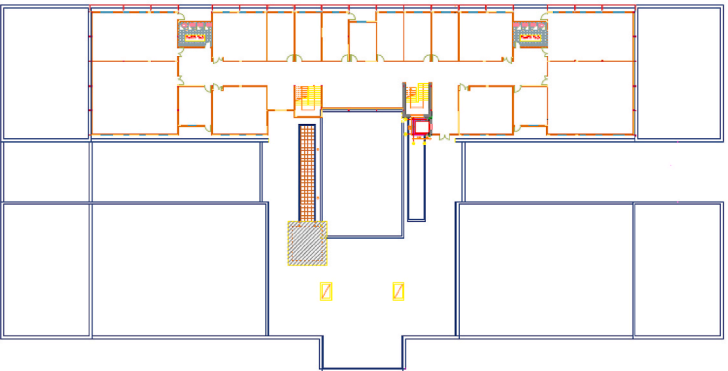


Fig. 2. (continued).

Table 1
Case study size and construction materials.

Parameter	Unit	Size
Building length (1st and 2nd Floors)	m	110
Building width (1st and 2nd Floors)	m	51
Total floor area (1st and 2nd Floors)	m ²	5670
Building length (3rd Floor)	m	80
Building width (3rd Floor)	m	20
Total floor area (3rd Floor)	m ²	1600
Number of storeys	-	3

Floor	Architectural Element	Material
1st and 2nd Floors	Windows	Metal
	Internal Doors	Timber
	Exterior Doors	Metal
	Internal Walls	Brick Masonry
	External Walls	3 cm Brick Façade
	Floor Finish	Mosaic
	Structure System	Steel Frame
3rd Floor	Ceiling	Plaster
	Windows	UPVC
	Internal Doors	Timber
	Exterior Doors	Stramit Panels
	Internal Walls	Brick
	External Walls	3 cm Brick Façade
	Floor Finish	Ceramic Tiles
	Structure System	Lightweight Steel Frame
	Ceiling	Plaster

efficient elements such as Phase Change Material (PCM) drywall for exterior and ceiling thermal mass, light-colored aluminum exterior finishes, and 60% Light-Emitting Diode (LED) lighting to enhance illumination efficiency. Additional conservation measures include 2-foot eaves and overhangs for passive shading, which improve occupant comfort

Table 2
Optimized design features.

Design Element	Optimized Specification
Windows	Rear-facing windows with high SHGC glazing
Window Area	15% overall; Front 20%, Back 40%, Left 20%, Right 20%
Doors	Fiberglass construction
Total Door Area	10 ft ²
Wall Sheathing	Oriented strand board with R-15 polystyrene insulation
Exterior Finish	Light-colored aluminum cladding
Interzonal Walls	2 × 4 wood framing at 16 in. spacing, insulated with R-13 fiberglass batt
Wood Stud Wall	2 × 6 framing at 24 in. spacing, uninsulated
Double Wood Stud	Dual 2 × 4 stud walls at 24 in. spacing, R-45 fiberglass insulation (Grade 1)
Steel Stud	2 × 6 steel framing at 24 in. spacing, R-19 fiberglass batt insulation
Internal Shading	Shading coefficient: 0.7 (summer and winter)
Eaves	2 ft projection
Overhangs	2 ft, first storey, applied to all window openings
Floor Thermal Mass	2 in. gypsum concrete
Exterior Wall Thermal Mass	Phase Change Material (PCM) drywall
Partition Wall Mass	Dual 5.8 in. drywall layers
Ceiling Mass	PCM drywall panels
Floor Covering	40% carpeted area
Roof Insulation	Structural insulated panels (SIPs) with R-47.5 rating
Roof Finish	Light-colored metal
Lighting System	60% Light-Emitting Diode (LED) fixtures
Pier and Beam Ceiling Insulation	R-19 fiberglass batt insulation

and reduce cooling demand.

The sequential process of energy analysis and optimization for the case study, as depicted in Fig. 1, begins with demand-side optimization.

Table 3
Boundary conditions and key simulation inputs.

Design Element	Parameter	Description/Source
Weather Data	Climate dataset	Meteonorm Typical Meteorological Year (TMY) for Dezful, Iran
	Variables used	Ambient temperature, dew point, Global Horizontal Irradiation, diffuse irradiation, wind speed, relative humidity
	Temporal resolution	Hourly weather data for annual simulation
Building Model	Geometry source	Architectural floor plans and as-built drawings of the faculty building
	Occupancy schedules	Standard academic building schedules based on teaching hours and office use
	Thermostat setpoints	Cooling and heating setpoints defined according to typical university comfort standards
	Internal loads	Lighting, equipment, and occupant density based on BEopt commercial building defaults adjusted to faculty use
	Ventilation and infiltration	Natural and mechanical ventilation rates are defined per BEopt defaults for educational buildings
Technology Assumptions	PV module efficiency	Manufacturer datasheet values for commercial crystalline silicon modules
	PV temperature coefficient	Standard performance derating factor included in the EES model
	Chiller performance	Coefficient of Performance (COP) derived from literature values for compression chillers in hot climates
		Market-average installation costs from recent renewable energy cost reports
Economic Parameters	Capital cost	Maintenance fractions of capital cost based on literature benchmarks
	Operating cost	25 years for the PV system, 15 years for the mechanical equipment
	System lifetime	Selected from the International Energy Agency's Emissions Factors 2025 database for the case study country, Iran (International Energy Agency (IEA), 2025)
	Grid CO ₂ emission factor	

This involves collecting climatic data using Meteonorm and employing BEopt software to simulate energy loads and analyze the impacts of materials and building design. The process includes modeling the faculty building in BEopt by inputting architectural parameters, selecting Dezful City in Iran as the location, and incorporating its specific weather conditions. Building load calculations are then performed to estimate the annual cooling, heating, and electricity demands, followed by material performance evaluation to determine optimal configurations for reducing energy use. The outputs from this stage include optimized energy loads, which serve as inputs for supply-side optimization.

The case study is located in Dezful, a city in Khuzestan Province, situated in the southwest of Iran. Fig. 3 shows Dezful's location, extracted from Google Earth. Dezful experiences a hot semi-arid climate, categorized as BSh under the Köppen classification, characterized by long, hot, arid summers and short, mild winters with low annual rainfall. These climatic conditions significantly impact the building's energy demands, particularly for cooling during the hotter months.

Fig. 4 summarizes the monthly climatic conditions of Dezful, extracted from Meteonorm (Meteonorm, 2024) used as boundary inputs for the BEopt and EES simulations. Ambient temperatures show a strong seasonal pattern, rising from 11.3 °C in January to 39.6 °C in July, while dew point varies more moderately between 6.1 °C and 12.8 °C, reflecting seasonal changes in atmospheric moisture. These conditions indicate a cooling-dominated climate with high summer thermal stress and comparatively milder winters. Solar availability is also strongly seasonal, with Global Horizontal Irradiation (GHI) peaking at 293 W/m² in June and remaining high through July and August. Diffuse Irradiation stays substantial across the year, exceeding 180 W/m² for extended periods, which supports consistent solar energy potential.

Wind speed and relative humidity exhibit inverse seasonal trends. Wind speeds reach a maximum of 3.55 m/s in June and drop to about 1.7 m/s in October and November. In contrast, relative humidity decreases from winter highs of about 72.38% to summer lows near 20%, indicating hot and dry summer conditions. These combined climatic characteristics directly influence building energy behavior and justify the study's focus on cooling load reduction, envelope performance, and



Fig. 3. Location of the selected case study (GoogleEarth, 2024).

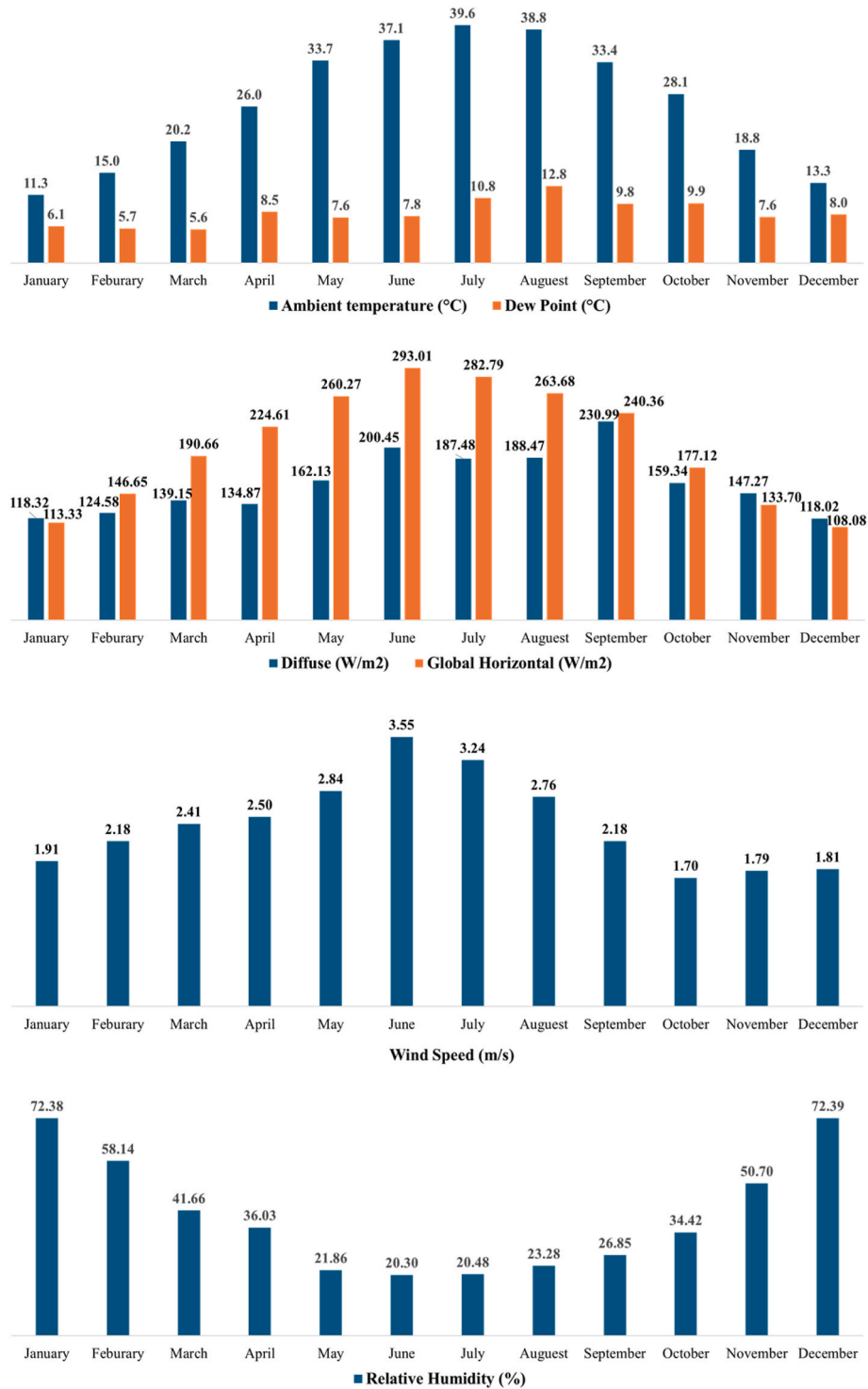


Fig. 4. Annual climatic conditions of Dezful shown as monthly average environmental parameters.

solar-driven energy supply.

3.2. Comparison of existing and optimized energy usage of the building

Fig. 5 compares the annual energy loads of the baseline and optimized building across cooling, heating, and electricity end uses. Cooling energy demand is reduced by approximately 15.8%, with the largest reductions occurring during warmer months when cooling loads dominate. Heating demand decreases by about 16.9%, reflecting improved envelope performance and thermal efficiency during winter operation.

Electricity consumption for non-lighting end uses is reduced by approximately 16.3%, indicating lower demand from ventilation and other electrical systems. Electricity use for lighting decreases by around 19.7%, associated with the adoption of efficient lighting systems and improved daylight utilization.

Table 4 summarizes the absolute and relative energy savings achieved through optimization. Cooling demand is reduced by 1,191,502 kWh (15.83%), while heating demand decreases by 1109 kWh (16.88%). Electricity use for non-lighting purposes shows the largest absolute reduction of 2,970,796 kWh (16.29%), followed by lighting

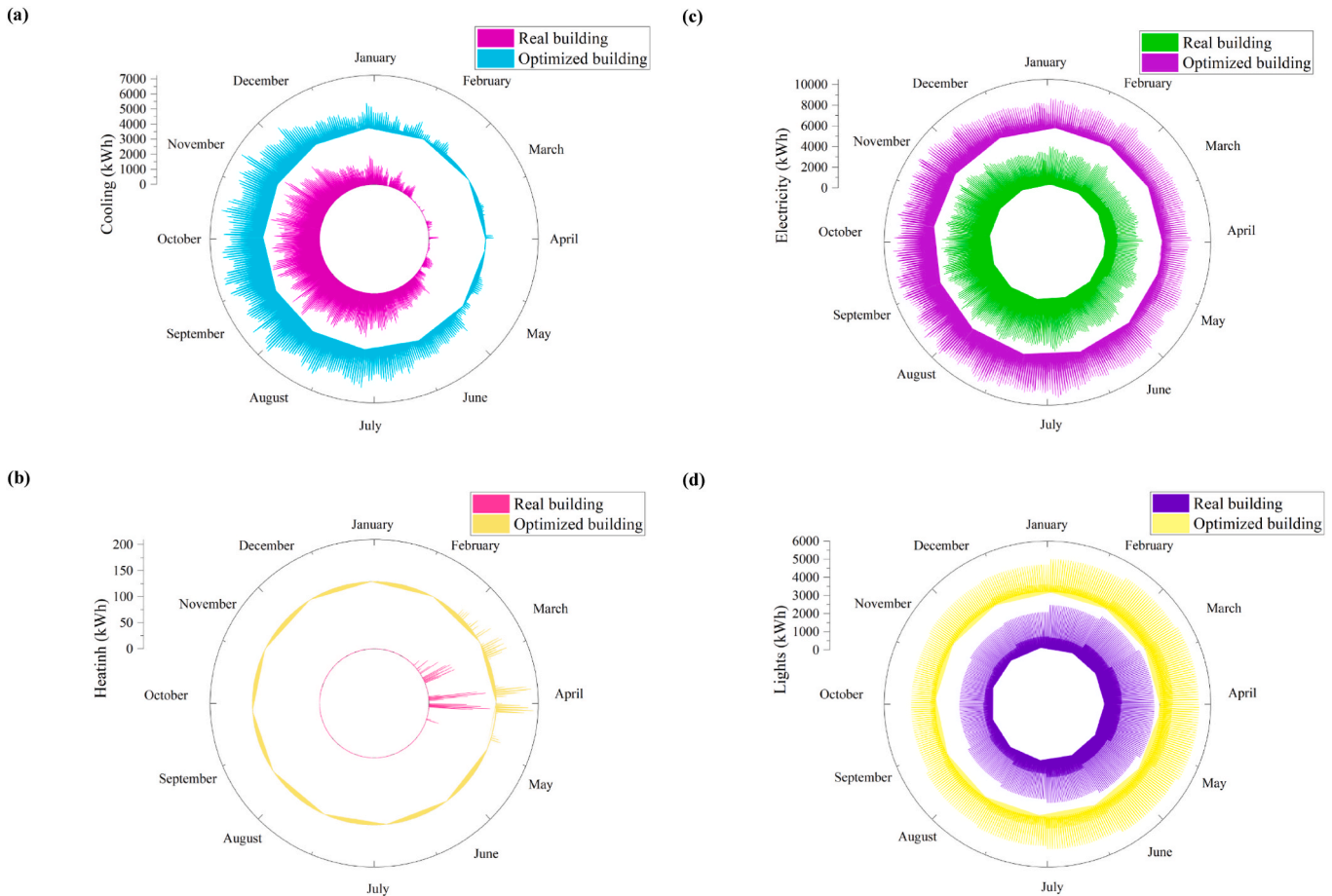


Fig. 5. Comparison of annual energy loads for the baseline and optimized building Design

Table 4
Energy savings from optimization in the case study building.

Energy	Unit	Existing Building	Optimized Building	Percentage Reduction (%)
Cooling	kWh	7,517,611	6,326,109	15.83
Heating	kWh	6571	5462	16.88
Electricity	kWh	18,238,280	15,267,484	16.29
Lighting	kWh	6,226,048	4,996,305	19.74

energy, which is reduced by 1,229,743 kWh (19.74%). These results quantify the contribution of demand-side improvements to overall energy reduction in the case study building.

Table 5 highlights the broader impacts of energy optimization measures, including cost implications, site energy use, and CO₂ emissions. While the Life Cycle Cost (LCC) increased slightly due to the initial investment required for implementing optimization measures, including advanced materials and technologies, the annualized energy cost decreased from 6478 to 6162 United States dollars (\$), reflecting

Table 5
Comparison of energy costs, usage, and emissions before and after optimization.

Parameter	Unit	Existing Design	Optimized Design	Change (%)
Energy Costs (Life Cycle Cost)	\$	224,315	239,571	−6.81
Annualized Energy Cost	\$/yr	6478	6162	4.88
Site Energy Consumption	MMBtu/yr	109,144	90,747	16.86
CO ₂ Emissions	Metric tons/yr	37	35	5.41

improved operational economic performance. Based on the BEopt simulation results and accounting for cooling, heating, electricity, and lighting end uses, total site energy consumption decreases from approximately 109,144 million British Thermal Units (MMBtu) per year (MMBtu/yr) in the existing building to 90,747 MMBtu/yr in the optimized design, corresponding to an overall reduction of 16.9%. This reduction reflects the cumulative effect of demand-side efficiency improvements. Similarly, annual CO₂ emissions decreased from 37 to 35 metric tons per year, demonstrating the environmental effectiveness of the optimization strategy. Over a typical building service life, these annual savings translate into meaningful cumulative emissions avoidance, and although performance degradation of building systems may slightly reduce long-term efficiency, the optimized design maintains a sustained operational carbon advantage compared with conventional campus buildings reliant on grid electricity and fossil-fuel-based heating. These results highlight the potential of integrated building design improvements to reduce energy demand, lower operational costs, and support sustainability objectives in large university buildings.

3.3. Design, modeling, and optimization

The framework integrates renewable energy resources with cutting-edge optimization methods to supply power, heating, and cooling demands concurrently. The proposed system leverages solar PV panels and a condensing chiller unit to enhance energy efficiency while minimizing reliance on non-renewable resources. To achieve this, a multi-stage optimization approach is employed, combining Response Surface Methodology (RSM), Artificial Neural Networks (ANNs), Genetic Algorithms (GAs), and thermodynamic modeling to refine system parameters and maximize performance. The following sections detail the design of

the energy system, the optimization methodologies utilized, and the thermodynamic analysis conducted to evaluate its effectiveness in achieving sustainable and cost-efficient energy solutions.

3.3.1. Solar multigeneration system overview

Fig. 6 presents the schematic design of the solar-driven system implemented for the case study building. Solar energy absorbed by the PV panels powers the building's operations, while the condensing chiller utilizes the generated electricity for thermal energy management. Key components of the system include the evaporator, which enables cooling by absorbing heat, and the condenser, which transfers heat to provide heating. The system also includes a valve, which regulates the refrigerant flow, and a compressor, which increases the refrigerant pressure for effective heat exchange. This system's integration, combining solar PV panels with components like the condenser, compressor, valve, and evaporator, demonstrates the practical application of renewable energy in addressing high cooling and heating demands. By reducing reliance on non-renewable resources and optimizing energy efficiency, it provides a replicable and sustainable energy solution, particularly suited for multifunctional buildings such as university buildings.

3.3.2. Response Surface Method (RSM)

To optimize the proposed system, the key design parameters must be identified while balancing technical performance and economic feasibility. RSM was specifically chosen over other methods due to its efficiency in modeling complex relationships between decision variables and objective functions with fewer computational resources (Kadrić et al., 2022; Ramos-Frutos et al., 2025). Unlike purely heuristic or simulation-based approaches, RSM creates a statistical model that facilitates the exploration of the design space, captures nonlinear interactions, and identifies trends that guide subsequent optimization stages. This ensures the design process effectively balances exergy efficiency and cost rate while minimizing computational effort, providing an efficient initial stage for narrowing the design space before surrogate modeling and global optimization.

The procedure began by defining decision variables and their ranges based on preliminary data. A Design of Experiments (DOE) approach was employed, specifically a Central Composite Design (CCD), to systematically generate a set of experimental designs for simulation. The CCD included factorial, axial, and center points for the three decision variables, yielding a structured set of simulation cases that uniformly covered the design space. For the three-factor design ($k = 3$), the CCD consisted of 8 factorial points (2^3), 6 axial points ($2k$), and n_0 replicated

center points, giving a total of $N (2^3 + 2k + n_0)$ simulation runs. In this study, $n_0 = 6$ center points were used, resulting in $N = 20$ CCD design points. The axial distance was set to $\alpha = 1.682$ (rotatable CCD), and the variables were coded to standard CCD levels (-1 , 0 , $+1$, and $\pm\alpha$).

These simulations provided results, which were then analyzed using Analysis of Variance (ANOVA) to assess the statistical importance of each parameter. Second-order polynomial response surfaces were fitted for both exergy efficiency and cost rate, and model adequacy was verified through ANOVA significance tests and lack-of-fit assessment. The fitted models for both responses were statistically significant ($p < 0.001$), while the lack-of-fit tests were not significant ($p > 0.05$), confirming that the second-order models adequately represent the simulation data within the studied design space. The response surfaces achieved $R^2 = 0.995$ and adjusted $R^2 = 0.991$ for exergy efficiency, and $R^2 = 0.997$ and adjusted $R^2 = 0.994$ for cost rate.

The iterative process ensured accurate model predictions and identified trends in the design space. This culminated in the extraction of the 100 best-performing candidate configurations using a desirability-based multi-objective screening approach. Before screening, both objective functions were normalized using min-max normalization. Exergy efficiency was treated as the maximization objective, and cost rate as the minimization objective. Individual desirability values were calculated for each response and combined using a weighted geometric mean, where the weights were set to $w_1 = 1$ for exergy efficiency and $w_2 = 1$ for cost rate. The 100 configurations with the highest overall desirability were selected as the screened dataset.

These results were subsequently used as inputs for advanced optimization using ANN and GA. Fig. 7 illustrates the RSM flow, from variable selection to optimization.

3.3.3. Artificial Neural Networks (ANNs)

ANNs are used in this study as a surrogate modeling tool to approximate the relationship between the solar farm design variables and system performance (Chen et al., 2024; Ghafariasl et al., 2024). The ANN takes the number of PV panels, panel width, and panel length as inputs, and predicts the corresponding exergy efficiency and cost rate. This approach significantly reduces the need for repeated thermodynamic simulations in EES during optimization. By learning from the high-quality dataset generated through the RSM screening stage, which consists of a simulation-generated design dataset created specifically for this study using high-fidelity EES thermodynamic evaluations of the screened design space rather than a standard or publicly available machine learning benchmark, the ANN captures the nonlinear behavior of

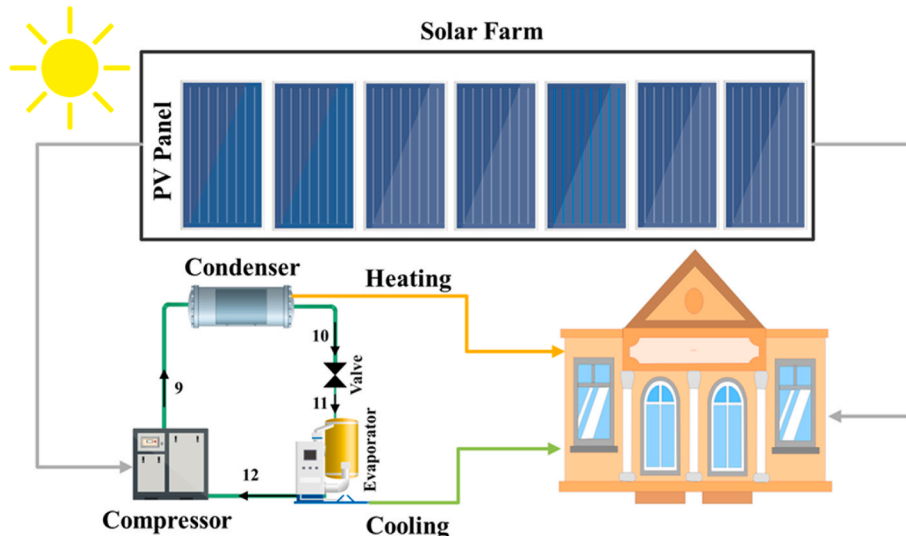


Fig. 6. Configuration of the solar-based multigeneration energy system for the case study.

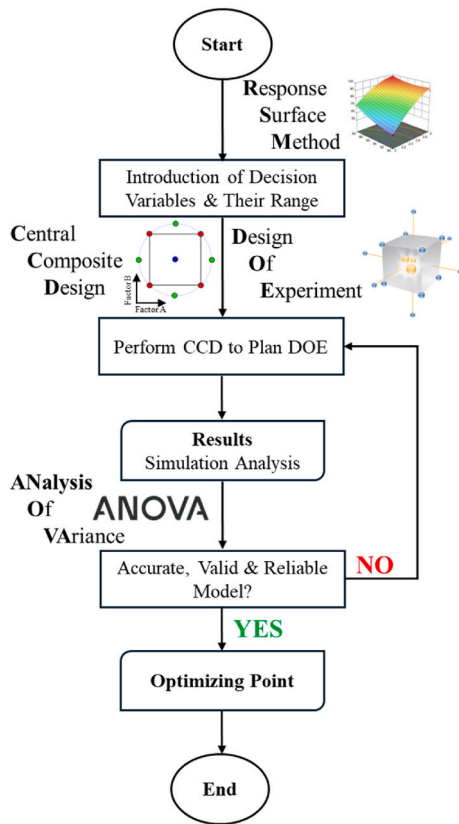


Fig. 7. Flowchart of the response surface methodology (RSM) for system optimization.

the system and provides fast performance predictions that are later used within the GA-based global optimization.

The ANN is implemented as a three-layer feedforward network trained via backpropagation. The input variables are PV panel number, width, and length, while the outputs are exergy efficiency and cost rate. All input and output variables were normalized using min-max scaling to the range [0, 1] before training to improve numerical stability and convergence. The ANN was trained using the 100 high-quality configurations obtained from the RSM-based screening stage. These simulation-generated data points were split into training, validation, and test sets at 70%–15%–15%, where the training set was used for model fitting, the validation set for model selection and early stopping, and the test set for independent performance evaluation. Because the dataset was generated specifically for this study through EES thermodynamic simulations, it is not a public benchmark dataset. The hidden layer consists of 10 neurons, with sigmoid activation functions in the hidden layer and linear activation functions in the output layer. Training was performed using the Levenberg–Marquardt backpropagation algorithm with a maximum of 1000 epochs, with early stopping triggered by validation error to prevent overfitting.

Once training was completed, the network was evaluated by comparing ANN predictions with corresponding EES simulation results for independent samples. For exergy efficiency, the ANN achieved $R^2 = 0.978$, RMSE = 0.455, and MAE = 0.398. For the cost rate, the ANN achieved $R^2 = 0.855$, RMSE = 0.424, and MAE = 0.373. These performance metrics confirm that the ANN surrogate, trained on the RSM-screened dataset described in Section 3.3.3, provides reliable predictions for use in the GA optimization stage. Final Pareto-optimal solutions are subsequently re-evaluated using EES to eliminate surrogate prediction error and ensure thermodynamic accuracy, as illustrated in Fig. 8.

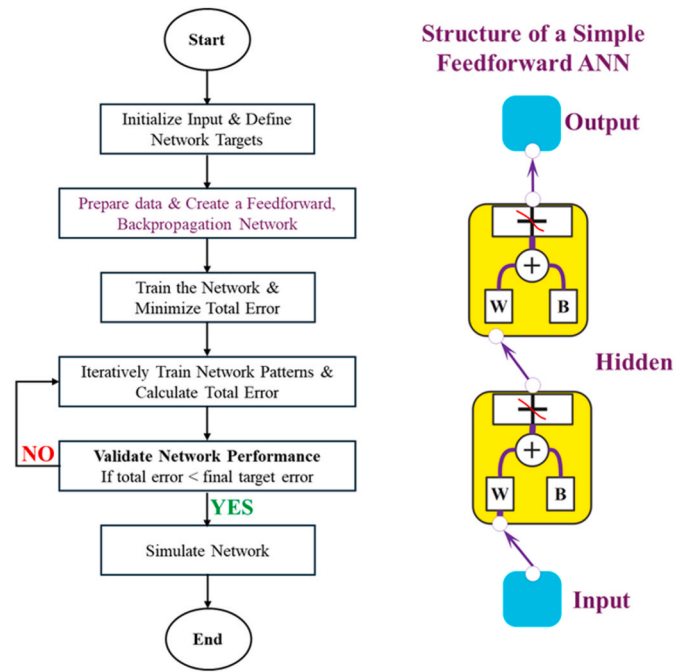


Fig. 8. Flowchart of the artificial neural network method training and simulation process.

mutation rate, and stopping criteria, were selected based on preliminary sensitivity trials to ensure stable convergence and avoid overfitting.

3.3.4. Coupling response surface method with artificial neural network for optimization

The hybrid process involves a sequential and data-driven integration of RSM, ANN, and GA, with each stage producing a defined output that is directly consumed by the subsequent stage. Initially, RSM employs a CCD to systematically explore the design space defined by the number of PV panels, panel width, and panel length, within the bounds reported in Table 7 (presented in Section 4.1). For each design point generated by the experimental design, the thermodynamic model is executed in EES to evaluate exergy efficiency and cost rate. A second-order response surface is then fitted to the EES-generated dataset and statistically validated using analysis of variance and lack-of-fit testing, as detailed in Section 3.3.2.

Based on the validated response surface, the top 100 candidate solutions are selected using desirability-based multi-objective screening, with the objective of maximizing exergy efficiency while minimizing cost rate. The desirability calculation follows the normalization and weighting scheme described in Section 3.3.2, ensuring consistent objective scaling before ANN training. These selected solutions form a high-quality dataset that captures the most promising regions of the design space. The full set of 100 configurations obtained from the RSM-based screening is reported in Appendix A.

This dataset is subsequently used to train a feedforward ANN capable of representing the nonlinear relationships between the design variables and the performance objectives. Once trained, the ANN is used as a surrogate model during the optimization stage (Ghafarinasl et al., 2024). GA performs multi-objective search using the neural network predictions for fitness evaluation, thereby avoiding repeated time-intensive thermodynamic simulations (He et al., 2023).

The GA was implemented using a population size of 80 individuals and evolved for 120 generations. Tournament selection was used as the selection operator, with a crossover rate of 0.85 and a mutation rate of 0.05. Elitism was applied by carrying forward the top two individuals in each generation. Optimization proceeded for a fixed number of generations, and convergence was confirmed when no significant

improvement ($<0.1\%$) in the Pareto front was observed over 15 consecutive generations. Constraint handling was enforced by bounding all decision variables within the limits defined in Table 7. To ensure robustness, the GA optimization was repeated for five independent runs with different random seeds, and consistent Pareto fronts were obtained across runs.

Finally, the Pareto-optimal solutions identified by the genetic algorithm are re-evaluated in EES to verify performance metrics and report the final optimal design. All nondominated solutions from the final Pareto front ($N = 32$) were re-simulated in EES to remove surrogate model error, and the reported optimal configuration is based on these EES-verified thermodynamic and economic outputs.

This hybrid structure offers advantages over single-method optimization approaches. Using RSM alone would limit the search to polynomial approximations and local trends, while GA alone would require a very large number of time-intensive thermodynamic simulations. ANN-only optimization would depend heavily on randomly generated training data and may miss promising regions of the design space. In contrast, the proposed RSM-ANN-GA sequence first identifies high-quality candidate regions using statistically structured sampling, then builds a fast nonlinear surrogate, and finally performs global multi-objective optimization with reduced computational cost. This combination improves search efficiency, avoids premature convergence, and preserves physical accuracy through final EES re-evaluation. Because literature methods were developed under different scales, models, and problem setups, their computational complexity is not directly comparable, so no cross-method timing or complexity claims are made. All model development, hyperparameter tuning, and performance evaluation described in Sections 3.3.2–3.3.4 apply only to the proposed RSM-ANN-GA framework. No alternative optimization algorithms from the literature were re-implemented, retrained, or re-tuned within this study; their reported performances, discussed later for contextual comparison, are taken directly from the original publications.

Fig. 9 illustrates the overall sequence of this hybrid RSM-ANN-GA optimization framework.

All model tuning, parameter selection, and performance evaluation described in this section apply only to the proposed RSM-ANN-GA framework. The performance of other systems discussed later for benchmarking purposes is reported from the original publications and those systems were not re-implemented or re-tuned in this study.

3.3.5. Solar farm evaluation

Thermodynamic evaluation of the solar system relies on several critical assumptions to simplify the problem while ensuring meaningful results:

- The thermodynamic analysis operates under steady-state conditions, eliminating the influence of transient effects.
- Water circulation within the piping network is considered uniformly distributed to maintain consistent thermal interaction across all sections.
- The analysis neglects dust deposition on PV panels, assuming stable optical performance and maximum efficiency.
- Lateral heat transfer losses are assumed to be minimal, allowing the focus to remain on the dominant energy exchange mechanism.
- Convective heat transfer coefficients along panel surfaces are treated as constant to simplify numerical calculations.
- Radiative exchange from the rear side of the panels is excluded due to its relatively minor contribution compared with direct solar input.
- The energy conversion process is modeled under quasi-steady-state conditions, enabling simplified thermodynamic computation without compromising accuracy.

These simplifications streamline the computational process while maintaining adequate precision for evaluating the solar system's thermal and energetic performance.

The input data used in this evaluation reflect the environmental and operating conditions of the solar farm. The ambient temperature (T_0) and atmospheric pressure (P_0) represent standard conditions, ensuring realistic simulation inputs. The solar temperature ($T_{\text{sun}} = 6000^\circ\text{C}$) assumes a blackbody approximation for solar irradiation, while the air mass flow rate ($\dot{m}_{\text{air}}$) and overall heat transfer coefficient (U_l) describe the thermal exchange dynamics across the system. The geometric properties of the panels, including their length (L), width (b), and area (A), were initially specified as nominal input values for the reference thermodynamic model and were later treated as optimization variables. The baseline environmental conditions and nominal reference-case input values used to initialize the solar farm model are summarized in Table 6. The number of PV panels and panel dimensions listed in Table 6 represent the initial reference-case configuration used for thermodynamic modeling, whereas the final optimized design values are reported later in Table 8. These parameters form the foundation for the initial

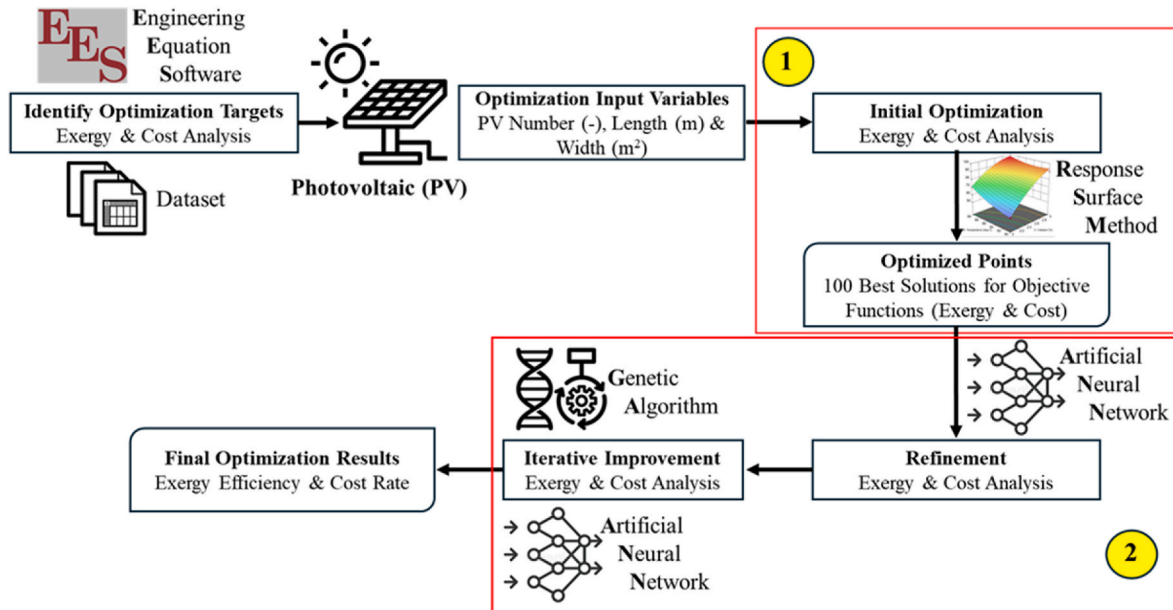


Fig. 9. Integrated hybrid AI workflow: The sequential RSM-ANN-GA optimization pipeline.

Table 6

Baseline environmental conditions and reference-case inputs for solar farm analysis.

Variable	Unit	Value
Ambient Temperature	°C	25
Atmospheric Pressure	kPa	101.3
Number of PV Panels	-	90
Solar Temperature	°C	6000
Air Mass Flow Rate	kg/s	1.9
Heat Transfer Coefficient	W/m ² ·K	4.71
Panel (Length/width)	m	2.5/0.8
Panel Area	m ²	2

Table 7

Problem decision variables range.

Variable	Unit	Minimum Value	Maximum Value
Number of PV Panels	-	90	140
PV Width	m	1	3
PV Length	m	3	6

Table 8

Optimal values of key decision variables and performance metrics.

Category	Decision Variables	Unit	Samples (N)	Optimal Value
Decision Factors	Number of PV Panels	-	100	127
	Panel Width	m	100	2.4
	Panel Length	m	100	3.3
Performance Objectives	Exergy Efficiency	%	100	29.23
	Cost Rate	\$/h	100	14.12

thermodynamic and economic efficiency.

Key thermodynamic principles and equations are applied to assess the performance of the solar system. The first law of thermodynamics (Eq. (6)) ensures energy conservation within each control volume, while Eq. (7) calculates the delivered energy generated by the PV panels based on specific heat capacity (C) and enthalpy (h). Eq. (8) determines the output power of the PV panels, and finally Eq. (9) evaluates their thermal efficiency. This framework allows for detailed thermodynamic and economic analysis of the solar farm, providing insights into its efficiency and performance under the given operating conditions.

$$\Delta E = \dot{Q} - \dot{W} + \sum \dot{m} \times h = \dot{Q} - \dot{W} + \sum_i \dot{m}_i \left(h_i + \frac{v_i^2}{2} + gz_i \right) - \sum_i \dot{m}_i \left(h_e + \frac{v_e^2}{2} + gz_e \right) = \frac{gze}{dt} \quad (6)$$

The equation represents the energy conservation within the control domain, accounting for heat transfer ($\dot{Q}$), work ($\dot{W}$), and energy changes associated with mass flow, kinetic energy, potential energy, and internal energy. The terms ($\dot{m}_i$) and ($\dot{m}_e$) represent the mass flow rates entering and exiting the control domain, with corresponding specific enthalpy (h), kinetic energy ($v^2/2$), and potential energy (gz). This equation combines conservation of energy principles and is essential for analyzing thermodynamic systems like turbines, compressors, and heat exchangers.

$$Q_{PV} = \frac{(\dot{m}_{air} \times \dot{C}_{air})}{U_l} \times (h_{p2g} \times Z \times \times GHI) - (U_f \times (T_{air,in} - T_0)) \times (1 - \exp(-b \times U_f \times \Sigma) \times \dot{m}_{eff}) \quad (7)$$

This equation models the heat transfer (Q_{PV}) in a PV system, incorporating factors related to air flow, thermal dynamics, and solar irradiance. It considers $\dot{m}_{air}$ and its specific heat capacity ($\dot{C}_{air}$) to account for the energy carried by air, adjusted by a flow or heat transfer

coefficient (U_f). Additional parameters include gravitational effects (g), geometric or height-related factors (Z), and solar input (GHI), which influence the energy absorbed by the system. Temperature differences, particularly between the inlet air temperature ($T_{air,in}$) and a reference temperature (T_0), drive heat exchange, modulated by system constants like b to refine thermal efficiency and summation terms (Σ) or system parameter to refine thermal efficiency. Effective mass flow rates ($\dot{m}_{eff}$) capture real-world variations in system properties, making the model applicable for analyzing and optimizing PV energy performance under dynamic conditions.

$$W_{PV} = \frac{\eta_c \times GHI \times B_c \times \tau_{au_g} \times A}{10} \quad (8)$$

This equation calculates the electrical power generated by a PV system, considering the solar irradiance (GHI), panel efficiency (η_c), area (A), and other factors like the angle of incidence and the transmittance of the panel's cover (τ_{au_g}). This equation highlights how factors like solar irradiance, panel orientation, and material properties (transmittance and efficiency) contribute to maximizing the power output of a PV system, particularly relevant for designing and optimizing PV installations, as it estimates the performance of PV systems under specific environmental and design conditions.

$$\eta_{th} = \frac{\dot{Q}_{PV}}{GHI \times b \times L} \quad (9)$$

This equation calculates the thermal efficiency (η_{th}) of a PV system by comparing the thermal energy output ($\dot{Q}_{PV}$) relative to the overall solar radiation received by the PV panel surface. The total solar energy is derived from solar irradiation input (GHI) and calculated based on the PV panel's surface. This equation is critical for evaluating and optimizing PV systems that generate both electricity and heat (e.g., PV-thermal systems). By maximizing thermal efficiency, the system can improve overall energy efficiency, especially in climates or applications where thermal energy demand is high.

Although these equations define the thermal efficiency (η_{th}) of a PV system to explain basic heat transfer dynamics, the present study focuses on exergy efficiency as the main metric for evaluating system performance. Exergy efficiency offers a more comprehensive assessment by accounting for both the quantity and quality of energy, particularly in systems involving electricity and thermal outputs.

4. Results and discussion

This section reports the outcomes of the simulation and optimization processes, beginning with a multi-objective analysis using RSM to identify optimal design parameters for the solar farm. It then extends the analysis through ANN- and GA-based optimization, followed by energy performance evaluation, scalability assessment, and comparison with existing systems.

4.1. Multi-objective optimization through response surface method

While thermal efficiency is introduced in the system description for explanatory purposes, all optimization analyses and reported results are based on exergy efficiency, which better reflects the actual useable work potential and energy quality in multigeneration systems. The multi-objective optimization aimed to enhance the solar farm's performance while minimizing its cost. Table 7 presents three key decision variables: PV panel number (ranging from 90 to 140), panel width (1–3 m), and panel length (3–6 m), while two objective functions were targeted to enhance exergy efficiency while reducing the associated cost rate. These parameters define the technical and economic search space for solar farm optimization.

Fig. 10 displays the effect of two input parameters, PV panel number and width (a) and number and length (b), on the exergy efficiency. The

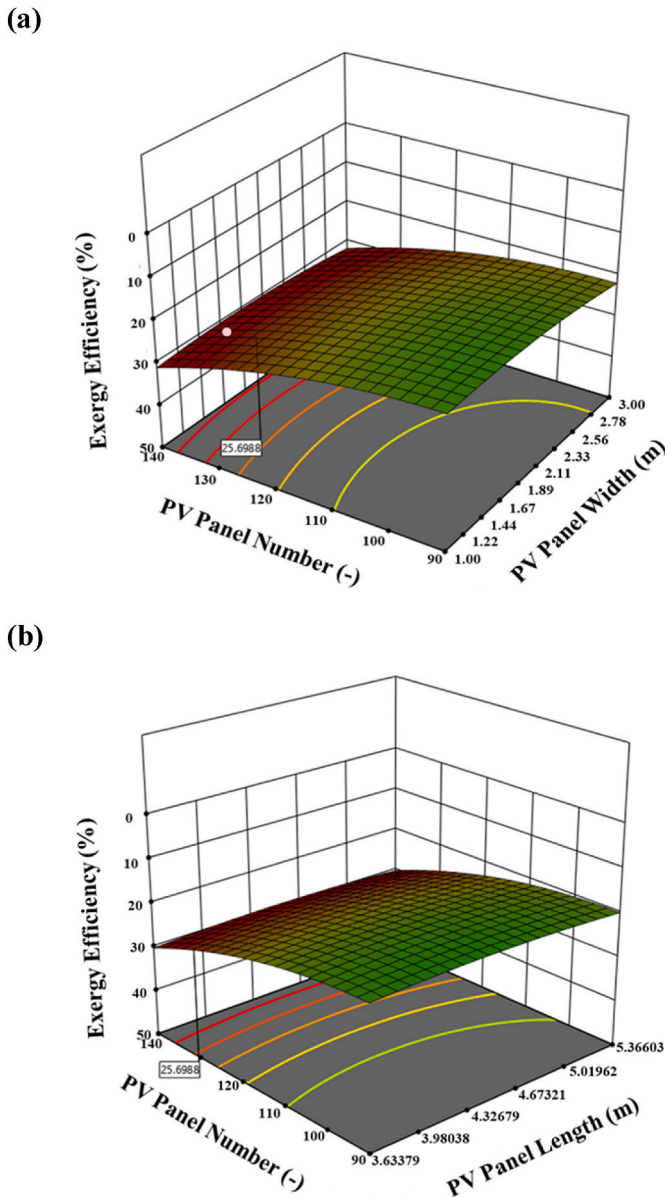


Fig. 10. Effect of PV panel number and width (a) and number and length (b) on exergy efficiency.

results illustrate that increasing all three decision variables has a meaningful effect on the performance of the solar farm. Among these variables, the number of panels demonstrates the strongest influence, indicating its pivotal role in optimizing the solar farm's performance. Exergy efficiency increases as more panels are installed, reaching a maximum of 25.6%, while changes in panel size have a smaller effect. These outcomes highlight the importance of choosing a suitable combination of the three design parameters to achieve the desired performance while maintaining economic feasibility. The trends observed in this figure validate the optimization results, showing the interplay between technical efficiency and the design variables in solar farm performance.

Fig. 11 illustrates how PV panel design variables influence the proposed solar farm's cost rate. Fig. 11a shows the combined impact of panel number and width, while Fig. 11b presents the interaction between panel width and length. The optimization objective is to minimize the cost rate, which is affected by all three design parameters. Results indicate that increasing the number of PV panels leads to a noticeable

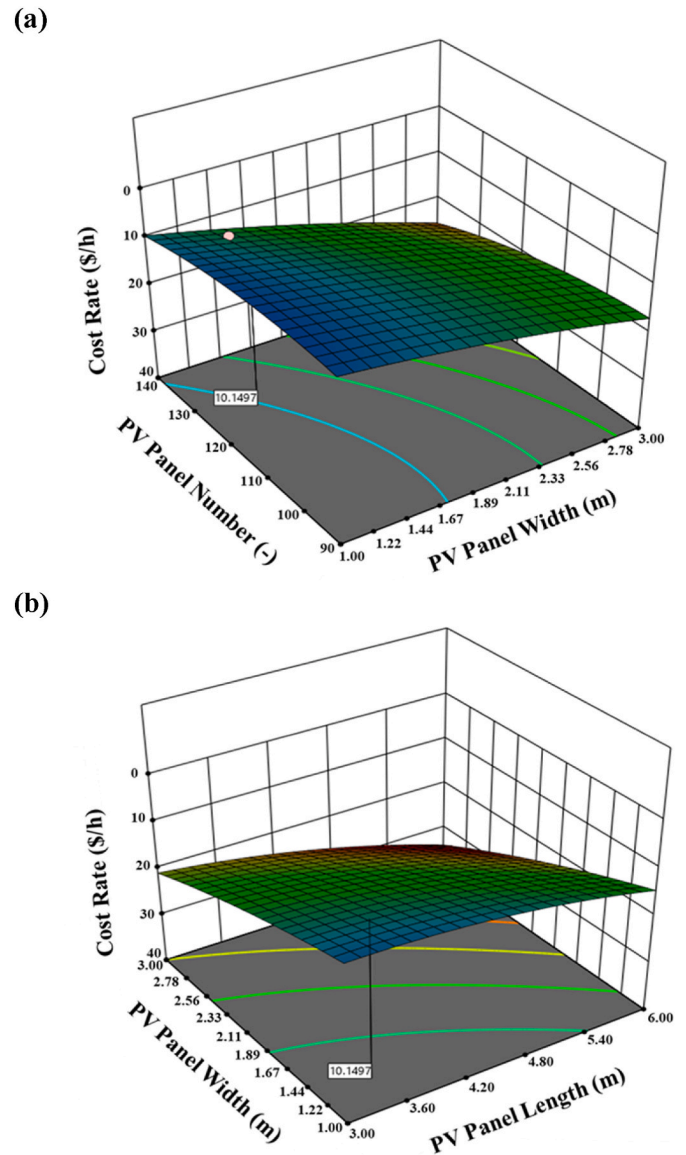


Fig. 11. Effect of PV panel width and number (a), and panel width and length (b) on cost rate.

rise in cost, and incremental increases in panel width further contribute to this increase. Similarly, simultaneous increases in panel width and length also raise the cost rate. These trends highlight the importance of balancing panel numbers and dimensions to meet budget constraints while maintaining system performance. Among the variables, panel numbers have the strongest influence on total cost, whereas width and length have a moderate impact, emphasizing the trade-off between system efficiency and economic feasibility.

Outcomes of the 100-point optimization are presented in the Appendix (Table A.1), showcasing a thorough evaluation of the PV system's design parameters. The process reveals the influence of the decision variables, including PV panel number, width, and length, on the objective functions. The results highlight a range of configurations that achieve exergy efficiencies between 17.3% and 25.7% and cost rates varying from 7.78 \$/h to 12.03 \$/h. Notably, higher panel numbers and larger dimensions contribute to improved efficiency, but they also result in increased costs, underscoring the trade-off between technical performance and economic feasibility. The optimal configuration corresponded to 130 panels with dimensions of 1.423 m in width and 3.634 m in length, yielding 25.6% exergy efficiency, a cost rate of 10.15 \$/h, and

an overall desirability of 0.801. These optimized configurations serve as a decision-making tool for selecting the most effective balance between performance and cost, supporting the aim of improving the solar farm's technical and economic viability. Furthermore, the analysis illustrates the RSM method's capacity to explore a wide design space, thereby facilitating informed decisions tailored to specific operational and budgetary constraints.

The analysis of the three design parameters, PV panel number, width, and length, reveals their distinct impacts on objective functions, underscoring the trade-offs between performance and economic feasibility. Among these, the PV panel number proves to be the most influential, significantly enhancing exergy efficiency while also increasing the cost rate due to higher material and operational expenses. Panel width and length contribute positively to both objectives, though their effects are less pronounced compared to the PV panel number. The optimal configuration identified through the optimization process, achieved the maximum exergy efficiency of 25.6% while maintaining a cost rate of 10.15 \$/h, representing the best trade-off between technical performance and economic viability. In conclusion, these findings highlight the importance of carefully balancing these parameters to design cost-effective and efficient solar farms, offering a robust framework for achieving renewable energy goals. The slopes and gradients of these response surfaces are climate dependent, as changes in cooling demand and solar availability would shift the response magnitudes, but the overall monotonic trends with respect to panel number and size remain consistent across climates.

4.2. Integrating artificial neural networks and genetic algorithms into optimization

Building on the RSM-based screening results, ANNs and GA were integrated to further refine the farm design. The ANN was trained using the high-quality dataset generated from the RSM stage to act as a fast surrogate model, predicting exergy efficiency and cost rate based on PV panel number, width, and length. This surrogate model was then embedded within the GA to enable efficient global search without repeated EES simulations (Ghafarinasl et al., 2024; Yilmaz et al., 2025).

Table 8 presents the final optimal configuration, which achieved an

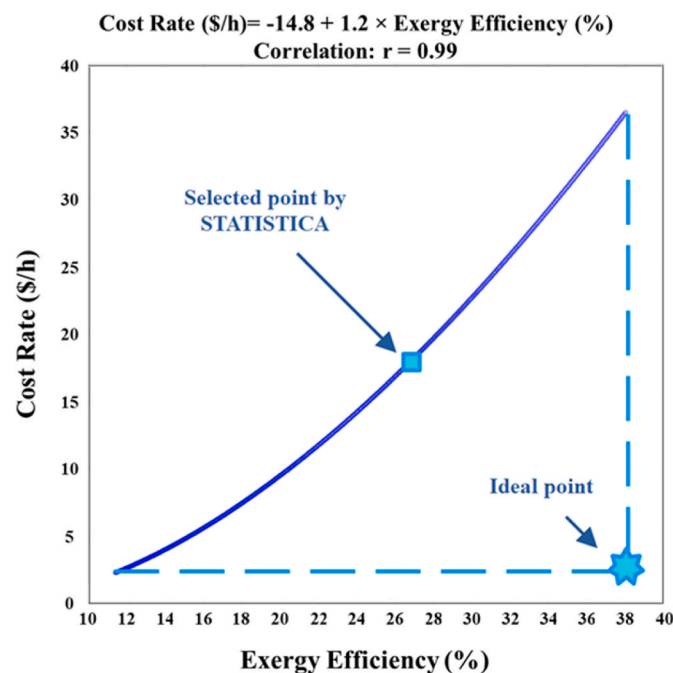


Fig. 12. Pareto front illustrating the trade-off between exergy efficiency and cost rate.

exergy efficiency of 29.23% and a cost rate of 14.12 \$/h, representing improvements of 14.2% in efficiency and 39.7% in cost rate compared with the best RSM-only results. The optimized solution consists of 127 PV panels with dimensions of 2.4 m in width and 3.3 m in length, demonstrating the importance of balancing system performance and economic feasibility within the multi-objective optimization framework.

Fig. 12 depicts the Pareto front generated from the multi-objective optimization, illustrating the trade-off between exergy efficiency and cost rate. The solution selected by STATISTICA achieves an exergy efficiency of 29.23% and a cost rate of 14.12 \$/h. This point, derived from the Pareto front, provides the best balance between improving system performance and limiting cost increases. The ideal is included only as a theoretical benchmark for comparison, indicating the theoretical maximum efficiency at the lowest cost and serving as a benchmark for further optimization efforts. The correlation ($r = 0.99$) highlights the strong relationship between the two objectives, confirming the impact of decision variables on optimization outcomes.

Although the optimization was performed for Dezful's hot climate, the Pareto front in Fig. 12 can be interpreted as climate-dependent. In cooler climates with lower cooling demand, the annual electricity load would shift downward, reducing the PV capacity required to reach the ZEB balance. This would move the feasible design region toward lower panel numbers and reduce the cost-rate values along the Pareto curve. Conversely, in hotter or more solar-abundant climates, higher cooling loads and increased solar availability would shift the trade-off surface toward larger PV capacities, altering both the exergy–cost relationship and the position of the Pareto-optimal solutions. Therefore, the shape of the Pareto front remains valid as a design logic, while its numerical location is climate-sensitive.

A first-order climate sensitivity perspective can be inferred by considering ± 10 –20% variations in annual electricity demand and solar availability. Under higher demand conditions, representative of more cooling-dominated climates, the optimal PV sizing shifts toward the upper bounds of panel number and area, increasing the cost rate while still maintaining ZEB feasibility. Under lower demand conditions, typical of milder climates, the optimal design region moves toward smaller PV arrays, reducing both system scale and cost rate. This indicates that although the numerical optima are climate-specific, the trade-off structure between exergy efficiency and cost remains robust.

Fig. 13 presents the histograms of the two objective functions to illustrate the distribution of exergy efficiency and cost rate across the evaluated solutions. Exergy efficiency values are concentrated mainly between about 15% and 30%, while cost-rate values are more concentrated at lower ranges, 0–15 \$/h, with a mild right-skewed pattern. These histograms are presented as descriptive summaries of the solution space generated by the ANN-GA optimization rather than as direct evidence of optimization quality or methodological validity. These histograms help visualize the spread, concentration, and overall shape of the objective-function values obtained under the studied conditions.

Fig. 14 compares the normal Probability Plots (P-Plots) and detrended normal P-Plots for exergy efficiency and cost rate as additional distributional illustrations of the optimized results. The plots suggest that exergy efficiency follows an approximately symmetric distribution with some deviation at the tails, whereas cost rate shows greater departure from normality, particularly at higher values. These figures are useful for visually characterizing the distribution of the objective-function outputs, but they are not used here as a standalone validation of surrogate-model accuracy or optimization performance. Validation of the proposed framework is based on the ANN prediction metrics, repeated GA runs, and EES verification of the Pareto-optimal solutions.

4.3. Solar farm performance and energy analysis

This section focuses on evaluating the performance and energy production capabilities of the solar farm integrated with a compression chiller system, emphasizing its ability to meet the diverse energy needs.

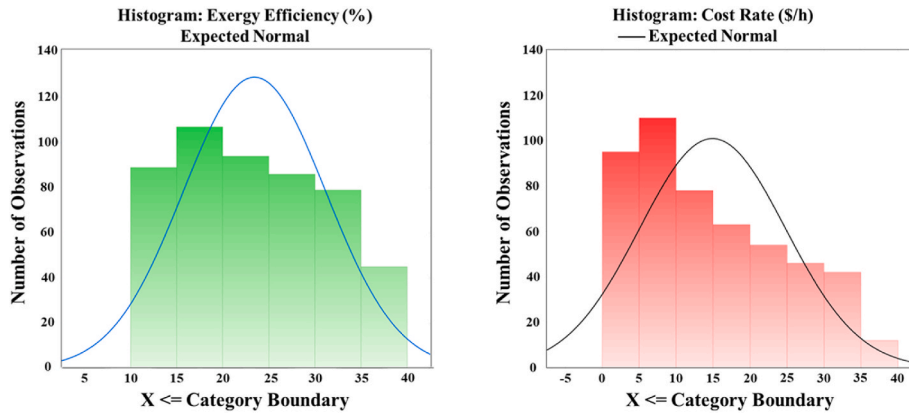


Fig. 13. Distribution of objective function values with fitted normal curves.

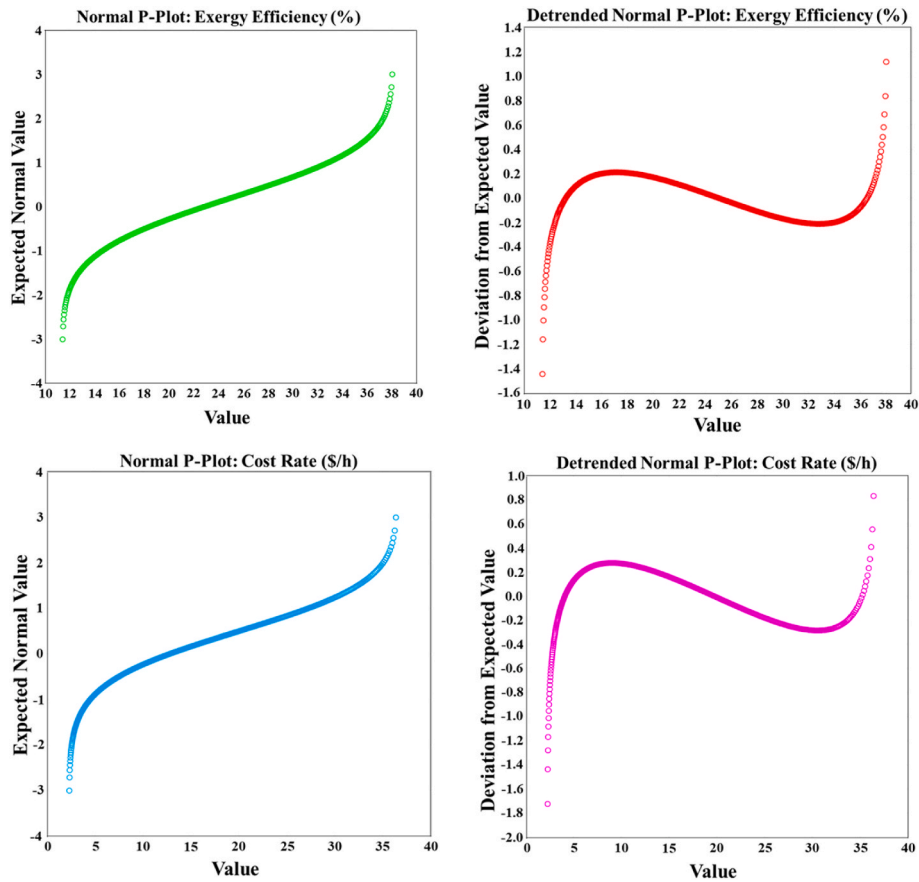


Fig. 14. Normal and detrended P-plots for exergy efficiency and cost rate.

It examines how the system supplies electricity, heating, and cooling while leveraging renewable energy to enhance efficiency and reduce waste. Fig. 15 provides an overview of the hourly cooling, heating, and electricity production over the year, showcasing the system's responsiveness to weather parameters. Fig. 15a depicts the hourly variations in cooling energy production, which are directly influenced by the electricity generated by the solar farm. The compression chiller converts solar-generated electricity into cooling energy, efficiently utilizing renewable resources. The cooling output fluctuates between 0 and 10,000 kWh, reflecting the system's adaptability to changes in solar irradiation and ambient temperature. This innovative integration reduces energy waste and aligns cooling production with real-time solar power availability, ensuring optimal performance.

Fig. 15b illustrates the heating energy production of the solar farm, which ranges from 0 to 12,000 kWh. This highlights the dual functionality of the compression chiller in simultaneously producing cooling and heating energy. By converting solar electricity into thermal energy, the system ensures a consistent heating supply even under varying weather conditions, optimizing energy utilization. Fig. 15c shows the net electricity production of the solar farm, ranging from 0 to 14,000 kWh, influenced by ambient temperature and solar irradiation. Together, these figures demonstrate the solar farm's capability to meet the electricity, heating, and cooling demands of the building while minimizing reliance on non-renewable energy sources. By addressing seasonal and hourly fluctuations in energy requirements, the proposed system exemplifies a sustainable solution for complex built environments,

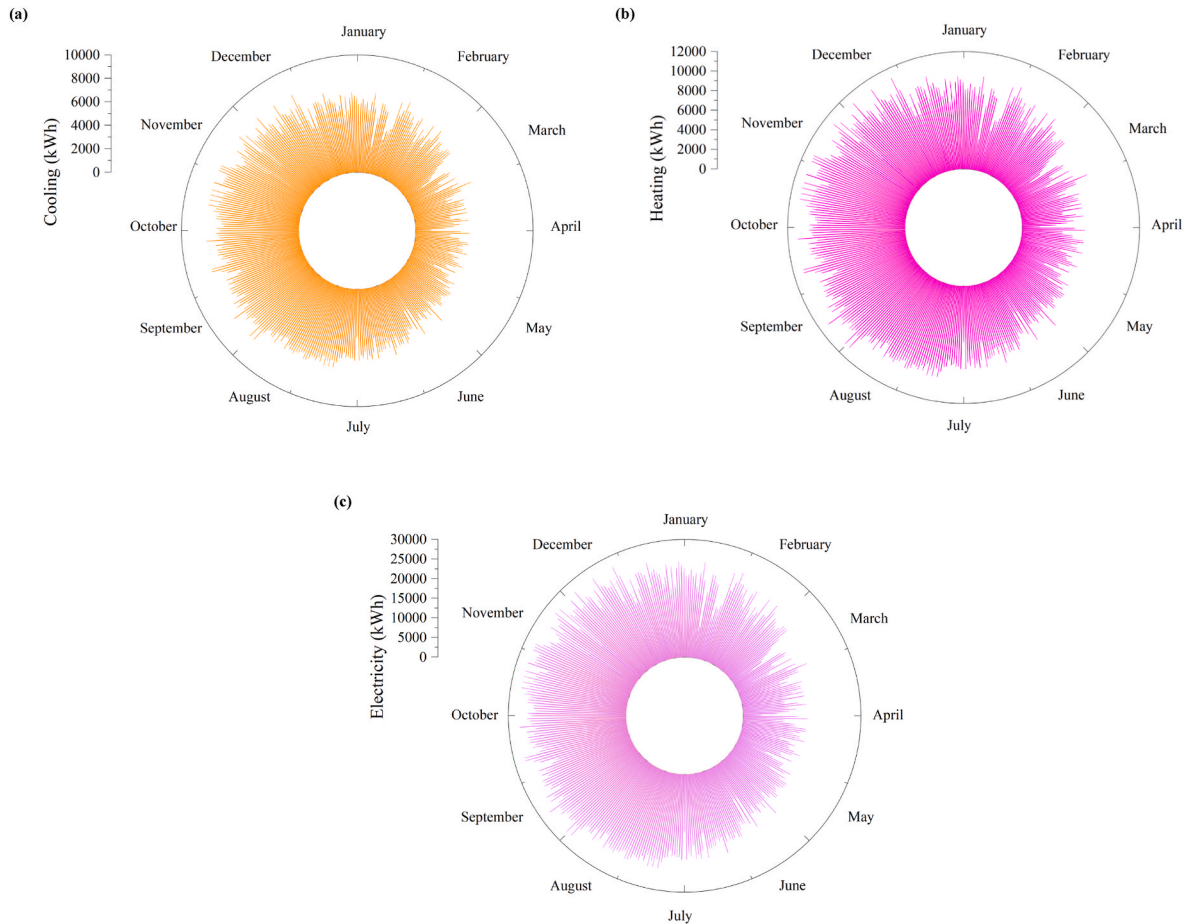


Fig. 15. Hourly cooling (a), heating (b), and electricity (c) production of the solar farm over one year.

effectively aligning renewable energy generation with diverse energy needs.

4.3.1. Comparison of energy production and consumption

This section reports energy demand reductions resulting from the combined demand-side and supply-side optimization implemented in the proposed framework. On the demand side, building energy requirements were reduced through envelope and material optimization using BEopt, lowering cooling, heating, and electricity loads before system sizing. On the supply side, the solar-based multigeneration system was resized using the hybrid Response Surface Methodology (RSM)–Artificial Neural Networks (ANNs)–Genetic Algorithms (GAs) framework by adjusting the number and geometric dimensions of PV panels to match the reduced building demands. Consequently, the optimized consumption values presented below represent post-retrofit building loads evaluated under the optimized system configuration.

As depicted in Fig. 16, the optimized building design significantly reduces energy demand across cooling, heating, and electricity, leading to improved alignment between production and consumption. These reductions contribute to more efficient utilization of renewable energy resources, ensuring that the solar farm not only meets the building's needs but also generates substantial surplus energy. The excess energy comprises cooling and heating that can be stored for later use, along with electricity that may be exported to the grid, improving the system's economic performance.

The analysis of surplus energy reveals the tangible benefits of this integration. For cooling, approximately 54.6% of the energy generated by the solar system exceeds the optimized building's energy needs, providing opportunities for energy storage or alternative uses. Similarly, heating production exceeds demand by more than 99%, as Dezful, the

case study's location, is cooling-dominant and requires heating only during three months of the year. Electricity production also results in a significant surplus, with nearly 67% of the energy generated exceeding the optimized building's consumption. These results underscore the effectiveness of this integrated approach in attaining a better balance between energy production and demand, maximizing resource efficiency, and advancing sustainable energy solutions in complex built environments.

Table 9 summarizes annual energy production and cooling, heating, and end-use consumption under baseline and optimized conditions. Optimization led to annual reductions of 15.8% in cooling demand, 16.9% in heating demand, and 16.3% in electricity demand. This decreased consumption enables substantial surplus energy generation, with cooling production exceeding optimized annual demand by 54.6%, heating by over 99%, and electricity by 67%. These results highlight that the system can reliably supply the building's energy needs and generate surplus energy for storage, redistribution, or grid integration, aligning with sustainability objectives.

4.3.2. Energy storage and surplus utilization

In this study, energy storage is represented implicitly through an annual and monthly surplus energy balance rather than through explicit physical storage modeling. Stored cooling, heating, and electricity are calculated as the positive difference between system energy production and optimized building demand at each time step. When production exceeds demand, the surplus is assumed to be available for storage, redistribution, or grid export. No dynamic storage constraints, losses, or capacity limits are imposed, allowing the analysis to isolate the effects of demand reduction and system sizing on surplus availability. This approach is consistent with system-level ZEB feasibility assessments

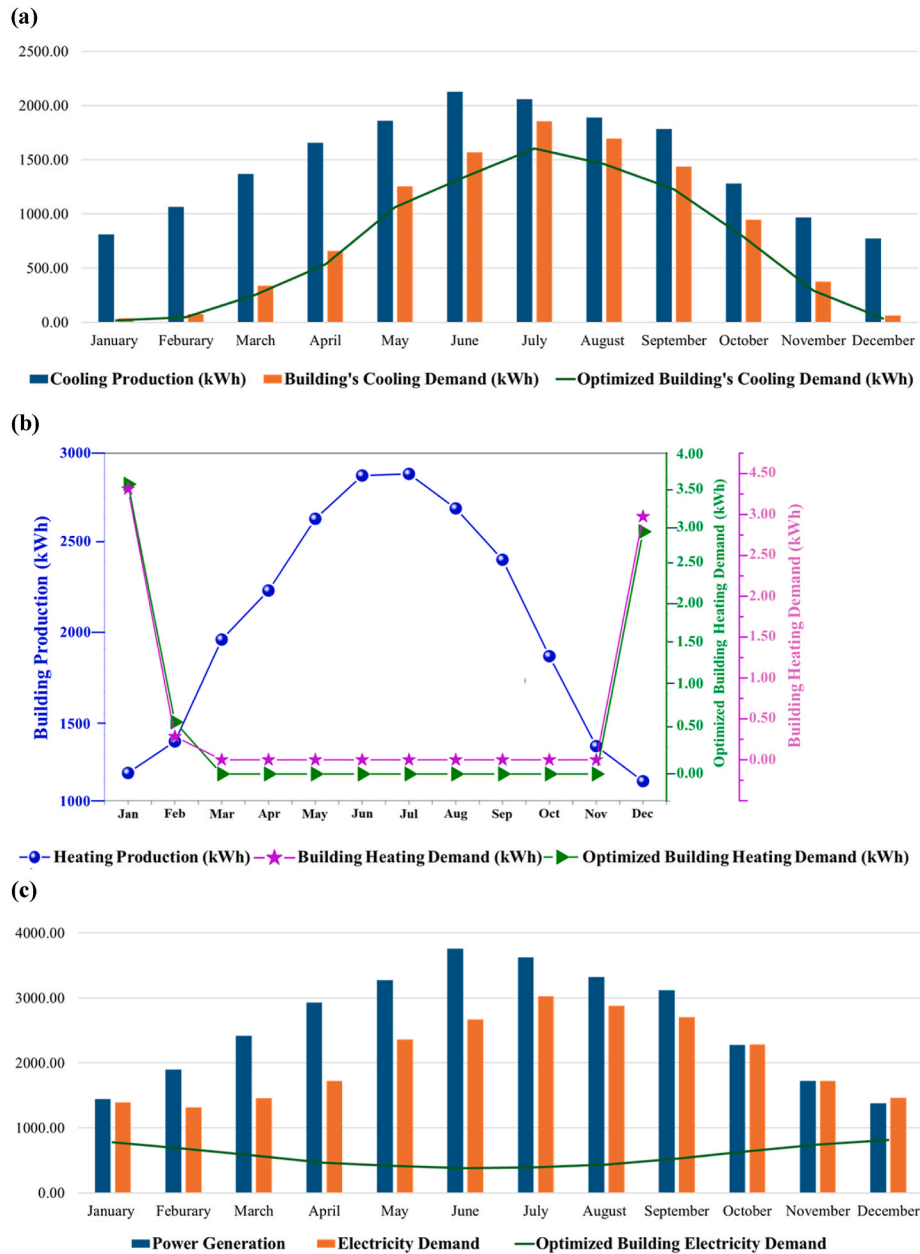


Fig. 16. Energy production versus demand: Baseline and optimized for cooling (a), heating (b), and electricity (c) under baseline and optimized conditions.

Table 9
Annual Energy Production and Consumption: Baseline vs. Optimized.

Energy Type	Unit	Production	Baseline Consumption	Optimized Building Consumption
Cooling	kWh	13,927,660	7,517,611	6,326,109
Heating	kWh	19,471,190	6571	5462
Electricity	kWh	49,545,386	18,238,280	15,267,484

focused on energy balance rather than storage technology design.

To provide a variability check under realistic seasonal changes, surplus calculations are evaluated at a monthly resolution using Meteorism-based solar inputs and BEopt-derived monthly demand profiles. The month-by-month results shown in Fig. 17 demonstrate that surplus availability is not driven by an annual average but varies throughout the year in response to concurrent changes in solar resource availability and building energy demand. These results, therefore, provide an indicative assessment of seasonal robustness; however, they

represent surplus energy potential and do not include explicit transient storage dynamics such as capacity limits, charging and discharging rates, round-trip efficiency, or temporal dispatch constraints. Incorporating such transient storage behavior is identified as an important direction for future work.

This section compares annual surplus energy availability under baseline and optimized scenarios, for cooling, heating, and electricity performance. The monthly surplus cooling, heating, and electricity energy for both the baseline and optimized building scenarios are illustrated in Fig. 17(a), (b), and 17(c). The optimized building consistently exhibits higher surplus availability across all categories, demonstrating the effectiveness of design enhancements. For cooling energy, the optimized building shows major improvements during the warmer months (June to September), with July surplus approaching 1,000,000 kWh compared to approximately 800,000 kWh for the baseline. This increase is attributed to reduced cooling demand resulting from improved thermal insulation and energy-efficient materials. Similarly, heating surplus is slightly higher in the optimized case during winter months such as

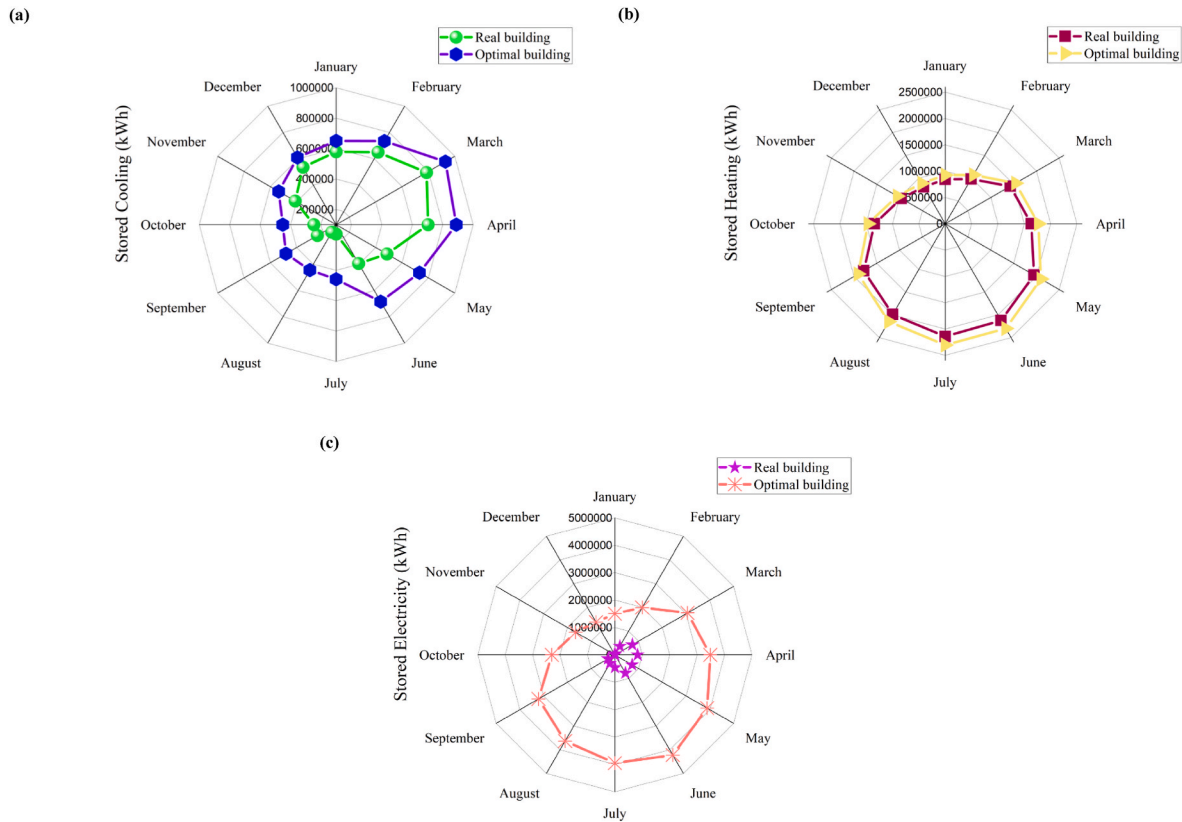


Fig. 17. Monthly Stored Cooling (a), Heating (b), and Electricity (c) Energy Baseline vs. Optimized.

January and December due to reduced heating loads, although overall heating surplus remains limited because Dezful is a cooling-dominant climate.

For electricity, the optimized building demonstrates a significant advantage, especially in summer. Surplus electricity in July reached nearly 5,000,000 kWh, compared to approximately 3,500,000 kWh in the baseline scenario. This improvement reflects the effectiveness of the integrated solar PV system and advanced energy management strategies, ensuring surplus electricity is available for redistribution or sale to the grid. Overall, the optimized building outperforms the baseline across all energy categories, highlighting the role of integrated efficiency measures and renewable system optimization in enhancing surplus energy availability.

Table 10 summarizes annual surplus energy for cooling, heating, and electricity under baseline and optimized conditions. Cooling surplus increases marginally due to the cooling-dominant climate, while heating and electricity show substantial absolute improvements of 1,191,447 kWh and 3,270,593 kWh, respectively, reflecting improved surplus capture and optimized solar PV integration.

To demonstrate the practical implications, Table 11 illustrates how surplus energy can support additional buildings. The number of buildings supported is estimated by normalizing the annual surplus cooling, heating, and electricity against the corresponding annual energy demand of the optimized case study building, assuming identical building size, occupancy, load profiles, and climatic conditions, and without applying load diversity or temporal coincidence effects. For

Table 11

System capability: Buildings supported by surplus energy.

Energy Type	Buildings Supported (Baseline)	Buildings Supported (Optimized)
Cooling	2	3
Heating	1	2
Electricity	2.963	3.564

reproducibility, the reference building used in this normalization has a total floor area of 7270 m² and annual optimized demands of 6,326,109 kWh for cooling, 5462 kWh for heating, and 15,267,484 kWh for electricity, corresponding to approximate energy intensities of 870.2, 0.75, and 2100.1 kWh/m².year, respectively. Under these assumptions, the optimized design enables surplus electricity to support approximately 3.6 buildings of a similar type, compared to about 3 in the baseline scenario, while surplus cooling and heating can support three buildings instead of two. These results represent surplus-based utilization potential rather than the performance of specific storage technologies, highlighting the system's capacity to redistribute excess energy under a ZEB-oriented energy balance framework and identifying detailed storage technology modeling as a direction for future work.

To make the scalability claim more explicit, a first-order adaptation to other building types is represented by scaling the optimized building's annual electricity, cooling, and heating demands by a load-intensity factor k , where $k < 1$ indicates lower-intensity uses, for example,

Table 10

Annual Surplus Energy: Baseline vs. Optimized Buildings.

Energy Type	Unit	Stored in Real Building (Baseline)	Stored in Optimized Building	Absolute Improvement	Improvement (%)
Cooling	kWh	19,464,618	19,465,728	1110	0.006
Heating	kWh	6,410,154	7,601,601	1,191,447	18.59
Electricity	kWh	31,308,057	34,278,650	3,270,593	9.49

office or teaching blocks, and $k >$ indicates higher-intensity uses such as laboratories or healthcare facilities. Under the same surplus-normalization approach used in Table 11, and keeping identical climate and technology assumptions, the equivalent number of supported buildings becomes ($N_k = \frac{N}{k}$), where N is the number of buildings supported in the optimized case. This illustration does not replace full re-optimization for a different building archetype, which would require re-running BEopt and retraining the ANN, but it provides a transparent example of how surplus utilization potential shifts with building-type energy intensity.

Based on the optimized case values (Cooling $N = 3$, Heating $N = 2$, Electricity $N = 3.564$), Table 12 presents a first-order parametric illustration for three representative building-type intensities: $k = 0.8$ (20% lower intensity, office/teaching), $k = 1.0$ (same intensity, similar university buildings), and $k = 1.3$ (30% higher intensity, laboratories/healthcare).

To further examine robustness, a first-order sensitivity analysis was conducted by varying annual solar irradiance and annual building demand by $\pm 10\%$ while keeping the optimized system configuration fixed. The results show that the system remains surplus-positive across the tested range, although the magnitude of annual surplus energy and the equivalent number of buildings supported vary predictably with changes in solar resource availability and demand level. For consistency with the surplus-normalization approach adopted in this study, the equivalent buildings supported by surplus electricity were calculated using the annual electricity demand of the existing case study building as the reference denominator. This analysis is intended as an indicative robustness check under moderate uncertainty and does not replace full re-optimization for other climates or building archetypes. The corresponding results are summarized in Table 13.

4.3.3. Scalability and modularity design

The framework developed in this study offers an innovative foundation for scalability and modularity by leveraging its AI-driven optimization and system integration capabilities. The adaptability of the RSM, ANN, and GA ensures that the framework is not constrained to the specific case study but can be applied to diverse building types and climatic conditions. By incorporating modular components and flexible optimization parameters, this approach allows designers to configure energy systems adapted to the unique requirements of different contexts. For example, insights from this study, such as the simultaneous optimization of objective functions, can guide the design of energy systems that dynamically adapt to changing energy needs, resource availability, and operational constraints in real-world applications.

The findings emphasize the potential to scale this framework for district-level energy systems or interconnected networks, where modularity becomes critical for integrating renewable energy sources and balancing supply and demand across multiple buildings. The understanding gained from the interactions between components, such as the compression chiller's dual functionality for cooling and heating, highlights opportunities to design systems that maximize resource utilization while remaining flexible for future expansion or retrofitting. AI models can also be retrained with localized datasets to accommodate the energy consumption patterns and renewable potential of other regions. By focusing on scalability and modularity, this framework provides a pathway for deploying innovative, efficient, and sustainable energy

Table 12
First-order scaling of surplus utilization across building types.

Energy Type	k	Equivalent buildings supported		
		Cooling	Heating	Electricity
Cooling	0.8	3.75	2.50	4.46
Heating	1.0	3.00	2.00	3.56
Electricity	1.3	2.31	1.54	2.74

Table 13

Sensitivity of surplus utilization to $\pm 10\%$ solar and demand changes.

Scenario	Solar irradiance	Annual demand	Electricity surplus (kWh/year)	Equivalent buildings supported (electricity)
Base case	0%	0%	13,069,777	0.72
Lower solar availability	-10%	0%	11,762,799	0.64
Higher solar availability	+10%	0%	14,376,755	0.79
Lower demand	0%	-10%	14,376,755	0.79
Higher demand	0%	+10%	11,762,799	0.64

systems globally, offering transformative solutions for real-world challenges.

4.3.4. Comparison with previous systems

Extensive research has explored the development and optimization of renewable-based multigeneration systems with varying success in balancing efficiency, cost, and environmental impact. To avoid misleading one-to-one comparisons across systems of different scales and configurations, the results are presented as contextual benchmarks rather than fully normalized performance rankings. The reported exergy efficiencies and cost rates are taken directly from the referenced studies and reflect each system's original design capacity, operating assumptions, and lifecycle boundaries. The comparison therefore focuses on order-of-magnitude performance, cost-efficiency trade-offs, and application scale, rather than implying direct equivalence across technologies or system sizes. Because the compared systems were developed under different problem formulations, scales, and datasets, formal statistical ranking tests (e.g., Friedman or Wilcoxon (Corder et al., 2014)) are not applicable, and the comparison is therefore presented as contextual benchmarking rather than controlled algorithm evaluation. Since these methods were not executed on identical datasets or under consistent modeling assumptions, statistical significance testing between them would be methodologically invalid rather than merely impractical.

Table 14 summarizes representative systems from the literature and compares their exergy efficiency, cost rate, and CO₂ reduction with those of the proposed solar-based system, positioning the present results within the broader research landscape. The performance metrics reported for the other systems are taken directly from the respective publications and reflect their original modeling assumptions, system scales, and optimization settings. Absolute CO₂ reductions are shown where mass-based values were available, while percentage reductions are listed separately when only relative metrics were reported. Values for the present study were generated by the authors using Building Energy Optimization Tool and Engineering Equation Solver (BEopt-EES) simulations combined with the proposed RSM-ANN-GA optimization framework, whereas all other values were extracted directly from the cited publications and were not re-simulated. Because these studies differ in system scale, modeling assumptions, and system boundary definitions, the results should be interpreted as contextual performance benchmarks rather than directly equivalent numerical comparisons.

Where available, cost rates are reported on an hourly basis as defined in the original studies; however, differences in system capacity, annual operating hours, and boundary definitions should be considered when interpreting cross-study comparisons. Although the present study uses cost rate (\$/h) as the primary economic objective, this metric is not directly equivalent to lifecycle indicators such as payback period or leveled cost of energy, which depend on additional assumptions, including electricity tariffs, discount rates, component replacement schedules, escalation, and policy incentives. For this reason, lifecycle-based economic metrics reported in the literature are considered here

Table 14
Performance comparison of reported multigeneration systems and the proposed system.

Reference	System Description	Optimization Approach	Approach Type	Cost Rate (\$/h) ↓	Exergy Efficiency (%) ↑	Carbon Dioxide (CO ₂) Decrease (absolute) ↑	Carbon Dioxide (CO ₂) Decrease (relative) ↑
Current System	Solar-based system with a compression chiller for cooling and heating, optimized for university buildings.	RSM, ANN, GA	Heuristic	14.12	29.23	2000 tons/year or 223.31 kg/h	-
Asadabadi et al. (2025)	Solar-geothermal system with hydrogen production and desalination for island energy needs.	ANN and GA (Asadabadi et al., 2025)	Heuristic	700.7	29.69	23,321.69 tons/year or 2663.32 kg/h	-
Aich et al. (2024)	Hybrid solar-biomass and PEM for hydrogen production	EES and Thermodynamic Analysis (Aich et al., 2024)	Analytical	722.3	32.9	2595.28 tons/year (emission index of 75.5 kg/MWh and output power of 3.927 MW)	-
Mouaky et al. (2024)	Hybrid solar-biomass multigeneration system with ORC for off-grid communities.	NSGA-II and TOPSIS (Mouaky et al., 2024)	Heuristic	-	5.39	-	10.6% Reduction
Korpeh et al. (2024)	Solar-biomass hybrid cogeneration for energy and hydrogen generation.	GA and Linear Programming Technique for Multidimensional Analysis of Preferences (LINMAP) (Korpeh et al., 2024)	Heuristic	324.6	31.75	-	32.4% Reduction
Ma et al. (2023)	Biomass–solar hybrid Combined Cooling, Heating, and Power (CCHP) with shaft power distribution (internal combustion engine and heat pump) for a hotel.	Hybrid optimization (design and operation strategies) (Ma et al., 2023)	Heuristic	3.25	-	-	88.93% CO ₂ reduction vs. separate production
Yadav et al. (2023)	Concentrated PV-Thermal (CPVT) multigeneration system for power, cooling, and water.	Economic and thermodynamic analysis (Yadav et al., 2023)	Analytical	6125	4.15	-	-
Esmailion et al. (2022)	Solar-geothermal multigeneration system producing power, heating, cooling, freshwater, and hydrogen.	Multi-Objective Particle-Swarm Optimization (MOPSO) (Esmailion et al., 2022)	Heuristic	-	41.07	2965.45 tons/year or 338.57 kg/h	-
Colakoglu et al. (2022a)	Solar tower-based Cogeneration with Brayton, Organic Rankine Cycle, and Goswami cycles.	Multi-objective Optimization (Parametric analysis) (Colakoglu et al., 2022a)	Heuristic	92.3	37.99	4501.39 tons/year or 513.8 kg/h	-
Colakoglu et al. (2022b)	Solar-driven gas turbine-based cogeneration system with Organic Rankine Cycle.	Multi-objective Optimization (Colakoglu et al., 2022b)	Heuristic	-	40.7	8305.51 tons/year or 948.7 kg/h	-
Cao et al. (2020)	Solar gas turbine-based multigeneration system with desalination and LNG cold energy recovery.	Multi-objective Spiral Optimization (MOSPO) algorithm (Cao et al., 2020)	Heuristic	36.75	60.05	485 tons/year or 55.37 kg/h	-
Saini et al. (2020)	Solar-driven compact CCHP with evacuated tube collectors, ORC, ejector refrigeration, and water heater for small buildings in remote locations.	Parametric study and GA (Saini et al., 2020)	Heuristic	0.23	3.159	13.10 tons/year or 1.50 kg/h	-

only as contextual benchmarks rather than directly comparable outputs. The proposed system achieves an exergy efficiency of 29.23%. While this value is not the highest among reported multigeneration systems, it is competitive for medium-scale applications and aligns with the operational and economic constraints typical of university campuses. Rather than maximizing efficiency alone, the proposed design emphasizes a balanced trade-off between performance, cost, and environmental impact.

Several studies report higher exergy efficiencies, including solar-geothermal multigeneration systems (41.07%) (Esmailion et al., 2022), solar tower-based systems (37.99% and 40.7%) (Colakoglu et al., 2022a, 2022b), and a solar gas turbine-based multigeneration system achieving 60.05% (Cao et al., 2020). However, these systems are generally designed for large-scale or industrial applications and involve substantially higher system complexity and cost. For instance, the solar gas turbine system in (Cao et al., 2020) achieves high efficiency but operates at a cost rate of 36.75 United States dollars per hour (\$/h), more than twice that of the proposed system, while delivering a lower annual CO₂ reduction (485 tons/year compared with 2000 tons/year).

Other systems with comparable or slightly higher efficiencies, such as hybrid solar-biomass and solar-geothermal configurations (Aich et al., 2024; Mouaky et al., 2024), operate at prohibitively high cost

rates exceeding 700.7 \$/h, limiting their applicability in medium-scale contexts. Conversely, systems with very low exergy efficiencies, such as the CPVT multigeneration system (4.15%) (Yadav et al., 2023), incur exceptionally high costs (6125 \$/h), further highlighting the importance of balanced system design rather than efficiency maximization alone.

As shown in Table 14, many high-performing systems rely on heuristic or metaheuristic optimization techniques, including GA, NSGA-II, PSO, and MOSPO. To provide a balanced benchmark, analytical and thermodynamic-only studies were also included (Aich et al., 2024; Yadav et al., 2023). The favorable cost–performance–emissions trade-off achieved by the proposed system indicates that its performance is not solely a result of algorithmic convergence but reflects its integrated design and suitability for university-scale deployment. With a cost rate of 14.12 \$/h and a CO₂ reduction of approximately 2000 tons/year at the integrated multigeneration system level (including surplus energy utilization and offset effects), the proposed system offers an affordable, environmentally effective, and scalable solution for medium-scale applications.

It should be noted that this comparative analysis is based on fixed assumptions regarding solar resource availability, building load profiles, and climatic conditions corresponding to the selected case study. Variability in solar irradiance, future climate conditions, and occupancy-

driven demand patterns may influence both exergy efficiency and cost outcomes. These factors were held constant to enable consistent benchmarking across systems, and incorporating uncertainty-aware analysis is identified as an important direction for future work.

5. Limitations and future directions

This section outlines the methodological and modeling limitations of the present study and then describes directions for future research and framework transferability.

5.1. Limitations

This study has limitations related to simplifying assumptions in the simulation process. The analysis is based on steady-state thermodynamic analysis and does not capture transient environmental dynamics. Practical parameters such as dust accumulation on PV panels and radiation exchange behind panels are also not included. While these simplifications enabled computational efficiency and modeling clarity, they may lead to an overestimation of system performance. The use of uniform convective heat transfer coefficients and quasi-steady-state conditions may also reduce the model's adaptability to daily and seasonal weather variations, particularly under Dezful's extreme climate. Results are therefore contingent on the operational schedules, equipment loads, technology performance parameters, and economic assumptions listed in Table 3. In addition, the economic assessment is limited to the cost-rate metric used for optimization and does not include simple or discounted payback period calculations, full lifecycle cost analysis with replacement cycles and residual value, or sensitivity of results to variations in energy prices, technology costs, or discount rates. Component performance degradation over time, such as PV efficiency decline and chiller aging effects, was also not modeled.

The AI-based optimization framework also has methodological constraints. The accuracy of the ANN surrogate model depends on the quality and representativeness of the RSM-generated training dataset, and predictions outside this range may be less reliable. The GA optimization process may converge to near-optimal rather than guaranteed global solutions, and heuristic methods introduce uncertainty when applied to different system scales or operating conditions. Generalizability across climatic zones was not validated through full re-optimization; applying the framework elsewhere requires re-running BEopt demand modeling and retraining the ANN using climate-specific datasets. Therefore, the reported performance is validated only for the studied building and climate. A first-order climate sensitivity perspective was explored through $\pm 10\text{--}20\%$ variations in annual demand and solar availability (see Section 4.2). While this indicates how ZEB balance margins may shift under different conditions, it does not replace full multi-climate re-optimization. Despite these limitations, the comparison between baseline and optimized models still provides reliable insight into relative performance improvements.

5.2. Future directions and framework transferability

Future research should incorporate dynamic simulations that account for transient system behavior and variable weather conditions to better represent real-world operations. Including time-dependent parameters and adaptive control strategies would improve system robustness under daily and seasonal climatic fluctuations. Expanding the framework for application to hybrid renewable configurations, such as solar-wind integrations, could improve resilience against environmental uncertainties. Modular system concepts suitable for district-level applications may further extend practical applicability by enabling integration with existing energy infrastructure and additional renewable technologies, including geothermal systems. More detailed economic evaluations that reflect regional energy prices, dynamic maintenance costs, and lifecycle financial performance are also needed to assess

feasibility across diverse contexts. Future work should also investigate operational implementation challenges, including real-time control coordination between generation, storage, and building loads, part-load performance of system components, and dispatch strategies required to maintain efficiency under variable demand and weather conditions. In practical deployments, these challenges may also require periodic retraining of the ANN surrogate as building loads and operating patterns change over time, as well as integration with Internet of Things (IoT)-enabled sensing and Building Management Systems (BMS) to provide reliable real-time data and control signals. These studies are essential for translating optimized designs into reliable real-world performance.

The framework is transferable as a workflow rather than as fixed performance outcomes. Applying it to other climates or building types requires recalibration through the following steps: replacing the climate inputs with a location-specific weather file; re-running BEopt to generate climate-specific demand profiles; reconstructing the Central Composite Design within revised decision-variable bounds; retraining the ANN surrogate model and repeating GA optimization; and verifying Pareto-optimal solutions in EES under new conditions. Within the scope of this study, a first-order climate sensitivity perspective was explored by varying annual demand and solar availability by $\pm 10\text{--}20\%$ (Section 4.2). This illustrates how ZEB balance margins and PV sizing trends may shift under different climatic conditions, but it does not replace full re-optimization for other locations.

6. Conclusion

Meeting the energy demands of multifunctional buildings such as university facilities with renewable sources remains a significant sustainability challenge. This study addressed these challenges by developing an Artificial Intelligence-based multi-objective optimization framework to design and evaluate a solar-based energy system tailored to such complex settings. By integrating Response Surface Methodology, Artificial Neural Networks, and Genetic Algorithms, the study established an innovative approach to balance exergy efficiency and cost rate, implemented as a transferable optimization workflow rather than a fixed climate-specific design.

The findings demonstrate the following key performance outcomes:

- Multi-objective optimization using Artificial Intelligence effectively balanced exergy efficiency and cost rate, achieving a 14.18% increase in exergy efficiency while identifying Pareto-optimal solutions capable of achieving surplus renewable electricity under the studied conditions.
- Integration of a compression chiller allowed solar energy to provide both cooling and heating simultaneously, reducing energy waste and improving overall system utilization.
- Demand-side optimization reduced energy demand by 16.3% for electricity, 15.8% for cooling, and 16.9% for heating compared to the baseline configuration.
- The system's surplus energy contributed to major reductions in site energy use and emissions, substantially lowering grid electricity dependence and operational CO₂ emissions within the defined operational system boundary, supporting sustained decarbonization over the building service life and contributing to institutional net-zero transition pathways.
- The Pareto-based optimization revealed a consistent trade-off structure between exergy efficiency and cost rate, supporting informed decision-making for balancing thermodynamic performance and economic feasibility.
- The proposed hybrid optimization framework is transferable to other complex facilities, such as hospitals, mixed-use developments, and district-scale networks, where efficiency, cost, and operational complexity must be balanced.

The comparative results presented should be interpreted as

contextual benchmarking rather than direct algorithmic competition, since alternative methods were not re-executed under identical modeling conditions. Future extensions can incorporate hybrid renewable configurations, such as combined solar and wind systems, and district-level modularity to improve resilience and energy sharing between buildings. Practical implementation will also require attention to real-time control integration, periodic ANN retraining under changing operating conditions, and compatibility with IoT and Building Management Systems platforms. The results confirm that integrating AI-driven multi-objective optimization with coordinated demand- and supply-side modeling provides an effective and adaptable framework for designing high-performance renewable multigeneration systems in complex buildings.

CRediT authorship contribution statement

Ehsanolah Assareh: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nima Izadyar:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project

administration, Methodology, Formal analysis. **Saleh Mobayen:** Writing – original draft, Software, Methodology, Formal analysis. **Elmira Jamei:** Writing – review & editing, Supervision, Resources. **Mohammad amin Monzavian:** Visualization, Software, Data curation.

Declaration of generative AI

During the preparation of this manuscript, the authors employed a language-editing tool powered by OpenAI and Grammarly to improve clarity and style. All scientific interpretations, analyses, and conclusions were developed solely by the authors. The authors carefully reviewed and refined the text after using the tool, and they accept complete responsibility for the final version of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Results of 100 Optimized Configurations

Appendix A presents the outcomes of multi-objective optimization using RSM. These results provide the optimal configurations of PV panel number, width, and length, along with their corresponding exergy efficiency and cost rate, highlighting the trade-offs and desirable configurations for the solar farm.

Table A.1
Results of 100 Optimized Photovoltaic Panel Configurations

Case No.	Number of Photovoltaic Panels (–)	Width (m)	Length (m)	Exergy Efficiency (%)	Cost Rate (\$/h)
1	130.001	1.423	3.634	25.601	10.151
2	129.401	1.511	3.602	25.691	10.163
3	129.276	1.423	3.634	25.643	10.123
4	129.434	1.423	3.641	25.685	10.164
5	129.434	1.427	3.634	25.694	10.178
6	129.087	1.423	3.634	25.576	10.092
7	129.434	1.423	3.649	25.671	10.171
8	128.964	1.423	3.634	25.533	10.072
9	128.847	1.423	3.634	25.492	10.052
10	129.434	1.423	3.657	25.654	10.183
11	129.434	1.433	3.634	25.688	10.214
12	128.729	1.423	3.634	25.451	10.033
13	129.434	1.423	3.671	25.629	10.202
14	129.434	1.440	3.634	25.681	10.256
15	129.433	1.423	3.679	25.613	10.215
16	129.434	1.446	3.634	25.675	10.295
17	129.434	1.423	3.693	25.588	10.235
18	129.434	1.423	3.722	25.539	10.277
19	129.434	1.423	3.735	25.514	10.331
20	129.431	1.466	3.634	25.656	10.422
21	126.450	1.423	3.634	24.679	9.674
22	126.465	1.423	3.641	24.671	9.686
23	126.293	1.423	3.634	24.628	9.651
24	129.434	1.423	3.761	25.471	10.341
25	128.854	1.469	3.634	25.453	10.339
26	129.429	1.478	3.634	25.643	10.497
27	125.537	1.423	3.634	24.383	9.539
28	129.433	1.490	3.634	25.636	10.569
29	129.433	1.423	3.798	25.411	10.401
30	125.264	1.423	3.635	24.293	9.501
31	129.433	1.446	3.761	25.444	10.496
32	129.433	1.499	3.634	25.627	10.631
33	129.434	1.423	3.846	25.339	10.483
34	129.434	1.516	3.634	25.614	10.737
35	129.433	1.513	3.654	25.577	10.746
36	123.396	1.423	3.634	23.717	9.241
37	129.433	1.532	3.634	25.604	10.825
38	129.433	1.423	3.915	25.246	10.606
39	129.425	1.423	3.991	25.154	10.748
40	120.991	1.423	3.634	23.018	8.937

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Table A.1 (continued)

Case No.	Number of Photovoltaic Panels (–)	Width (m)	Length (m)	Exergy Efficiency (%)	Cost Rate (\$/h)
41	120.021	1.423	3.634	22.751	8.825
42	126.178	1.423	3.969	24.086	10.171
43	118.141	1.423	3.634	22.256	8.622
44	116.647	1.423	3.634	21.885	8.475
45	129.432	1.423	4.217	24.974	11.233
46	129.434	1.714	3.634	25.518	12.033
47	129.434	1.423	4.382	24.919	11.638
48	111.812	1.423	3.634	20.822	8.089
49	111.492	1.423	3.634	20.759	8.068
50	126.889	1.423	4.384	24.068	11.190
51	122.671	1.676	3.634	23.363	10.679
52	110.573	1.423	3.634	20.583	8.012
53	109.674	1.423	3.634	20.418	7.962
54	119.192	1.423	4.166	21.922	9.601
55	106.673	1.423	3.634	19.919	7.828
56	129.434	1.423	4.677	24.986	12.466
57	105.672	1.423	3.634	19.771	7.795
58	105.232	1.423	3.634	19.709	7.782
59	104.662	1.423	3.634	19.635	7.768
60	104.557	1.423	3.634	19.616	7.765
61	102.373	1.423	3.634	19.345	7.728
62	100.791	1.423	3.635	19.174	7.718
63	121.491	1.423	4.744	22.597	11.359
64	100.567	1.423	4.016	18.717	8.166
65	100.566	1.423	4.366	18.639	8.778
66	100.732	1.450	3.943	18.639	8.778
67	110.809	1.450	3.946	20.658	8.987
68	110.434	1.451	3.951	20.559	8.962
69	110.059	1.451	3.957	20.461	8.937
70	109.684	1.451	3.963	20.363	8.913
71	109.309	1.451	3.969	20.265	8.888
72	108.934	1.452	3.975	20.167	8.863
73	108.559	1.452	3.980	20.068	8.838
74	108.184	1.452	3.986	19.970	8.813
75	107.809	1.453	3.992	19.872	8.789
76	107.434	1.453	3.998	19.774	8.764
77	107.059	1.453	4.003	19.676	8.739
78	106.684	1.453	4.009	19.577	8.715
79	106.309	1.454	4.015	19.479	8.690
80	105.934	1.454	4.021	19.381	8.665
81	105.559	1.454	4.026	19.283	8.641
82	105.184	1.454	4.032	19.185	8.616
83	104.809	1.455	4.038	19.086	8.591
84	104.434	1.455	4.044	18.988	8.566
85	104.059	1.455	4.050	18.895	8.542
86	103.684	1.456	4.052	18.792	8.517
87	103.309	1.456	4.061	18.694	8.492
88	102.934	1.456	4.067	18.596	8.467
89	102.559	1.456	4.073	18.497	8.442
90	102.184	1.457	4.078	18.399	8.418
91	101.809	1.457	4.084	18.301	8.393
92	101.434	1.457	4.091	18.203	8.369
93	101.059	1.457	4.096	18.105	8.344
94	100.684	1.458	4.102	18.006	8.319
95	100.309	1.458	4.107	17.908	8.294
96	99.933	1.458	4.113	17.810	8.270
97	99.559	1.459	4.119	17.712	8.245
98	99.183	1.459	4.125	17.614	8.220
99	98.808	1.459	4.130	17.515	8.195
100	98.433	1.459	4.136	17.417	8.171

Table A.2 summarizes the preliminary hyperparameter trials carried out for the Artificial Neural Network and Genetic Algorithm models, together with the final selected settings used in the study. These settings were chosen based on their ability to provide stable convergence, reliable prediction accuracy, and robust optimization performance while keeping the computational effort manageable.

Table A.2 Summary of ANN and GA Hyperparameter Trials and Final Selected Values

Model	Hyperparameter	Trial Range/Tested Values	Final Value
ANN	Hidden neurons	5, 10, 15, 20, 25	10
ANN	Training algorithm	Levenberg-Marquardt, Bayesian regularization, Scaled conjugate gradient	Levenberg-Marquardt
ANN	Data split ratio	60:20:20, 70:15:15, 70:20:10, 80:10:10	70:15:15
ANN	Maximum epochs	500, 1000, 1500, 2000, 3000	1000
ANN	Hidden activation	tanh, logsig (sigmoid), purelin	logsig (sigmoid)

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Model	Hyperparameter	Trial Range/Tested Values	Final Value
ANN	Output activation	logsig (sigmoid), purelin (linear)	purelin (linear)
GA	Population size	20, 40, 60, 80, 100	80
GA	Number of generations	100, 120, 150, 200, 300	120
GA	Crossover rate	0.7, 0.75, 0.8, 0.85, 0.9	0.85
GA	Mutation rate	0.01, 0.02, 0.05, 0.1	0.05
GA	Elitism	No elitism, top 1 individual, top 2 individuals	top 2 individuals
GA	Convergence criterion	Maximum generations; no significant improvement over 10 generations; no significant improvement over 15 generations	No significant improvement over 15 generations

Data availability

The datasets generated during this study consist of simulation-derived design points used for ANN development, along with the trained ANN model parameters and optimization workflow scripts created by the authors. These materials are available from the corresponding author upon reasonable request for academic research purposes. The study relies on licensed third-party software (BEopt and EES), which are not redistributed; users must obtain these tools independently.

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