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Thermoeconomic optimization of climate-adaptive solar and wind multi-generation systems using artificial intelligence and thermal energy recovery

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ABSTRACT

This study presents a hybrid multi-generation energy system designed to overcome solar intermittency while meeting the global demand for integrated delivery of electricity, water, cooling, and sustainable fuels in the transition to decarbonization. The engineering application integrates solar thermal and wind energy with a modified Brayton cycle, a Steam Rankine Cycle (SRC), and a Thermoelectric Generator (TEG) to simultaneously produce electricity, fresh water via Reverse Osmosis (RO), hydrogen and oxygen via Proton Exchange Membrane Electrolyzer (PEME), and cooling (via absorption chiller) within a unified optimization framework. The system was modeled using Engineering Equation Solver (EES) and optimized via Response Surface Methodology (RSM) based on 11 decision variables. To address the complexity of optimization, a second phase applied Artificial Intelligence (AI) techniques: Adaptive Boosting (AdaBoost) for predictive modelling and Particle Swarm Optimization (PSO) for global optimization. Under optimal conditions, the Response Surface Methodology yielded an exergy efficiency of 45.8 % with a cost rate of 576.76 United States Dollars per hour (USD/h), while AI reduced costs to 211.2 USD/h with a moderate efficiency trade-off. Simulation of the optimized configuration across eight diverse climates identified Quebec as most viable, generating 22,629.6 Megawatt-hours per year (MWh/year) of electricity and avoiding 4616.4 tons of Carbon Dioxide (CO₂) emissions annually. Integration of wind energy stabilizes solar variability, enhancing performance. AI contributes to optimizing complex interactions, nonlinear constraints, and multiple conflicting objectives. The methodology offers a scalable, generalizable framework for

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designing intelligent, climate-resilient infrastructures. Future research includes AI-enabled real-time control, experimental validation, and broader deployment strategies.

1. Introduction

The escalating impacts of climate change, including growing economic burdens, ecological degradation, and stress on water and energy resources, have exposed the limitations of traditional energy infrastructures that rely heavily on fossil fuels and deliver single-purpose outputs (Rahman et al., 2025; IEA, 2023; Attfilio et al., 2024). In response, the global energy transition increasingly prioritizes integrated renewable systems capable of simultaneously delivering electricity and additional benefits such as freshwater, cooling, and clean fuels in a climate-resilient manner (Mohtasim et al., 2025; Ismail et al., 2025; Wei et al., 2024). This has fueled interest in multi-generation renewable energy platforms, which maximize resource efficiency by coupling diverse outputs like electricity, hydrogen, potable water, and thermal comfort within a unified system (Kariuki et al., 2024; Asadabadi et al., 2025). For instance, Kariuki et al. (2024) reviewed hybrid geothermal-solar multi-generation systems and highlighted significant improvements in power production and energy efficiency (up to 50 %). Solar energy, widely available and technologically mature, remains a dominant renewable source (Khan et al., 2025; Sarvar-Ardeh et al., 2024; Lykas et al., 2023; Osman et al., 2025). Khan et al. (2025) emphasized the role of solar power in driving thermal desalination, enabling sustainable multi-generation of electricity, water, and heat with lower emissions. However, systems relying solely on solar inputs suffer from diurnal variability and seasonal intermittency, undermining reliability for critical loads across multiple domains (Thakkar et al., 2025; Saini et al., 2024). This highlights the need for hybridized, performance-optimized multi-generation platforms that address both energy security and environmental imperatives in real-world conditions (Chou et al., 2023; Jurasz and Beluco, 2022).

To overcome intermittency and enhance reliability, renewable-based multi-generation systems commonly integrate hybrid energy sources such as biomass, geothermal, or wind with solar inputs, thereby sustaining continuous outputs year-round (Pérez Uc et al., 2024; Tian et al., 2024). Among hybrid configurations, solar-wind systems offer a particularly advantageous synergy (Alhijazi et al., 2023; Guo et al., 2018; Pawar et al., 2024), as solar power peaks during daylight and warmer seasons, while wind resources are often more abundant during evenings and colder months (Ahmadullah et al., 2025; Gao et al., 2024; Farhani et al., 2024; Mertens, 2022). This complementary relationship enhances system robustness, reduces dependency on extensive energy storage, and simplifies operation, especially given recent advancements in solar and wind technologies (Hassan et al., 2023; Khurshid et al., 2024). Nonetheless, effective design of solar-wind multi-generation systems requires precise optimization strategies capable of simultaneously balancing multiple competing objectives such as energy and exergy efficiencies, economic feasibility, and environmental impacts (Giedraityte et al., 2025; Nwagu et al., 2024). Advanced multi-objective optimization frameworks, incorporating detailed thermodynamic modeling, scenario-based climatic analyses, and sophisticated computational techniques, are thus essential for managing the complexity of hybrid renewable systems and ensuring their practical sustainability (Liu et al., 2023; Tezer, 2025; Lotfollahi et al., 2024; Nasrabadi et al., 2023).

Several advanced optimization methods have been developed to manage the complex interactions within hybrid multi-generation platforms (Mohtasim et al., 2025; Bagherian et al., 2021). Techniques such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II), hybrid machine learning-thermodynamic models (e.g., AdaBoost integrated with thermodynamic principles), Response Surface Methodology (RSM), and the Technique for Order Preference by Similarity to an Ideal

Solution (TOPSIS) have demonstrated strong capability in improving system performance and supporting decision-making under computational constraints (Bakircioglu et al., 2025; Mouaky and Rachek, 2024; Assareh et al., 2025a). These methods can enhance energy and exergy efficiencies, lower operational costs, and reduce Carbon Dioxide (CO₂) emissions (Sami et al., 2024; Assareh et al., 2024, 2025b). For instance, Al-Hamzawi et al. (2025) optimized a solar-driven multi-generation system with parabolic trough collectors and Multi-Effect Distillation (MED) using RSM, achieving a 20 % efficiency gain and demonstrating the role of thermal energy storage (TES) in ensuring stable operation. Likewise, Sun et al. (2024) used a hybrid Genetic Algorithm (GA) and machine learning approach in a Concentrated Solar Power (CSP)-based multi-generation system, achieving 6.4 % higher exergy efficiency and a 4 % reduction in levelized electricity cost compared to a stand-alone Brayton cycle. However, the successful application of these techniques heavily depends on accurately modeling thermodynamic complexities, which often lead to challenging trade-offs between computational simplicity and predictive precision (Xia et al., 2025; Qiao et al., 2024). A hybrid optimization strategy, starting with interpretable methods like RSM and refining with Artificial Intelligence (AI)-driven techniques, such as Particle Swarm Optimization (PSO), can effectively balance these trade-offs and deliver robust, adaptable solutions across diverse scenarios (Fu, 2015; Kim et al., 2025). As reviewed by Bagherian et al. (2021), modern heuristics such as GA and PSO outperform classical methods in optimizing the thermoeconomic performance of integrated energy systems. However, most existing studies apply these methods to simplified configurations or isolated subsystems, leaving a gap in the development of a unified, deeply integrated multi-generation platform with co-optimization of all components, an area this study directly advances.

Despite advances in hybrid renewable system optimization, there remains a clear need for integrated multi-generation models that combine multiple renewable inputs and deliver diverse outputs with high efficiency, economic viability, and climate adaptability (León Gómez et al., 2023; Thirunavukkarasu et al., 2023). Existing studies often focus on isolated components or single optimization strategies, leaving a gap in comprehensive, system-wide solutions (Hassan et al., 2023; Giedraityte et al., 2025). A review paper by Hassan et al. (2023) showed that there is limited ability to fully harness the synergistic benefits of solar and wind combinations due to the absence of integrated control and optimization frameworks. Moreover, seasonal and climate-specific variations, such as fluctuations in solar irradiance, wind availability, and ambient temperatures, necessitate thorough performance assessments to ensure year-round reliability (Agency, 2023; Bamisile et al., 2025). Xu et al. (2024) also emphasized that meeting these challenges requires resilient platforms capable of maintaining high performance across diverse environmental conditions. A promising approach involves hybrid solar-wind multi-generation systems integrated with advanced power generation technologies (e.g., integration of modified Brayton cycle and Steam Rankine Cycle (SRC), thermoelectric generators) (Bustamante et al., 2021), desalination (e.g., Reverse Osmosis) (Lotfy et al., 2022; Jiang et al., 2022), hydrogen production like Proton Exchange Membrane Electrolyzer (PEME) (Nasser et al., 2022), and cooling technologies (e.g., absorption chillers) (Tawil et al., 2018), offers a promising solution by efficiently producing electricity, freshwater, hydrogen, and cooling. However, holistic optimization and performance evaluation of such integrated systems, particularly under varied seasonal and climatic conditions through combined thermodynamic and economic analyses, remain limited (Hassan et al., 2023; Ren et al., 2025; Saini et al., 2025), highlighting a critical research gap addressed by this study.

This study introduces a novel, fully integrated solar-wind hybrid multi-generation system that simultaneously produces electricity, freshwater, hydrogen, and cooling. This system integrates modified Brayton and Rankine cycles (SRC), thermoelectric generator, Reverse Osmosis (RO) desalination, PEME, and absorption chiller, all coupled through thermal energy recovery loops. Unlike prior works that focus on individual subsystems, this research holistically co-optimizes six interconnected units through a dual-stage optimization strategy, initially applying RSM, followed by refinement using AdaBoost and PSO. The system performance is further validated under diverse environmental conditions across eight global cities, enabling generalization to different climate zones, which is rarely addressed in prior literature. This approach highlights thermoeconomic trade-offs and adaptive wind-solar allocation for PEME and RO, offering a scalable solution for real-world multi-vector energy demands. While demonstrated on an energy-focused application, the proposed AI-based optimization framework is broadly applicable to other complex engineering and cyber-physical systems facing similar nonlinearities, scalability constraints, and multiple conflicting objectives, thereby advancing the practical use of AI methodologies in diverse engineering contexts. The remainder of the paper presents the system model, outlines the methodological framework, describes the optimization strategy, discusses results across diverse climatic conditions, and concludes with future directions and practical implications.

2. System description and modeling

The proposed system brings together multiple renewable energy technologies within a unified framework to meet diverse energy demands sustainably. It was modeled as a modular and scalable platform, capable of providing continuous output under varying environmental conditions. Each subsystem, solar thermal, wind, thermoelectric, desalination, and hydrogen production, was carefully designed and integrated to maximize efficiency, minimize losses, and enable multifunctional performance. The following sections describe the physical configuration, modeling methods, and validation process applied in this study.

2.1. System design and configuration

The proposed hybrid multi-generation system, shown in Fig. 1, integrates solar thermal and wind energy to co-produce electricity, fresh water, hydrogen, and cooling through a series of interconnected subsystems. At its core is a heliostat field that concentrates solar radiation onto a central receiver (stream 2), which heats air flowing into a thermal energy storage unit (stream 3). This stored heat drives a modified Brayton cycle by replacing the conventional combustion chamber with solar thermal input, enabling cleaner, fuel-free operation. The heated air powers a gas turbine (stream 4), generating electricity via a connected generator, while the turbine's exhaust (stream 6) is routed through a heat recovery system linked to a Steam Rankine Cycle (SRC). The SRC subsystem includes a pump (10), an evaporator (5), and a secondary turbine (8) that generates additional electricity. A thermoelectric generator (11) integrated into this loop captures waste heat from the SRC and converts it into further electrical output while supporting the cooling process. This dual use of thermal energy improves the overall efficiency of the system and allows for reliable operation across a variety of climatic conditions.

In addition to electricity generation, the system strategically allocates power to deliver multiple outputs, as shown in Fig. 1:

- **Electricity:** Generated directly by the gas turbine and SRC, with additional recovery from the thermoelectric generator. Surplus wind-generated electricity is also supplied to the main grid.
- **Freshwater:** Generated in the RO desalination unit, which processes seawater (22) and delivers freshwater (25) to a storage tank (24).
- **Hydrogen:** Produced by the proton exchange membrane electrolyzer (PEME, 28), which splits water into hydrogen and oxygen, stored in separate tanks (27).
- **Cooling:** Supplied through an absorption chiller loop comprising the generator (12), absorber (13), evaporator (21), and heat exchangers (18–20), with additional thermal support from the thermoelectric generator.

This modular and adaptive configuration enables flexible power distribution under varying environmental conditions, allowing the

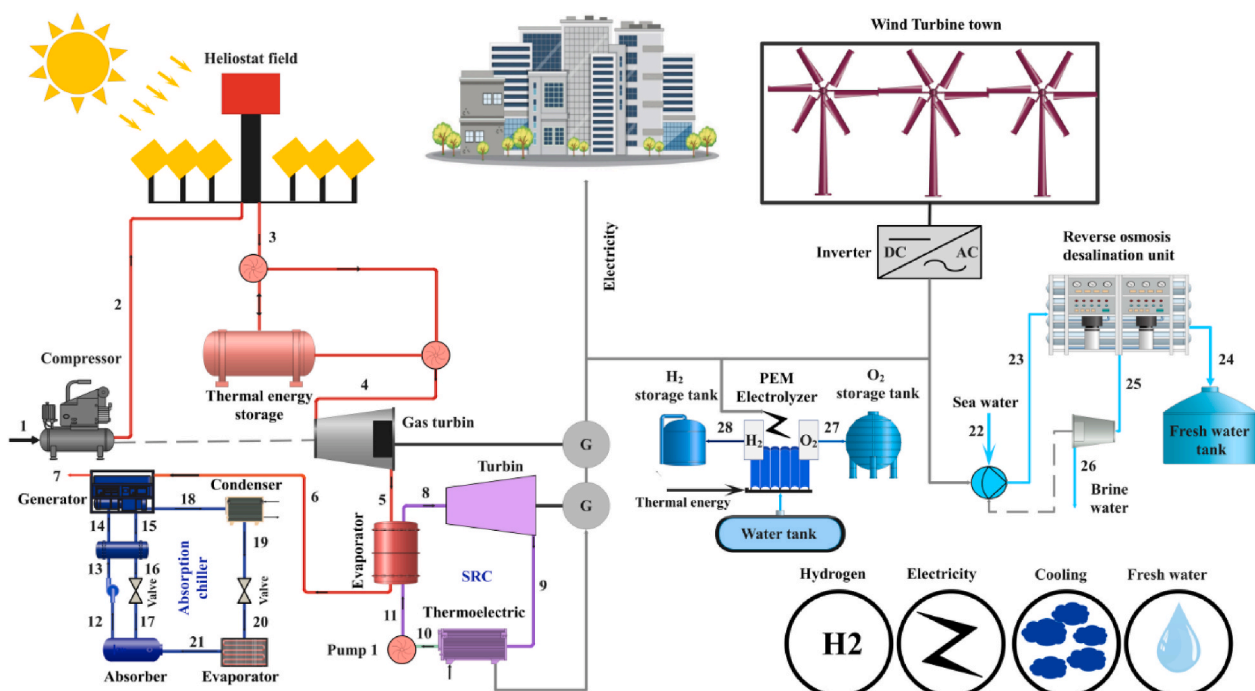


Fig. 1. Hybrid solar-wind multi-generation system with integrated outputs.

system to respond effectively to seasonal fluctuations and diverse demand. By integrating solar and wind energy across multiple outputs, the design enhances reliability, improves resource efficiency, and broadens applicability.

2.2. Thermodynamic modeling

To ensure accurate and reliable results, the thermodynamic behavior of the proposed hybrid multi-generation system was modeled using well-established engineering principles and validated data sources. The analysis applied the first and second laws of thermodynamics to evaluate energy and exergy flows across each major subsystem, including the solar thermal unit, wind turbines, modified Brayton and Rankine cycles, thermoelectric generator, and auxiliary components such as the electrolyzer and desalination plant. Exergy destruction rates and exergy efficiency were calculated to determine how effectively input energy was converted into useful output. Key performance metrics were determined through energy and mass balance equations using Engineering Equation Solver (EES), allowing both component-level and system-wide assessments. Reference values and thermophysical properties were taken from the literature to ensure accuracy and consistency with prior studies.

To simplify the complex thermodynamic behavior of the integrated system while maintaining computational efficiency, several modeling assumptions were adopted. These included steady-state operation, isentropic turbine performance, negligible pressure drops in pipelines, and the exclusion of potential and kinetic energy variations. Major components, such as the gas turbine, were modeled under idealized conditions with specified efficiencies (e.g., 80 % for the gas turbine). The energy required for hydrogen compression was not included at this stage, but is planned for future analysis. To make the modeling assumptions and fixed values more transparent, the constant parameters applied across the integrated subsystems are summarized in Table 1, together with their corresponding references.

Each subsystem was mathematically represented using governing thermodynamic equations under steady-state, one-dimensional flow conditions. For the solar collector, the useful heat gain is calculated based on the energy transferred to the Heat Transfer Fluid (HTF) (Duffie and Beckman, 2013; Kalogirou, 2023):

$$Q_{\text{useful}} = \dot{m} \cdot c_p \cdot (T_3 - T_2) \quad (1)$$

Where ($\dot{m}$) is the mass flow rate of the HTF (kg/h), c_p is the specific heat (kJ/kg.°K), and T_{in} and T_{out} are the inlet and outlet temperatures of the fluid (°K). The thermal efficiency of the collector is expressed as (Duffie and Beckman, 2013; Kalogirou, 2023):

$$\eta_{\text{collector}} = \frac{Q_{\text{useful}}}{A \cdot I_s} \quad (2)$$

Table 1
Constant Parameters used in Thermodynamic Modeling of the System.

Parameter	Unit	Value	Subsystem/ Application	Reference
Gas turbine efficiency (η_{Turbine})	%	80 (assumed)	Brayton cycle	(Çengel and Boles, 2014; Tchanche et al., 2011)
Pump efficiency (η_{pump})	%	85 (typical)	RO, SRC	Singh (2014)
Specific heat ratio for air (γ)	–	1.4	Brayton cycle	(Çengel and Boles, 2014; Moran et al., 2010)
Air density (ρ)	Kg/m ³	1.225	Wind turbine	Manwell et al. (2010)
Specific heat of air (c_p)	KJ/Kg.°K	1.005	Brayton/SRC cycles	(Çengel and Boles, 2014; Moran et al., 2010)

Where A is the collector area (m²) and I_s is the incident solar radiation (W/m²).

Turbine efficiency is defined as (Çengel and Boles, 2014; Tchanche et al., 2011):

$$\eta_{\text{Turbine}} = \frac{h_1 - h_2}{h_1 - h_{2s}} \quad (3)$$

Where h_1 and h_2 are the inlet and outlet enthalpies of the turbine (kJ/kg) and h_{2s} is the outlet enthalpy under isentropic conditions. The pump work input is given by Equation (4):

$$W_{\text{pump}} = \frac{\dot{m} \cdot (h_4 - h_3)}{\eta_{\text{pump}}} \quad (4)$$

Equation (5) gives the net power output of the SRC (Çengel and Boles, 2014):

$$W_{\text{net}} = W_{\text{Turbine}} - W_{\text{pump}} \quad (5)$$

For the Brayton cycle, the turbine and compressor work are (Çengel and Boles, 2014; Moran et al., 2010):

$$W_{\text{Turbine}} = \dot{m} \cdot c_p \cdot (T_3 - T_4) \quad (6)$$

$$W_{\text{Compressor}} = \dot{m} \cdot c_p \cdot (T_2 - T_1) \quad (7)$$

The ideal thermal efficiency of the Brayton cycle is expressed as (Çengel and Boles, 2014; Moran et al., 2010):

$$\eta_{\text{Brayton}} = 1 - \left(\frac{P_1}{P_2} \right)^{\frac{\gamma-1}{\gamma}} \quad (8)$$

where P_1 and P_2 are the compressor inlet and outlet pressures (kPa), and γ is the specific heat ratio.

The wind turbine power output is estimated using the following equation (Manwell et al., 2010):

$$P = 0.5 \times \rho \cdot A \cdot V^3 C_p \quad (9)$$

where ρ is air density (kg/m³), A is the rotor swept area (m²), V is the wind velocity (m/s), and C_p is the power coefficient.

For the RO unit, the required pump work is calculated as (Singh, 2014):

$$W_{\text{pump}} = \frac{\Delta P \cdot Q_f}{\eta_{\text{pump}}} \quad (10)$$

where ΔP is the pressure difference across the membrane (kPa), Q_f is the feed flow rate (m³/s), and η_{pump} is the pump efficiency.

The salt rejection ratio is determined by (Singh, 2014):

$$SR = \frac{C_{\text{feed}} - C_{\text{product}}}{C_{\text{feed}}} \quad (11)$$

where C_{feed} and C_{product} are the salt concentrations in the feed and product streams (ppm).

To evaluate system performance, several Key Performance Indicators (KPIs) were used:

- Thermal Efficiency of each subsystem (Çengel and Boles, 2014):

$$\eta_{\text{thermal}} = \frac{W_{\text{net}}}{Q_{\text{in}}} \quad (12)$$

- Exergy Efficiency (Dincer and Rosen, 2012):

$$\eta_{\text{exergy}} = \frac{\text{Exergy Output}}{\text{Exergy Input}} \quad (13)$$

- Freshwater Production Rate (FWP) of the RO subsystem (Wilf et al., 2007):

$$FWP = \dot{m}_{\text{product water}} \quad (14)$$

- Specific Energy Consumption (SEC) for desalination (Al-Karaghoul and Kazmerski, 2013):

$$SEC = \frac{W_{\text{pump}}}{\dot{m}_{\text{water}}} \quad (15)$$

- Overall System Efficiency:

$$\eta_{\text{overall}} = \frac{\text{Net Useful Outputs}}{\text{Total Energy Input}} \quad (16)$$

where useful outputs include electricity, thermal energy, freshwater, and hydrogen, while total energy input accounts for solar and wind energy.

These equations were implemented in EES to simulate system performance under various operating conditions. The modelling framework supports subsystem validation and guides optimization and design improvements for hybrid energy systems.

2.3. Validation of the thermodynamic modeling

To validate the reliability of the thermodynamic model, a comprehensive component-level comparison was conducted between the results of the current study and those reported in prior validated studies.

Table 2
Validation of RO, SRC, and solar subsystems results against referenced study.

Subsystem	Variable	Unit	Current Study	Referenced Study (Nafey and Sharaf, 2010)	Error (%)
RO	M_f	m^3/h	485.9	485.9	0.00
	SR	–	0.9	0.9	0.00
	X_b	ppm	64180	64180	0.00
	X_d	ppm	252	250	0.80
	ΔP	kPa	6843	6850	0.10
	$\dot{W}_{\text{pump,RO}}$	kW	1120	1131	0.97
Subsystem	Variable	Unit	Current Study	Referenced Study (Rad et al., 2020)	Error (%)
SRC	Heat source temperature	$^{\circ}\text{C}$	300	300	0.00
	Turbine inlet pressure	bar	3.988	3.988	0.00
	Mass flow rate	kg/h	3096	3009.6	2.87
	Turbine power	kW	541.2	541.3	0.02
	Net power	kW	519.3	516.6	0.52
	Total energy efficiency	%	14.09	14.03	0.43
Subsystem	Variable	Unit	Current Study	Referenced Study (Saghafifar, 2016)	Error (%)
Solar System (Heliostat & Receiver)	Generated Thermal Energy	Megawatt-hours per year (MWh/year)	102.3	102.95	0.63

Table 2 presents the key performance parameters for the RO, SRC, and Solar Receiver-Collector (Heliostat) subsystems. For the RO subsystem, key variables, such as freshwater flow rate (M_f), Salt Rejection (SR) ratio, brine and product water concentrations (X_b and X_d), pressure drop (ΔP), and pump power consumption ($W_{\text{pump,RO}}$), showed excellent agreement with the referenced data, with errors below 1 %. For instance, the pump power differed by only 0.97 %, while salt rejection and water concentrations matched exactly, confirming the accuracy of the model.

Similarly, the SRC subsystem demonstrated strong validation, with a maximum deviation of 2.87 % for mass flow rate and all other parameters (net power, turbine power, efficiency) below 1 %. The solar subsystem validation focused on generated thermal energy from the receiver and heliostat, showing only a 0.63 % deviation. These results establish confidence in the reliability of the modeling framework across all thermal subsystems and support its suitability for system integration and performance optimization.

In addition to thermal subsystems, the PEME and solar system efficiencies were validated and are summarized in Table 3. The PEME cell voltage exhibited deviations below 1 % across current densities from 0 to 6000 A/m², confirming the model's accuracy in capturing electrochemical behavior under variable loads. Similarly, the thermal and optical efficiencies of the solar collector system, including receiver and heliostat field efficiencies across receiver temperatures from 20 $^{\circ}\text{C}$ to 90 $^{\circ}\text{C}$, showed strong alignment with benchmark data, with a maximum error of 1.67 %.

These validations strengthen the reliability of the model across both thermal and electrochemical domains, supporting its use for comprehensive system analysis and optimization.

2.4. Economic analysis

The economic viability of the hybrid system was assessed using a cost-rate approach, which evaluates the capital investment, operating expenses, and maintenance costs of each component. The cost rate of each subsystem was computed and aggregated to determine the overall financial performance and benchmark it against conventional energy systems.

The cost rate of each component ($\dot{C}$) and the total cost rate was

Table 3
Validation of PEME and solar system efficiencies at varying operating conditions.

Subsystem	Variable	Cell potential (Volt)		
	Current Density (Amperes/m ²)	Current Study	Referenced Study (Ilori et al., 2002)	Error (%)
PEME	0	1.58	1.565	0.96
	250	1.61	1.594	1.00
	500	1.635	1.62	0.93
	750	1.66	1.645	0.91
	1200	1.696	1.68	0.95
	1600	1.72	1.705	0.88
	2000	1.735	1.72	0.87
	3000	1.757	1.744	0.75
	4000	1.774	1.761	0.74
	5000	1.785	1.774	0.62
6000	1.8	1.789	0.62	
Subsystem	Variable	Receiver Thermal Efficiency (%)		
	Heliostat Field Efficiency (%)	Current Study	Referenced Study (Khan et al., 2023)	Error (%)
Solar System (Heliostat & Receiver)	20	0	0	0.00
	30	26.3	26	1.15
	40	48	48	0.00
	50	61	60	1.67
	60	67	66	1.52
	70	70	69	1.45
	80	76	75	1.33
	90	79	78	1.28

calculated as (Bejan et al., 1995; Karabuga et al., 2024):

$$\dot{C}_{Compressor} = Z \times \dot{E}_{in} \quad (17)$$

$$\dot{C}_{tot} = \sum \dot{C}_{Component} \quad (18)$$

where Z is the unit cost per exergy input (\$/kWh) and $\dot{E}_{in}$ represents the exergy rate supplied to the component (kW).

For components with significant capital cost, the annualized cost was determined using (Ma et al., 2024):

$$Z = \frac{C_{inv} \times CRF}{\dot{E}_{Op} - h_{op}} \quad (19)$$

where C_{inv} is the investment cost (\$), $\dot{E}_{Op}$ is the average operating exergy rate (kW), and h_{op} is the annual operating hours. The Capital Recovery Factor (CRF) formula is adopted as in (Chen et al., 2021) to annualize investment costs over the system lifetime and interest rate as below:

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1} \quad (20)$$

where i is the interest rate and n is the system lifetime (years).

To improve transparency, the constant economic parameters adopted in the analysis are summarized in Table 4, together with their sources.

This methodology provides a consistent basis for comparing component-level and system-level economic performance, ensuring that both technical efficiency and financial feasibility are accounted for in the optimization phase.

2.5. Environmental performance assessment

To assess the environmental benefits of the proposed system, CO₂ emissions reduction was estimated by comparing the electricity and thermal energy generated by the hybrid solar-wind system with the equivalent emissions from conventional fossil-fuel-based energy systems. The baseline emission factor was assumed to be 0.85 kg CO₂ per

Table 4
Constant economic parameters used in economic analysis.

Parameter	Unit	Value	Application	Reference
Interest rate (i)	%	6.5	CRF and discounting investment cost	Conservative value
System lifetime (n)	years	20	CRF for major components (turbine, electrolyzer, etc.)	(National Renewable Energy Laboratory (NREL), 2013)
Operating hours per year (h_{op})	hours/year	8000	Annual usage for cost calculations (Exergy efficiency)	(National Renewable Energy Laboratory (NREL), 2013)
Operation & Maintenance cost fraction	% of initial capital cost per year	3	Annual maintenance & operation costs used for subsystem cost estimation	(National Renewable Energy Laboratory (NREL), 2013)
Unit cost of electricity (benchmark)	\$/kWh	0.10	Economic performance vs conventional grid electricity	U.S. Energy Information Administration (2024)
Water production cost (RO)	\$/m ³	0.5	RO subsystem cost benchmarking	Conservative value
Hydrogen production baseline cost	\$/kg	4.00	PEME hydrogen production benchmarking	Hydrogen Council (2023)

kWh, representative of electricity generated from coal- and gas-fired power plants. This value is consistent with emission intensities reported for fossil-fuel-based grids by the IPCC (2019) (Intergovernmental Panel on Climate Change (IPCC), 2019) and Australia's National Greenhouse Accounts Factors (2023) (Department of Climate Change, 2023).

Because hydrogen, freshwater, and cooling are all produced by processes (Fig. 1) that consume the system's renewable electricity (or electricity-derived thermal energy), avoided operational CO₂ is calculated on an electricity-displacement basis as (European Commission, 2021):

$$CO_{2Total\ Avoided} = EF_{grid} \times EF_{ERN} \quad (21)$$

where EF_{grid} is the baseline grid emission factor (kg.CO₂/kWh) and EF_{ERN} is the renewable electrical energy generated and used/exported by the plant (kWh). This convention means the carbon savings associated with all useful products, electricity delivered to the grid, RO freshwater, PEME hydrogen/oxygen, and absorption-chiller cooling, are inherently included in EF_{ERN} .

This approach ensures that the avoided emissions for all co-products are transparently embedded in the overall displacement calculation. Exergy efficiency was also used as a supplementary indicator to evaluate the thermodynamic quality of energy conversions and their implications for environmental sustainability. These metrics provide a comprehensive assessment of the system's environmental contribution under different climatic conditions. While the current analysis focuses on operational emissions, life-cycle impacts from manufacturing and disposal were not included and are recommended for future investigation.

3. Research methodology

This study follows a structured eight-step methodology, as illustrated in Fig. 2, to design, model, optimize, and evaluate a hybrid solar-wind multi-generation system. The methodology includes: (1) system design and configuration, (2) thermodynamic and economic modeling, (3) validation, (4) multi-objective optimization using RSM, (5) wind power allocation, (6) performance simulation across eight climates, (7) environmental and stability assessment, and (8) re-optimization using AI. The system integrates heliostat-driven solar thermal input, wind turbines, a modified Brayton cycle, an SRC, and thermoelectric generators, enabling simultaneous production of electricity, cooling, hydrogen, oxygen, and freshwater. Thermodynamic modeling is conducted using EES (Klein and Frank, 2023), applying the first and second laws of thermodynamics, while cost estimation is performed for components to support economic analysis.

Model validation was conducted through a detailed component-level comparison between the current study and previously validated sources, covering the RO, SRC, PEME, and solar subsystems. Design-Expert® software (Stat-Ease, 2024) was used to implement the Design of Experiments (DoE) methodology, including the application of Analysis of Variance (ANOVA) to assess the significance and interactions of 11 key decision variables such as pressure ratio, mass flow rates, and temperature ranges. A total of 1057 simulation runs were performed. Multi-objective optimization was carried out using RSM within Design-Expert®, aiming to maximize exergy efficiency while minimizing cost. TOPSIS statistical analysis (Mahmudova, 2020) was then applied within Design-Expert® to rank the optimal configurations, providing a systematic decision-making framework based on proximity to the ideal solution. RSM was chosen for its computational efficiency and statistical clarity in early-stage exploration, while a subsequent AI-based optimization phase (using AdaBoost and PSO) was included to address RSM's limitations in capturing complex nonlinear relationships. An intermediate step was introduced to determine the most effective wind power allocation between the PEME and RO units based on energy

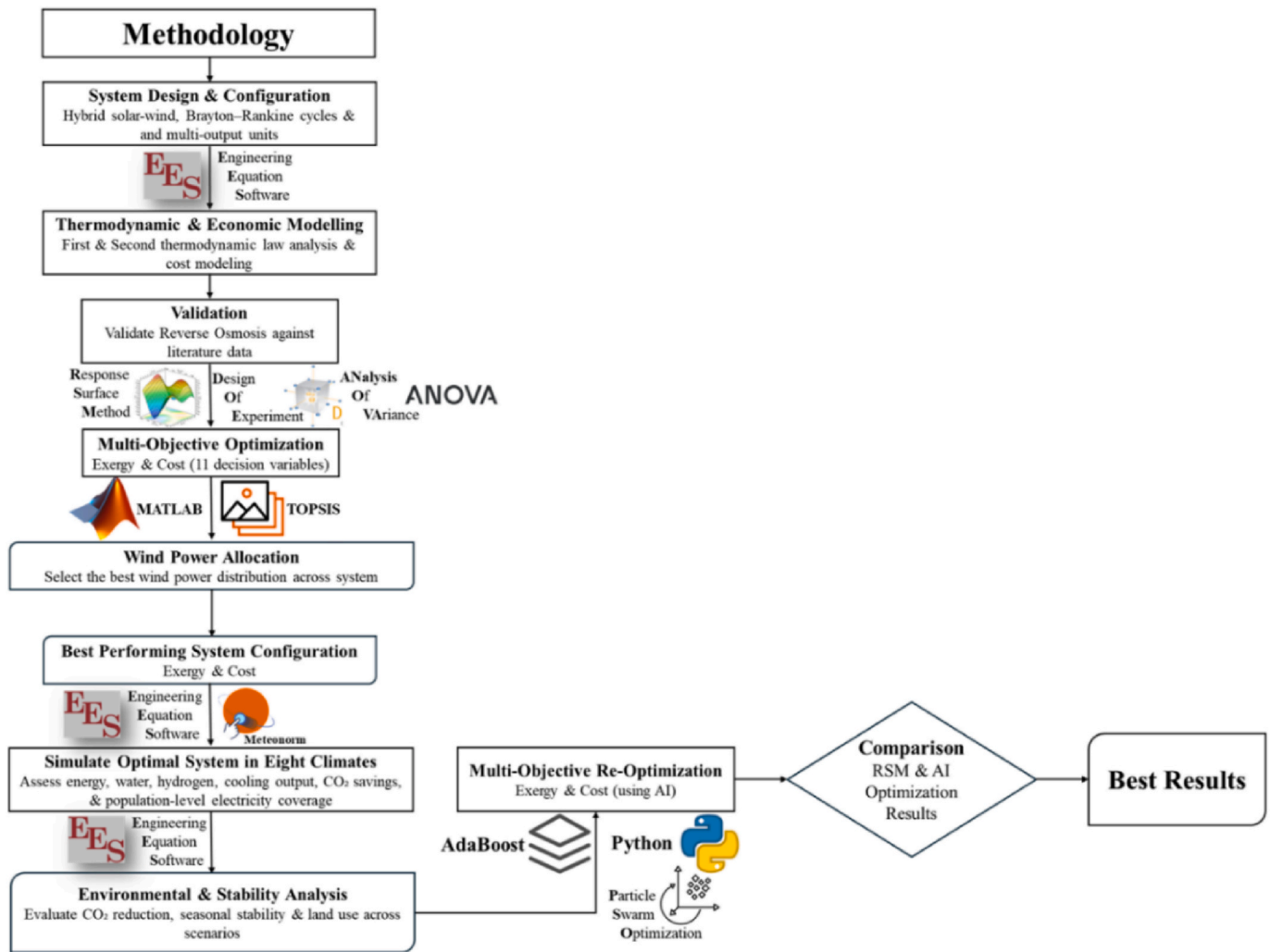


Fig. 2. Step-by-step system design, modeling, optimization, and evaluation process.

demand and operational priorities.

The best-performing configuration is then evaluated under eight climatically diverse global locations, using meteorological data, including ambient temperature, wind speed, and solar radiation, were obtained from the Meteonorm 8.0 (Meteotest, 2020) to assess seasonal adaptability. Key performance indicators include energy output, fresh-water and hydrogen production, CO₂ emission reduction, and electricity supply relative to population needs. To enhance robustness, a secondary optimization phase is conducted using AdaBoost and PSO in Python (Python Software Foundation, 2024), enabling a comparison of statistical and AI-driven approaches. The AI-based optimization using AdaBoost was trained on a structured dataset of 2500 validated simulation records, which, due to their thermodynamic fidelity and diversity across 11 design variables, provided sufficient coverage for reliable training and generalization. This dual optimization strategy identifies the most reliable and cost-effective configuration under real-world conditions.

4. Optimization and scenario analysis

This section presents the optimization strategy and performance assessment of the proposed hybrid multi-generation energy system. Following the development of a validated thermodynamic and economic model, multi-objective optimization is carried out to identify the most efficient and cost-effective configuration. The analysis integrates statistical and artificial intelligence approaches to evaluate design trade-offs and performance outcomes under diverse operating scenarios. The

optimization process begins with an RSM framework, as detailed below.

4.1. Multi-objective optimization using Response Surface Methodology

Multi-objective optimization was carried out using RSM to simultaneously maximize the system's exergy efficiency and minimize its overall cost rate (in USD per hour of operation). A statistical DoE approach was employed to explore the high-dimensional design space of the hybrid solar-wind system. Using Design-Expert software (DoE), a set of simulations was carefully designed and executed to capture the effects of key parameters on the system's performance. In total, 1057 simulation runs were conducted as part of the RSM study. This DoE-driven strategy enabled the systematic variation of multiple inputs and produced a robust dataset for constructing empirical models that relate decision variables to exergy efficiency and cost rate outcomes. The workflow of the RSM optimization process is illustrated in Fig. 3.

4.1.1. Selection of decision variables

Eleven decision variables were selected as the primary inputs for optimization, based on their anticipated influence on thermodynamic performance and economic cost. These variables span subsystem design parameters, operating set-points, and key efficiency metrics. The decision variables included: solar field size (number of heliostats to control solar thermal input capacity), number of wind turbines (wind capacity), Brayton cycle pressure ratio of the gas turbine's compressor in the modified Brayton cycle, Brayton cycle high temperature (T_{10}), Rankine

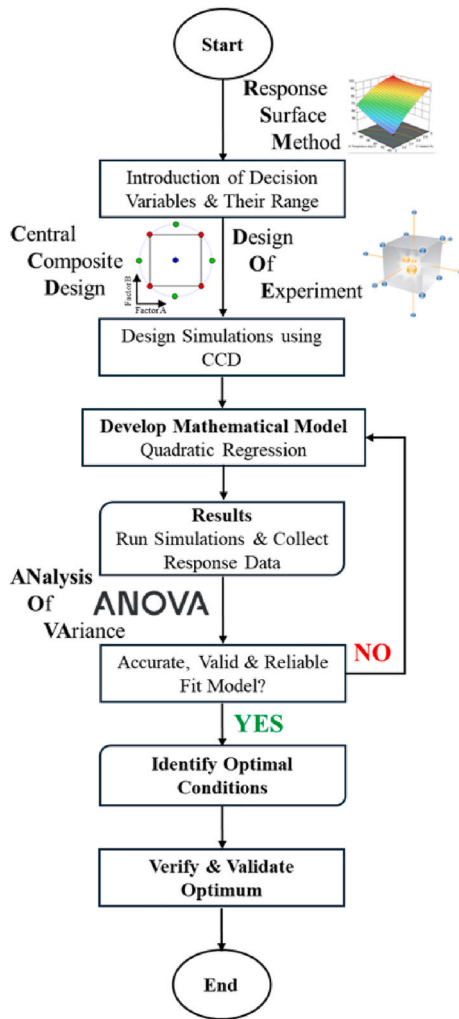


Fig. 3. Response surface methodology workflow for multi-objective optimization.

cycle boiler pressure (P_8), steam cycle exhaust pressure (P_{10}), feed pump efficiency, gas turbine efficiency, compressor efficiency, and steam turbine efficiency, and evaporator pinch point. To streamline reference and analysis throughout the optimization process, each design variable was assigned a unique identifier (A–L). These variables collectively address all major aspects of the integrated system, from renewable input sizing and thermal cycle operation to component-level performance. Each was allowed to vary within defined lower and upper bounds, informed by design constraints and prior research, as shown in Table 5.

In addition to defining the bounds of the decision variables shown in Table 5, several physical and operational constraints were incorporated

into the optimization model to ensure the feasibility and reliability of the system configuration. These include:

- Thermodynamic constraints, such as minimum temperature differences in heat exchangers (e.g., evaporator pinch point $\geq 5^\circ\text{C}$) and limits on turbine inlet and exhaust conditions to avoid condensation and mechanical failure.
- Component efficiency constraints, maintaining minimum acceptable efficiencies for the pump, compressor, and turbines (e.g., not less than 70 %).
- Pressure ratio constraints, ensuring that Brayton cycle operations remain within safe and efficient working ranges (e.g., pressure ratio between 6 and 14).
- Resource availability constraints, limiting solar and wind inputs based on local resource potential and avoiding over-sizing of heliostats or turbines.
- Hydrogen and water production constraints, ensuring that minimum daily demands are met to sustain the intended output levels of the PEME and RO desalination units.

These constraints were embedded within the Design-Expert optimization environment to guide the search for optimal system configurations that are not only thermodynamically and economically efficient but also practically implementable.

4.1.2. Model Formulation

Using the simulation data generated from the DoE, RSM was employed to construct separate response surface models for each objective, exergy efficiency and cost rate. A second-order polynomial regression model (quadratic form) was selected to approximate the response behavior due to its ability to capture both curvature and interaction effects among variables. Equation (17) shows the RSM quadratic model for a given response Y :

$$Y = \beta_0 + \sum_{i=1}^{11} \beta_i x_i + \sum_{i=1}^{11} \beta_{ii} x_i^2 + \sum_{1 \leq i < j \leq 11} \beta_{ij} x_i x_j \quad (1)$$

Where x_i represents the coded value of the i th decision variable (for $i = 1, \dots, 11$). The coefficients ($\beta_0, \beta_i, \beta_{ii}, \beta_{ij}$) were determined by least-squares regression using the results of the 1057 simulations. Design-Expert was utilized to fit this model and perform ANOVA to verify the significance and goodness-of-fit. The quadratic response surface models for efficiency and cost compactly approximate how each combination of the 11 inputs influences the two outputs. This approach greatly facilitated subsequent optimization, as the continuous RSM models could be searched for optima more efficiently than running additional high-fidelity simulations for every trial design.

4.1.3. Multi-objective optimization setup

With the RSM models in place, a multi-objective optimization was performed using the desirability function approach, which is commonly used in RSM-based multi-response optimization. This method converts each response into a dimensionless desirability value ranging from 0 (completely undesirable) to 1 (fully desirable), based on the pre-defined goal. For the hybrid system optimization, exergy efficiency was defined to be maximized (higher efficiency yields higher desirability), while the cost rate was defined to be minimized (lower cost yields higher desirability). Using the observed range of each response from the DoE simulations as a basis, desirability functions were formulated for both objectives. A composite desirability index (D) is obtained as the geometric mean of the individual desirability for efficiency and cost. This composite index balances the two objectives, effectively giving equal priority to improving thermodynamic efficiency and reducing cost. The optimization algorithm in Design-Expert searched the response surface models for the point that maximizes D , i.e. the design configuration that provides the best combined outcome for efficiency and cost. This

Table 5
Decision variables.

Decision variable	Unit	Lower bound	Upper bound	Identifier
Number of Heliostats	–	250	500	A
Number of Wind Turbines	–	10	40	B
Pressure ratio	–	6	14	C
T_{10}	$^\circ\text{C}$	30	50	D
P_8	kPa	2800	3200	E
P_{10}	kPa	80	120	F
Pump Efficiency	%	0.75	0.9	G
Gas turbine Efficiency	%	0.7	0.95	H
Compressor Efficiency	%	0.7	0.95	J
Turbine Efficiency	%	0.75	0.9	K
Pinch Point Evaporator	$^\circ\text{C}$	5	12	L

desirability-based multi-objective optimization yielded a single optimal solution representing a favorable trade-off between the competing criteria.

4.2. Wind power allocation and decision analysis

In the proposed design, the solar-driven power cycle, comprising Brayton and Rankine cycles with thermal storage, operates primarily during sunny periods. Meanwhile, the wind farm plays a complementary role, supplying electricity during low-sun intervals and directly powering the PEME and the RO desalination unit. This allocation ensures that hydrogen, oxygen, and freshwater can be continuously produced, regardless of solar fluctuations. In this setup, any excess wind energy not used by the PEME and RO units is redirected to support the main power cycle or exported to the city's electricity grid. This flexible integration enhances the system's stability, supports peak demand in the host city, and reduces dependency on conventional energy sources.

To evaluate the most effective distribution of wind energy among these subsystems, 14 scenarios with varying wind power allocation coefficients were developed. These scenarios were created by systematically varying the percentage of wind electricity supplied to the PEME and RO units, ranging from 5 % to 30 %, and assessing their combined impact on total cost rate, exergy efficiency, and co-product outputs (hydrogen, oxygen, and freshwater). The optimized number of wind turbines ensures that sufficient electricity is consistently available to meet the needs of both subsystems, even under fluctuating wind conditions. By carefully balancing wind power contributions, the system maintains high operational efficiency while minimizing cost and performance disruptions caused by wind variability.

To identify the most favorable scenario among the 14 tested, the TOPSIS method was applied. These multi-criteria decision-making tool ranks alternatives based on their relative distance from an ideal and a negative-ideal solution. In this analysis, exergy efficiency and cost rate were selected as the two primary decision criteria, each assigned an equal weight of 0.5. The TOPSIS process involves normalizing the criteria to a common scale, assigning weights based on their importance, and calculating each alternative's closeness to the ideal solution. The scenario with the highest relative closeness is identified as the optimal wind power distribution strategy.

4.3. Performance simulation across diverse climates

To evaluate the hybrid system's performance under varying environmental conditions, simulations were conducted across climatically diverse cities in Asia, Europe, and North America. These locations, St. John's, Quebec, Odense, New York, Nice, Madrid, Tabriz, and Isfahan, were selected to represent a broad spectrum of solar radiation and wind availability. Table 6 summarizes the geographic and climatic characteristics of these cities, including latitude, longitude, and Köppen climate classification. This selection covers a mix of cold continental climates (e.g., St. John's, Quebec), temperate oceanic and Mediterranean regions (e.g., Odense, Nice), semi-arid zones (e.g., Madrid, Tabriz), and transitional desert climates (e.g., Isfahan). The wide range of climate types allows for a robust assessment of how well the system

adapts to different renewable energy resource profiles throughout the year.

Meteorological data, including ambient temperature, wind speed, and solar radiation, were sourced from Meteonorm and used as input for modeling the hybrid system. As shown in Fig. 4, the selected cities span a wide climatic range, with average monthly temperatures varying from -11.15°C in Quebec (January) to 30.4°C in Isfahan (July). These differences highlight the seasonal extremes that influence system performance. Cold-climate cities like Quebec and St. John's have long, harsh winters, with sub-zero averages from December through March, while summer temperatures remain relatively mild (below 19°C). Such conditions favor wind-supported operation in winter, reducing reliance on solar input. Odense and New York, as temperate cities, show moderate winters and warm summers, ranging from about -1 to 25°C , offering balanced opportunities for both wind and solar generation throughout the year. Meanwhile, Isfahan and Tabriz experience hot, dry summers with sustained high temperatures above 25°C from June to August, indicating high solar potential but also increased cooling demand. Cities like Madrid and Nice reflect similar trends, reaching 27.5°C and 25°C in July, respectively, and maintaining mild winters. These seasonal dynamics directly impact the performance of the proposed hybrid multi-generation system, supporting the need for climate-responsive design and control strategies that can leverage solar and wind complementarity for consistent energy, water, and cooling output year-round.

Fig. 5 illustrates the monthly variation in average Global Beam Irradiance (GBI) across the selected cities, highlighting clear seasonal and geographical differences in solar energy availability. Isfahan, Tabriz, and Madrid, all located in low-latitude or arid regions, consistently exhibit the highest solar irradiance levels, with summer peaks reaching up to 336.03 W/m^2 in Tabriz (July) and 324.17 W/m^2 in Isfahan (July), reflecting excellent conditions for solar thermal energy generation during high-demand cooling months. Madrid similarly shows strong solar input, with irradiance rising above 300 W/m^2 in summer. In comparison, temperate cities like Nice, New York, and Odense experience moderate solar potential year-round, peaking between 230 and 290 W/m^2 in summer, which still supports efficient solar operation. Cold-climate cities such as St. John's and Quebec receive the lowest solar irradiance during winter, with monthly averages falling below 50 W/m^2 in December, but maintain adequate levels in summer, exceeding 230 W/m^2 in July. These seasonal variations demonstrate that while the solar contribution fluctuates by location and season, every city in the study maintains periods of strong solar availability, either seasonally or year-round, confirming the suitability of solar-based components in the hybrid system design. This also highlights the system's resilience, as each site offers at least one dominant renewable resource, solar or wind, capable of sustaining system performance across diverse climate zones.

Fig. 6 presents the monthly variation in average wind speed across the selected cities, highlighting distinct seasonal patterns that influence the availability of wind energy. Coastal and higher-latitude cities such as St. John's, Quebec, and Odense consistently show higher wind speeds throughout the year, with St. John's peaking at 5.30 m/s in January and remaining above 4.0 m/s in most months. Quebec also exhibits stable wind availability, ranging from 4.09 m/s in May to 5.09 m/s in December, reinforcing its strong wind energy potential during colder

Table 6

Geographic location and climate classification of study cities (Beck et al., 2018; GeoDatos.net, 2025).

City	Country	Latitude ($^{\circ}\text{N}$)	Longitude ($^{\circ}\text{E}$)	Köppen Climate Classification	Climate Description
St. John's	Canada	47.5615	-52.7126	Dfb	Humid continental, cool summer, snowy
Quebec	Canada	46.8139	-71.2082	Dfb	
Odense	Denmark	55.4038	10.4024	Cfb	Temperate oceanic, mild summer, no dry season
New York	USA	40.7128	-74.0060	Cfa	Humid subtropical, hot summer, no dry season
Nice	USA	43.7102	7.2620	Csa	Mediterranean, hot dry summer
Madrid	Spain	40.4168	-3.7038	BSk	Cold semi-arid, steppe
Tabriz	Iran	38.0962	46.2738	BSk	
Isfahan	Iran	32.6525	51.6746	BWh/BSk	Hot desert/cold semi-arid (transition)

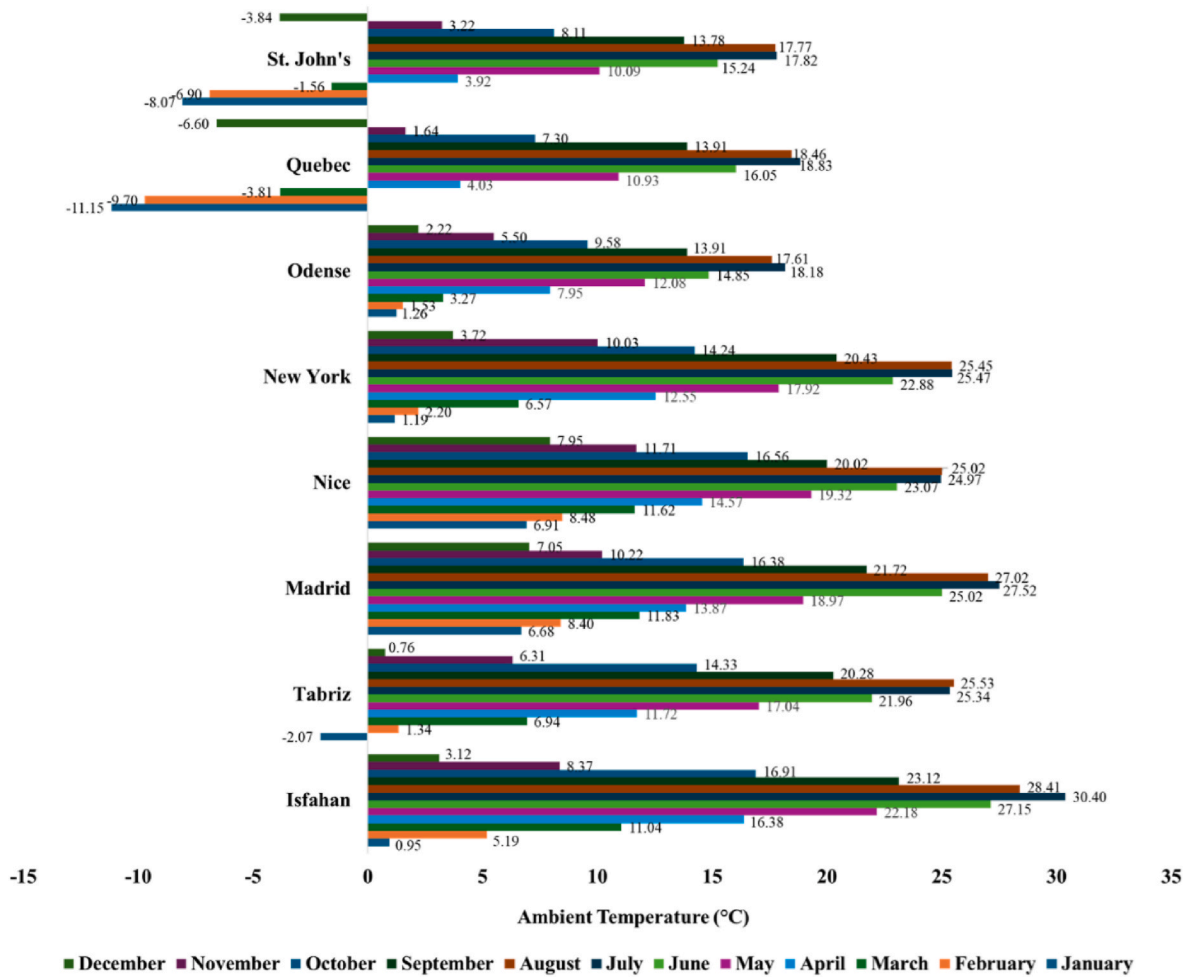


Fig. 4. Monthly average ambient temperature in study cities (Meteotest, 2020).

months when solar output is reduced. Odense maintains moderate wind conditions year-round, with speeds hovering between 3.24 and 4.64 m/s, supporting balanced system operation. In contrast, more inland and lower-latitude cities like Isfahan, Nice, and Tabriz show lower and more variable wind speeds. Isfahan records the lowest values, with a minimum of 1.48 m/s in August and a maximum of just 2.02 m/s in December, suggesting limited standalone wind energy viability. Similarly, Nice and Madrid stay mostly below 3.0 m/s, with minor seasonal peaks. These observed wind patterns emphasize the importance of location-specific system configuration: wind-rich areas can maintain energy output during low-solar periods, while solar-dominant locations require greater thermal storage or grid integration to stabilize annual energy supply.

5. Results and discussion

This section presents and discusses the technical, economic, and environmental performance of the proposed hybrid solar-wind multi-generation system under various optimization strategies and climatic conditions.

5.1. Multi-objective optimization using Response Surface Methodology

A multi-objective optimization, targeting both thermodynamic and economic performance, was conducted using RSM to maximize exergy efficiency and minimize the total cost rate of the hybrid multi-generation system. After 1057 simulation runs, the RSM-based optimization produced an optimal solution with a desirability index of 0.679,

indicating a relatively acceptable compromise between the two competing objectives. Table 7 displays the optimal values of the 11 decision variables and the corresponding objective function results. These parameters span subsystem sizing, cycle pressures and temperatures, and component efficiencies. By optimizing these variables, the system achieved a maximum exergy efficiency of 45.8 % and a cost rate of \$576.76/h. These results demonstrate the system's technical and economic viability and serve as a benchmark for further enhancement using advanced optimization methods. The identified optimal configuration can guide the design and operation of future solar-wind multi-generation platforms.

To contextualize the optimization outcome, Table 8 presents the variation range of the two objective functions, exergy efficiency and cost rate, observed during the full simulation space. Exergy efficiency values ranged from a minimum of 27.36 % to a maximum of 54.13 %, while the cost rate varied between \$368.60/h and \$1000/h. The optimized configuration achieved an exergy efficiency of 45.8 % and a cost rate of \$576.76/h, placing it well within the high-performance zone of the design space. This outcome demonstrates the RSM model's ability to strike a balanced trade-off between energy performance and cost, effectively pushing the system toward the upper end of thermodynamic efficiency while maintaining a moderate operating cost.

These results validate the strength of the RSM approach in capturing complex nonlinear relationships and interaction effects between design variables and system responses, providing a reliable and interpretable baseline for comparison with more advanced AI-based optimization techniques in the subsequent section.

Fig. 7 presents the impact of paired decision variables on the

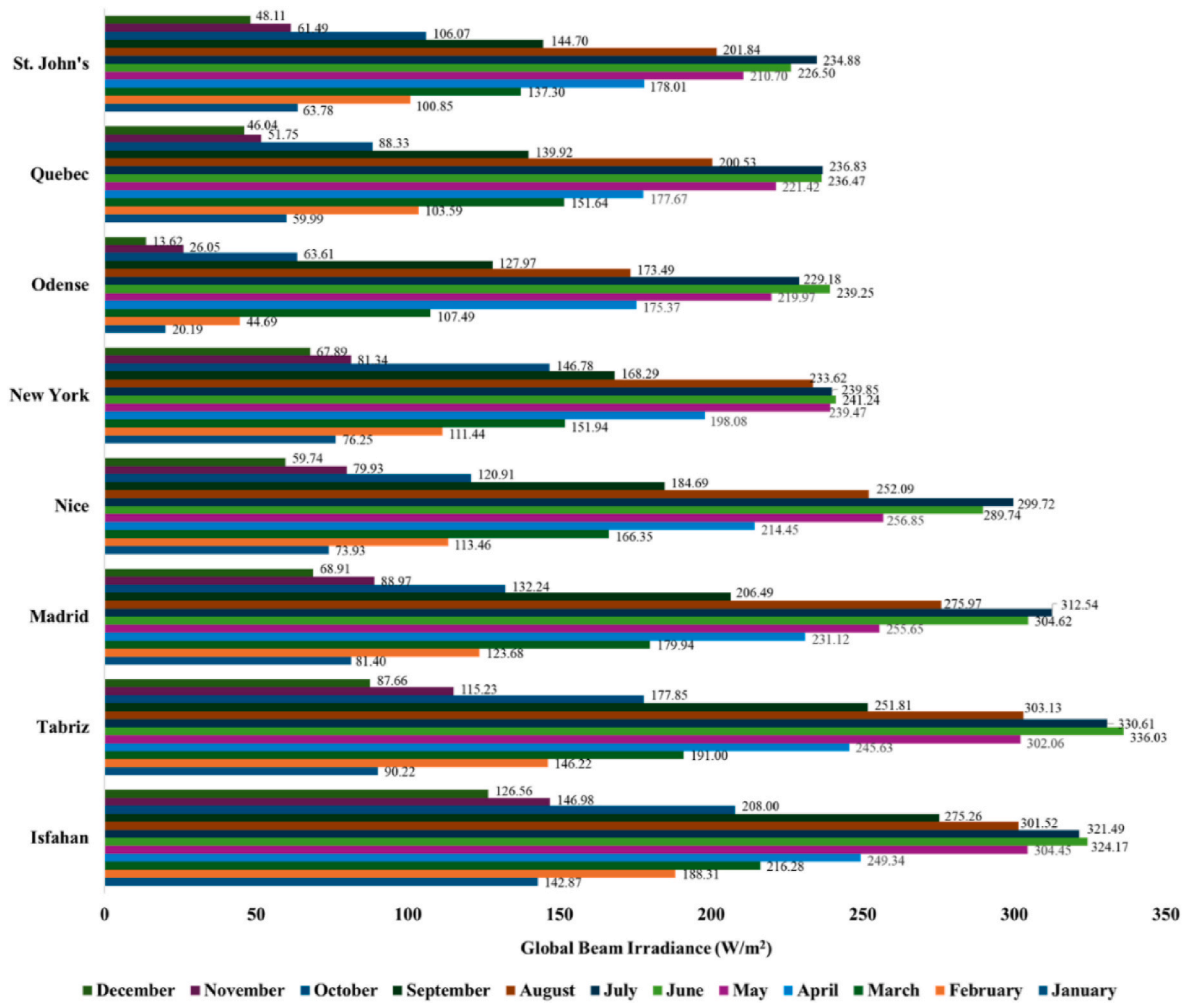


Fig. 5. Monthly average global Beam irradiance in selected cities (Meteotest, 2020).

system's exergy efficiency (%), ordered based on their influence from strongest to weakest. The analysis focuses on five main variables: number of wind turbines (B), number of heliostats (A), gas turbine efficiency (H), compressor efficiency (J), and pressure ratio (C). Each plot displays a contour map where red indicates high exergy efficiency and blue indicates low. The predicted optimal exergy efficiency of 45.8 % is marked in all subplots. The first plot, impacts of the A and B on exergy efficiency, shows a steep gradient and strong influence on efficiency: higher wind turbine counts and moderate heliostat numbers substantially improve exergy performance. The second plot reveals that increasing both the number of wind turbines and the pressure ratio leads to notable efficiency gains, pushing values beyond 50 % under optimal conditions.

The remaining plots show more gradual improvements in efficiency. The combination of compressor efficiency and pressure ratio yields moderate gains, peaking near 48 % in upper ranges. Similarly, enhancing gas turbine efficiency and increasing the number of wind turbines leads to exergy levels above 50 %, especially when both parameters are maximized. Interestingly, while high gas turbine efficiency values consistently improve efficiency across all pairings, their impact is most pronounced when combined with the number of heliostats (A) or wind turbines (B). In contrast, the influence of compressor efficiency is less dominant but still contributes to marginal improvements when paired with the number of wind turbines or pressure ratios. Overall, the results highlight the importance of carefully tuning system parameters, particularly wind turbine quantity, pressure ratio, and turbine efficiency, to achieve higher energy utilization and optimal thermodynamic

performance.

Fig. 8 displays a series of contour plots used to visualize the interaction effects of five key decision variables on the system's cost rate (\$/h), based on RSM analysis. These variables include the number of wind turbines (B), gas turbine efficiency (H), compressor efficiency (J), pressure ratio (C), and the number of heliostats (A). The plots examine two-variable interactions at a time, where the cost rate is represented through a color gradient from deep blue (low cost) to red (high cost). The optimal cost rate, predicted at \$576.76/h, is annotated in each subplot. The figure order follows the decreasing influence of variable pairs on cost rate, starting with the most impactful interaction (B and H) and ending with the least (C and J).

Among all variables, gas turbine efficiency (B) and compressor efficiency (J) show the most substantial influence. Increasing gas turbine efficiency (H) from 0.75 to 0.9 while keeping the number of wind turbines (B) around 22 leads to a sharp drop in cost, from above \$700/h to below \$580/h, approaching the optimal. A similar trend is observed for compressor efficiency (J). These steep contour gradients reflect the high sensitivity of cost rate to turbine and compressor efficiencies, particularly when paired with optimal wind turbine quantities. These two parameters, being performance-based rather than size-based, offer efficient cost reduction without large-scale infrastructure changes.

The subsequent plots illustrate combinations with moderate to lower impact. Pressure ratio (C) and heliostat count (A) influence cost more gradually. For example, increasing the pressure ratio from 6 to 14 at constant B shows only mild reductions in cost, while adding more heliostats beyond 350 units tends to increase cost, likely due to rising

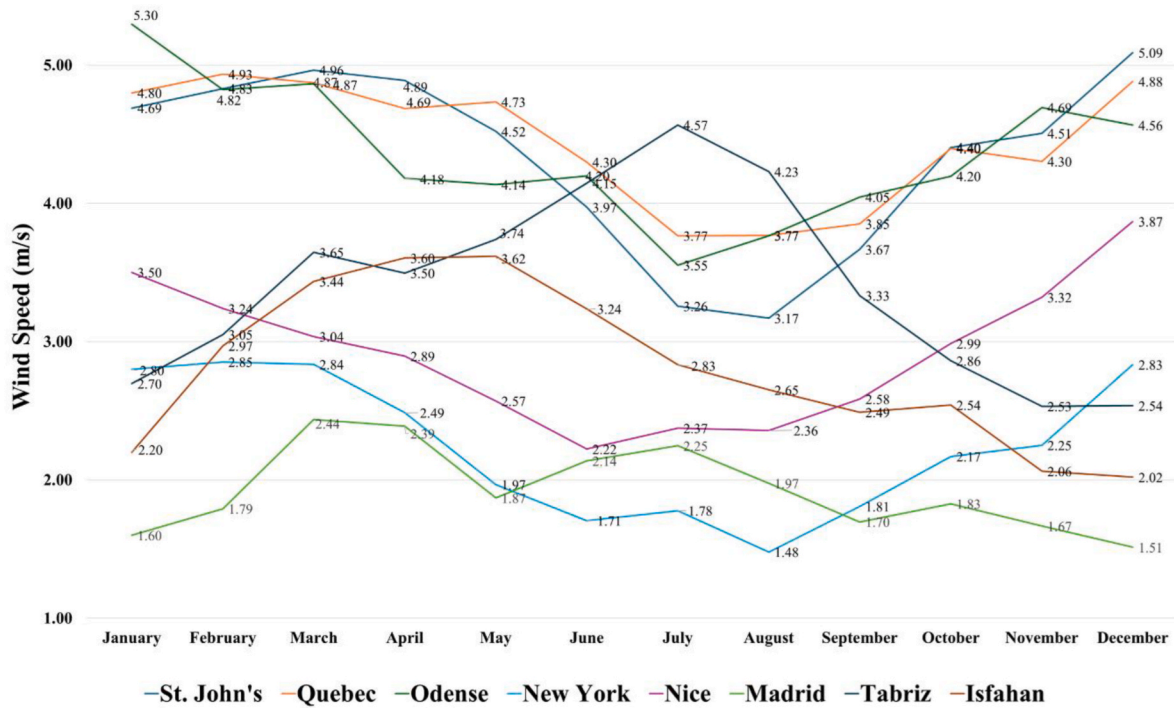


Fig. 6. Monthly average wind speed in selected cities (Meteotest, 2020).

Table 7

Optimal decision variables and objective function results.

Decision variable	Unit	Optimal Value
Number of Heliostats	–	250
Number of Wind Turbines	–	10
Pressure ratio	–	6
T ₁₀	°C	30
P ₈	kPa	2800
P ₁₀	kPa	80
Pump Efficiency	%	0.75
Gas turbine Efficiency	%	0.7
Compressor Efficiency	%	0.7
Turbine Efficiency	%	0.75
Pinch Point Evaporator	°C	5
Exergy Efficiency	%	45.8
Cost Rate	\$/h	576.76
Desirability	–	0.67

Table 8

Range of objective function variations during optimization.

Objective	Unit	Goal	Lower Limit	Upper Limit
Exergy Efficiency	%	Maximize	27.36	54.13
Cost Rate	\$/h	Minimize	368.6	1000

capital and maintenance demands. The final plot, pressure ratio and compressor efficiency show the flattest contour lines, indicating a weaker combined influence on cost rate. These results highlight the most effective levers for cost reduction and guide practical decision-making by prioritizing design variables that yield the greatest economic benefits.

5.2. Exergy flow and destruction analysis

Fig. 9 illustrates the exergy distribution and destruction within the proposed system using a Sankey diagram, providing a detailed thermodynamic map of energy quality across the integrated components. Under optimal conditions, the system receives a total solar exergy input

of 7681 kWh, degraded across several stages before final energy outputs are realized. The heliostats and solar receiver emerge as the largest contributors to exergy destruction, together accounting for over half of the system's total losses, 3127 kWh and 1493 kWh, respectively. This highlights a critical bottleneck at the very beginning of the energy conversion chain, suggesting that optical and thermal inefficiencies in the solar field dominate the system's irreversibility.

In contrast, the gas turbine, while processing a high exergy input of 9617 kWh, demonstrates relatively strong performance with comparatively lower exergy destruction (509 kWh) and substantial electricity generation. Similarly, the steam turbine and thermoelectric generator exhibit efficient energy conversion, with minimal losses and useful outputs. The absorption chiller, however, presents a more modest performance profile, producing cooling from a limited share of the evaporator's exergy and incurring moderate losses. The system's total exergy destruction rate of 7307 kWh/h reflects areas of both strength and vulnerability, highlighting the need for targeting upstream improvements through future optimization, particularly within the heliostat field and receiver unit, while maintaining and refining the relatively efficient downstream thermal and mechanical component.

5.3. Economic analysis

Fig. 10 presents a detailed breakdown of the cost rate distribution across the system's components, grouped into major functional units: the solar unit, the wind turbine system, and the SRC. The total operational cost of the system under optimal conditions is calculated to be approximately \$576.8 per hour. Among all components, the wind turbine unit represents the largest share, contributing \$359.8/h, more than 62 % of the total cost. This is attributed to the deployment of 24 wind turbines, which, while effective in boosting exergy efficiency, significantly increase capital and maintenance costs.

Fig. 10 shows that the solar unit, comprising the heliostat field, receiver, gas turbine, and compressor, ranks as the second-largest contributor with a combined cost of approximately \$180.75/h. Within this group, the heliostat is the most expensive component at \$92/h, followed by the gas turbine (\$42.67/h) and receiver (\$36.77/h).

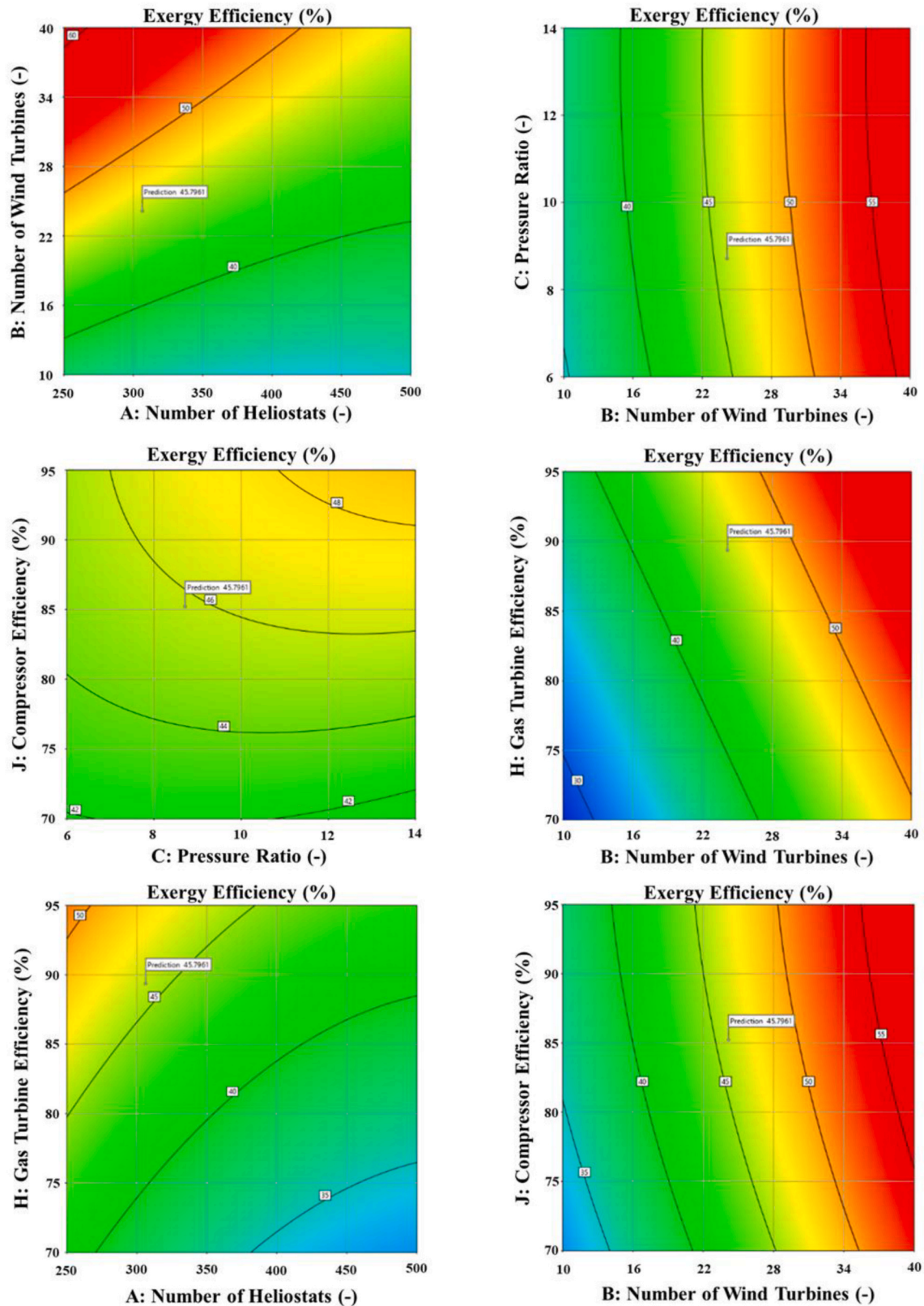


Fig. 7. Effects of key design variables on exergy efficiency.

Notably, the receiver alone costs over 22 times more than the RO unit and more than 16 times the cost of the Thermoelectric Generator (TEG), highlighting its substantial financial impact relative to smaller components. This figure highlights that while the solar unit is essential for renewable energy input, it remains cost-intensive and warrants further

optimization, particularly in optical design and material efficiency.

By contrast, the SRC unit, including the evaporator, steam turbine, and associated components, incurs a much lower cost burden at \$22.4/h, with the chiller and pump contributing minimally (<\$1/h each). The lowest-cost contributors, such as the pump (\$0.16/h) and evaporator

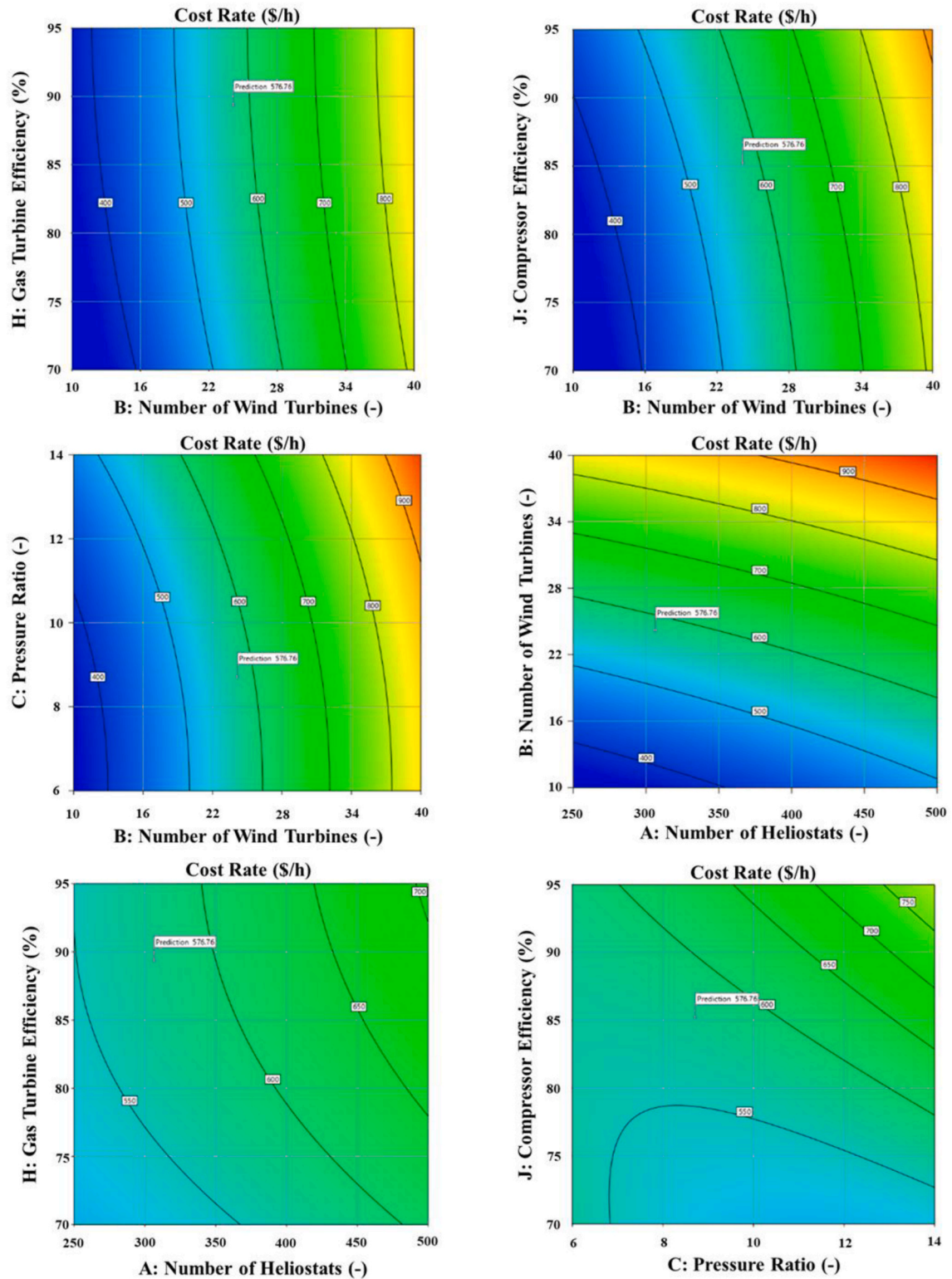


Fig. 8. Effects of key design variables on cost rate (\$/h).

(\$0.14/h), have a negligible impact on total expenditure yet play important roles in energy recovery and distribution. This cost distribution analysis reveals that the system's economic performance is heavily influenced by high-cost components in the wind and solar sectors. Therefore, design refinements focused on reducing heliostat and wind turbine costs, either through technology advancement or component scaling, could yield substantial improvements in overall cost-

effectiveness without compromising performance. The operational costs were benchmarked against manufacturer specifications and published industrial data, confirming that all major subsystem costs, particularly wind turbine, heliostat, and thermal cycle components, are representative of real-world operating conditions under optimal load profiles.

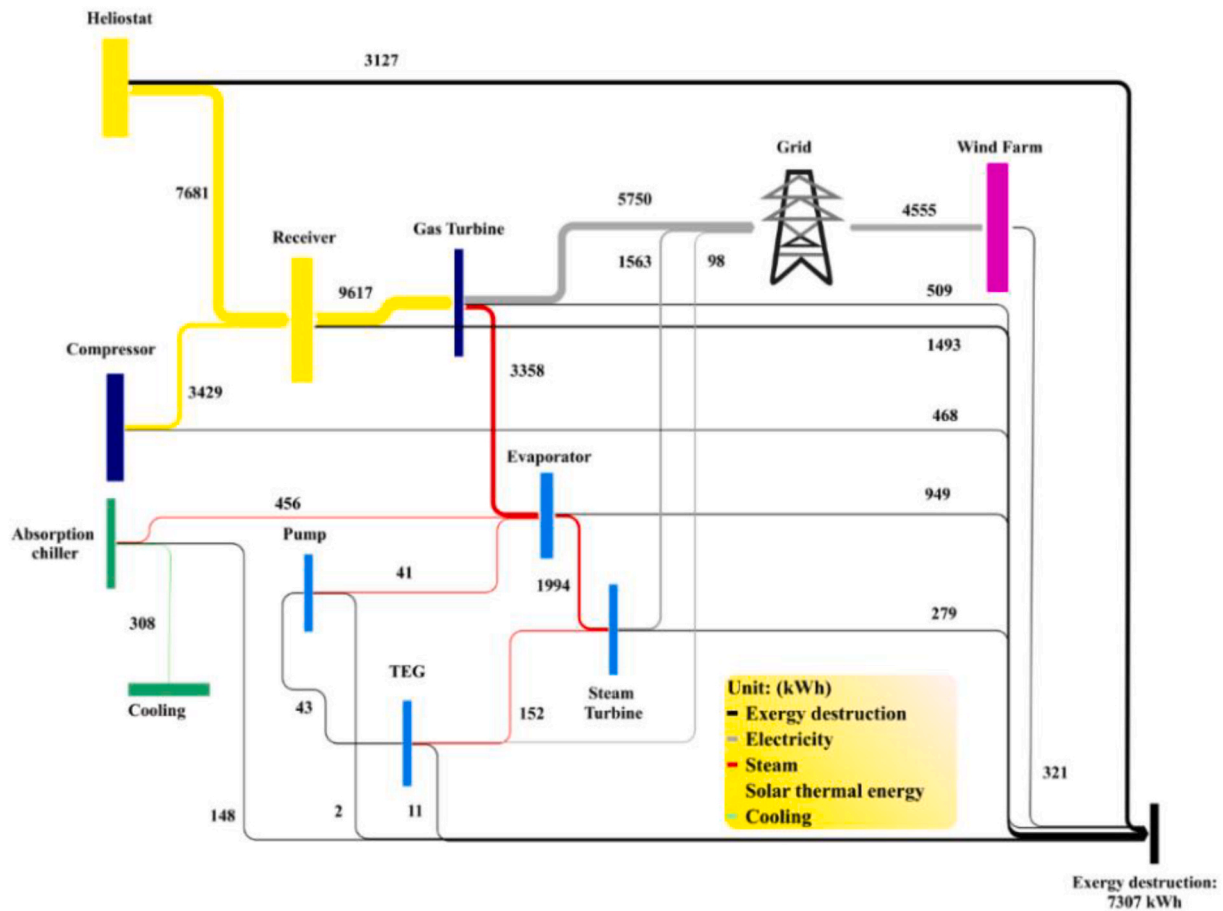


Fig. 9. Sankey diagram of exergy flow and destruction under optimal conditions.

5.4. Wind allocation optimization

To refine the system configuration identified through multi-objective optimization, fourteen scenarios were developed to evaluate how different allocations of wind power to the PEME and RO desalination units affect system performance. These scenarios explored trade-offs between co-product generation (hydrogen, oxygen, and freshwater), exergy efficiency, and total cost rate. The results showed that increasing the share of wind energy directed to PEME and RO led to higher co-product outputs but generally resulted in lower exergy efficiency and higher operational costs. For example, Scenario 11, which allocates 30 % of wind energy to both PEME and RO, achieved the highest co-product yields, 11.46 kg/h of hydrogen, 5.74 kg/h of oxygen, and 147.6 m³/h of freshwater, but also recorded the lowest exergy efficiency (38.9 %) and the highest cost rate (\$514.6/h). In contrast, Scenario 2, with only 5 % of wind energy allocated to each unit, resulted in the highest exergy efficiency (43.2 %) and the lowest cost rate (\$497/h), though it produced the smallest co-product quantities. These findings highlight the importance of selecting a balanced wind energy distribution that ensures overall system efficiency and cost-effectiveness without excessively compromising output. Full results are presented in Table 9.

To determine the most favorable configuration, the TOPSIS method was applied, using exergy efficiency and total cost rate as the two primary decision criteria, each assigned an equal weight of 0.5. This multi-criteria decision-making approach ranks alternatives based on their relative proximity to an ideal solution (highest efficiency and lowest cost) and distance from a negative-ideal solution (lowest efficiency and highest cost). After normalizing the data and calculating the closeness coefficient for each scenario, Scenario 2 emerged as the optimal configuration, achieving the highest closeness coefficient (1.0). This

scenario offers a well-balanced trade-off between thermodynamic and economic performance, with an exergy efficiency of 43.2 %, a cost rate of \$497/h, and steady co-product outputs of 2.02 kg/h of hydrogen, 1.01 kg/h of oxygen, and 35.3 m³/h of freshwater. Identified as the Best Performing System Configuration, this setup will be used in the following section to simulate system performance across eight different climate zones.

5.5. Simulation of optimal system in eight climates

In this section, the optimal system configuration identified in the previous stage is simulated across eight climatically distinct cities. The eight cities, St. John's, Quebec, Odense, New York, Nice, Madrid, Tabriz, and Isfahan, were strategically selected to represent a broad spectrum of climatic conditions across North America, Europe, and Asia. These cities span diverse temperature regimes, solar irradiance levels, and wind profiles, allowing for a comprehensive assessment of system performance across varying environmental stresses. For instance, St. John's and Odense represent cold, wind-rich northern climates with limited solar input, while Isfahan and Tabriz reflect arid, sun-intensive zones with lower wind potential. Mid-latitude cities like Madrid and Nice offer balanced seasonal profiles, and New York provides an urban temperate benchmark. By simulating system behavior across this carefully curated set, the study evaluates not only thermodynamic performance but also the scalability and resilience of the proposed hybrid system in different geographic and climatic contexts, supporting broader applicability and transferability of findings. Hourly climatic data, including ambient temperature, solar irradiance, and wind speed, were obtained from Meteonorm and used as inputs in EES to simulate the system's energy performance over a full year. This phase of the study is essential for

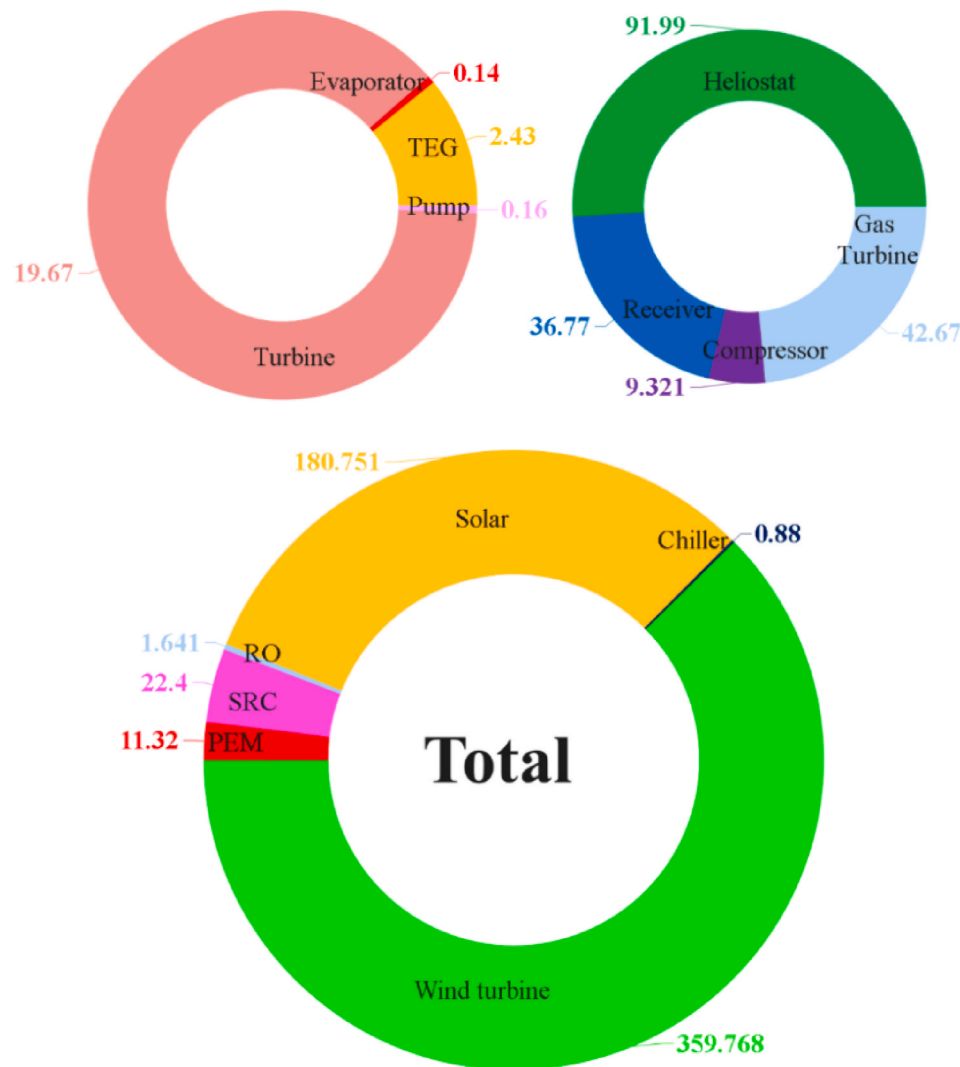


Fig. 10. Cost rate distribution of components and subsystems under optimal conditions.

Table 9
Performance of different wind power allocation scenarios.

Scenarios	PEME (% of Wind Farm)	RO (% of Wind Farm)	H ₂ (kg/h)	O ₂ (kg/h)	Fresh Water (m ³ /h)	Exergy Efficiency (%)	Total Cost Rate (\$/h)
1	10	10	3.951	1.977	63.7	42.3	500.6
2	5	5	2.024	1.012	35.3	43.2	497
3	15	15	5.851	2.927	87.9	41.5	504.2
4	20	20	7.733	3.869	109.5	40.6	507.7
5	15	10	5.851	2.927	63.7	42.3	503.8
6	5	15	2.024	1.012	87.9	41.4	497.9
7	5	10	2.024	1.012	63.7	42.3	497.5
8	20	5	7.733	3.869	35.31	43.2	506.5
9	5	20	2.024	1.012	109.5	40.6	498.2
10	10	5	3.951	1.977	35.31	43.1	500.2
11	30	30	11.46	5.735	147.6	38.9	514.6
12	10	30	3.951	1.977	147.6	38.9	502
13	30	20	11.46	5.735	109.5	40.6	513.9
14	30	5	11.46	5.735	35.3	43.1	512.7

assessing the adaptability and operational robustness of the hybrid solar-wind system under real-world environmental variability.

Fig. 11 illustrates how seasonal and climatic variations influence electricity generation by solar and wind systems across the eight cities. Solar output peaks in June–July, particularly in sun-rich cities, Isfahan (336.03 W/m²) and Tabriz (330.61 W/m²), reaching nearly five times the output of St. John’s, where winter irradiance drops below 50 W/m².

Mid-latitude cities such as Madrid and Nice maintain strong solar generation through spring and summer, while northern cities like St. John’s, Odense, and Quebec face limited solar contribution in winter due to irradiance often below 65 W/m², sharply limiting solar contribution during these months. Wind generation complements this variability, with St. John’s, Quebec, and Odense exceeding 2500 MWh in January and February due to high wind speeds (>5 m/s), far above those in

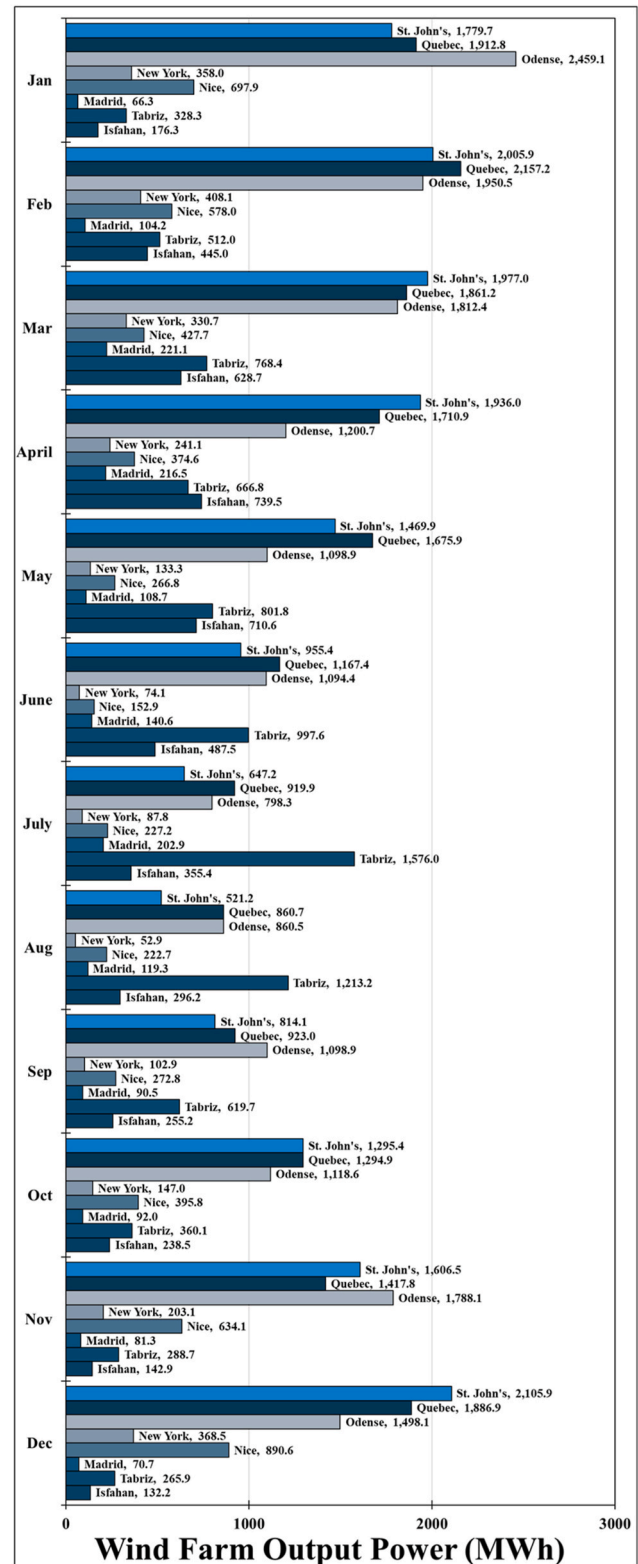
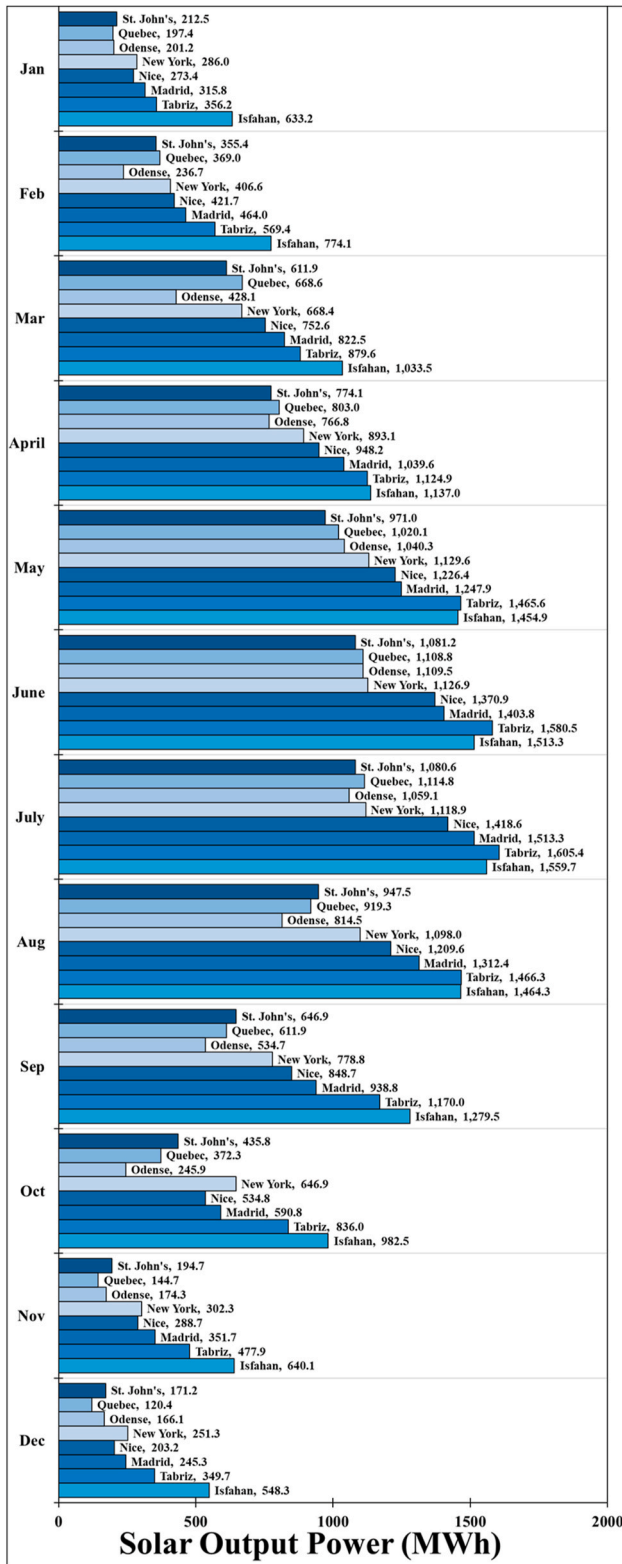


Fig. 11. Monthly solar and wind energy generation across eight selected cities.

Isfahan and Madrid (<2 m/s). This seasonal synergy, solar dominance in summer and wind in winter, enhances system resilience, reduces storage needs, and ensures stable year-round performance across diverse climates.

Fig. 12 shows seasonal variations in net power and cooling outputs across the cities. Net output peaks in wind-dominant Odense (3070

MWh in January) and in solar-rich Isfahan (2957 MWh in July), while cities like Nice and New York remain below 1800 MWh due to moderate solar and wind availability. St. John's demonstrates the wind's stabilizing effect, maintaining consistent output across seasons. Cooling output, reliant on recovered waste heat, is highest in hot climates, with Isfahan and Tabriz exceeding 83,000 kWh in July, over 15 times more

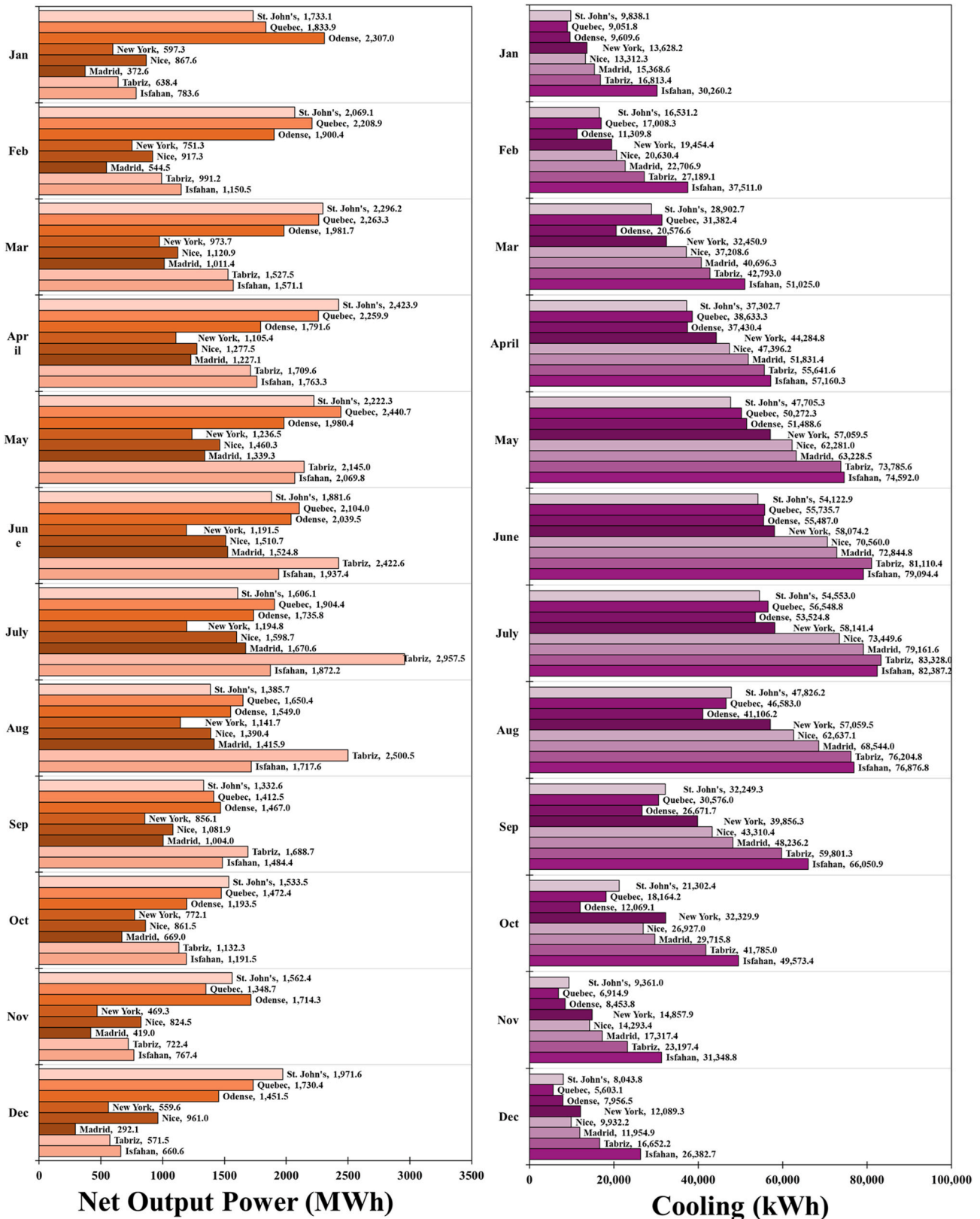


Fig. 12. Monthly net output work and cooling energy production across study cities.

than St. John's. While power output tracks resource availability, cooling is limited by thermal demand and system capacity, highlighting the system's ability to balance diverse energy services.

Fig. 13 shows seasonal trends in freshwater, oxygen, and hydrogen

production. Wind-dominant cities like Odense and St. John's peak in winter, with freshwater output surpassing 57,000 m³/h and hydrogen reaching 2264 kg/h in January. In contrast, summer output is higher in solar-rich cities like Isfahan but remains 30–50 % lower for gases due to

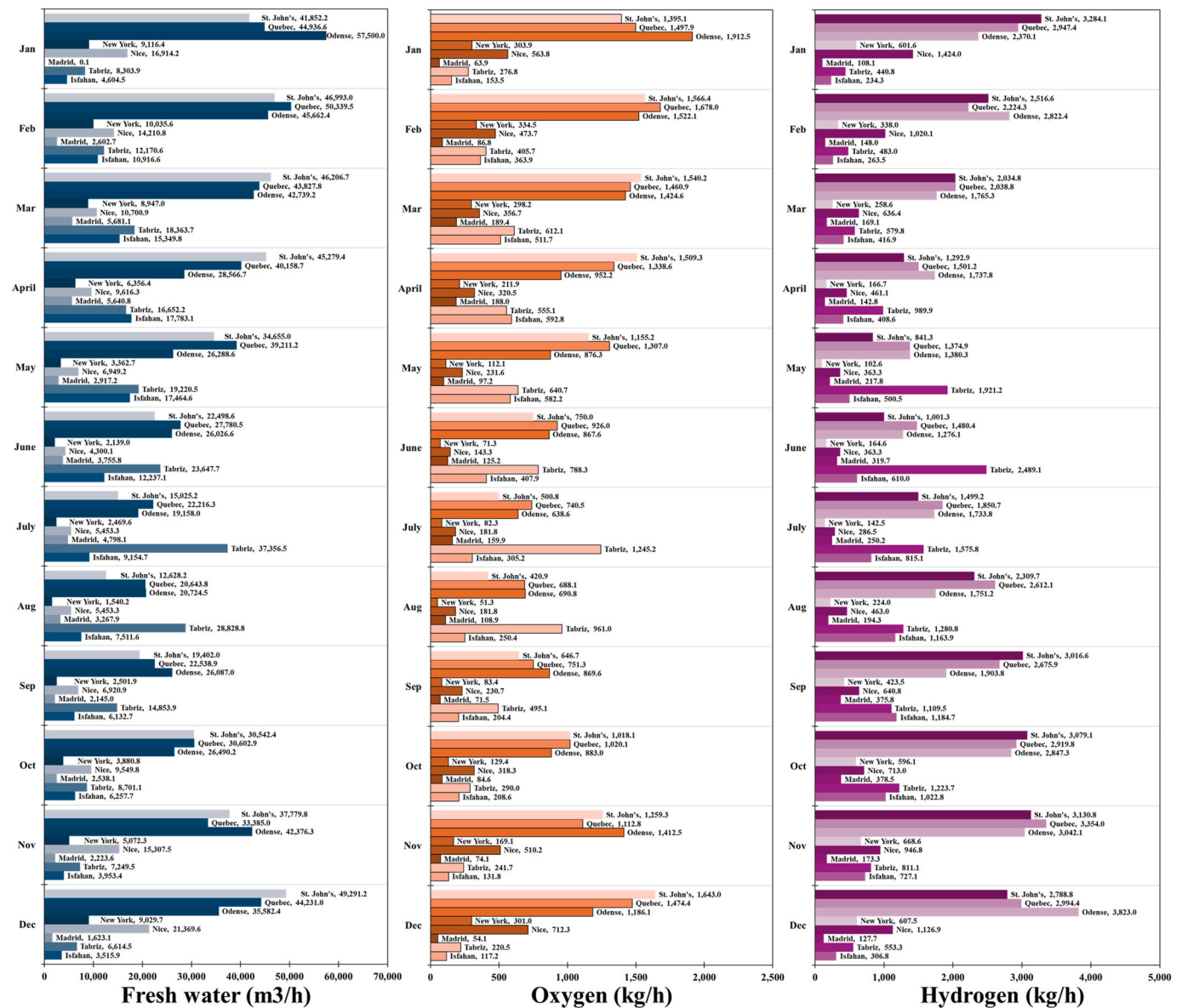


Fig. 13. Monthly freshwater, oxygen, and hydrogen production across eight cities.

weaker wind. RO desalination and PEM electrolysis units are powered by wind, explaining the strong winter performance in northern sites. These patterns highlight the system's adaptability, using seasonal wind and solar variation to maintain diverse outputs across climates.

5.6. System capability to meet annual electricity demand

A fundamental objective of renewable energy systems is to reliably meet the annual electricity needs of users across residential,

commercial, and industrial sectors. This section evaluates the performance of the proposed hybrid solar-wind system in delivering sufficient electrical output to meet per capita energy demand in eight diverse cities. The analysis is based on the annual electricity generated by the system in each location and the typical per capita electricity consumption. By comparing these values, we determine how many individuals the system could support annually under real-world climate conditions. This assessment is essential for validating the system's effectiveness in contributing to urban energy resilience and sustainability.

Table 10
System capability to meet annual electricity demand in different cities.

City	Annual Electricity Usage (kWh/per capita)	Annual Generated Power (kWh/per year)	Number of People Served
St. John's	14,612	22,018,080	1506
Quebec	14,612	22,629,600	1548
Odense	5620	21,111,552	3756
New York	12,154	10,849,440	892
Nice	6702	13,872,096	2069
Madrid	5131	11,490,057	2239
Tabriz	3072	19,007,117	6187
Isfahan	3072	16,969,344	5523

Table 10 shows significant variations in the number of people served by location due to differences in both electricity generation and per capita demand. The system performs particularly well in Tabriz and Isfahan, where lower consumption rates allow the system to meet the needs of 6187 and 5523 people, respectively. Conversely, in high-consumption cities like St. John's and New York, the same system supports fewer individuals, 1506 and 892, despite high generation outputs. Odense and Quebec emerge as strong candidates for implementation, with the system meeting the annual needs of over 1500 to 3700 individuals due to a favorable balance between wind potential and moderate demand. These results highlight the importance of matching system capacity with local consumption profiles and confirm the adaptability of the proposed hybrid system across a range of urban climates.

5.7. Stability and system resilience through wind-solar integration

Among the eight evaluated cities, St. John's, Quebec, and Odense offer the most promising conditions for deploying the proposed hybrid energy system due to their favorable balance of wind and solar resources throughout the year. As shown in Fig. 14, all three cities benefit from relatively stable solar generation, averaging around 300 to 400 kWh/day, with only moderate seasonal variation. However, it is the complementarity of wind energy that plays a critical role in stabilizing total energy output. In St. John's, wind energy exhibits a sharp increase in output during the final quarter of the year, reaching peaks above 80,000 kWh/day in December, precisely when solar production

declines. This makes St. John's especially resilient during winter when energy use peaks. Similarly, Quebec demonstrates strong wind activity in early and mid-year (peaking over 100,000 kWh/day around day 180), effectively offsetting lower solar input in spring and autumn. Odense, while exhibiting lower wind energy output overall, typically under 30,000 kWh per day, benefits from consistent wind patterns and steady solar input, making it a reliable, though lower-yielding, option.

The integrated system's design efficiently leverages these seasonal wind-solar dynamics to ensure year-round energy supply stability without excessive reliance on auxiliary sources like gas turbines. The data suggest that Quebec offers the highest peak wind capacity, followed closely by St. John's, while Odense provides more uniform but modest renewable input, which may be advantageous for operational predictability. These opposite patterns between solar and wind generation emphasize the importance of hybrid systems in temperate and cold climates. By enabling the system to compensate for solar intermittency with wind energy, particularly during winter months, this integration strengthens the grid's reliability and advances the feasibility of sustainable, off-grid solutions in wind-rich regions.

Fig. 15 illustrates the seasonal variation in electricity generation from the solar system and wind farm in Quebec City, showing that wind power consistently dominates across all months. In winter, wind production reaches its highest levels, 2061 MWh in February and 2102 MWh in January, which is over six times greater than solar output in the same months (360 MWh and 198 MWh). Even during peak solar months like June and July, wind still leads with 1163 MWh and 1110 MWh, compared to 950 MWh and 924 MWh from solar, respectively. The only

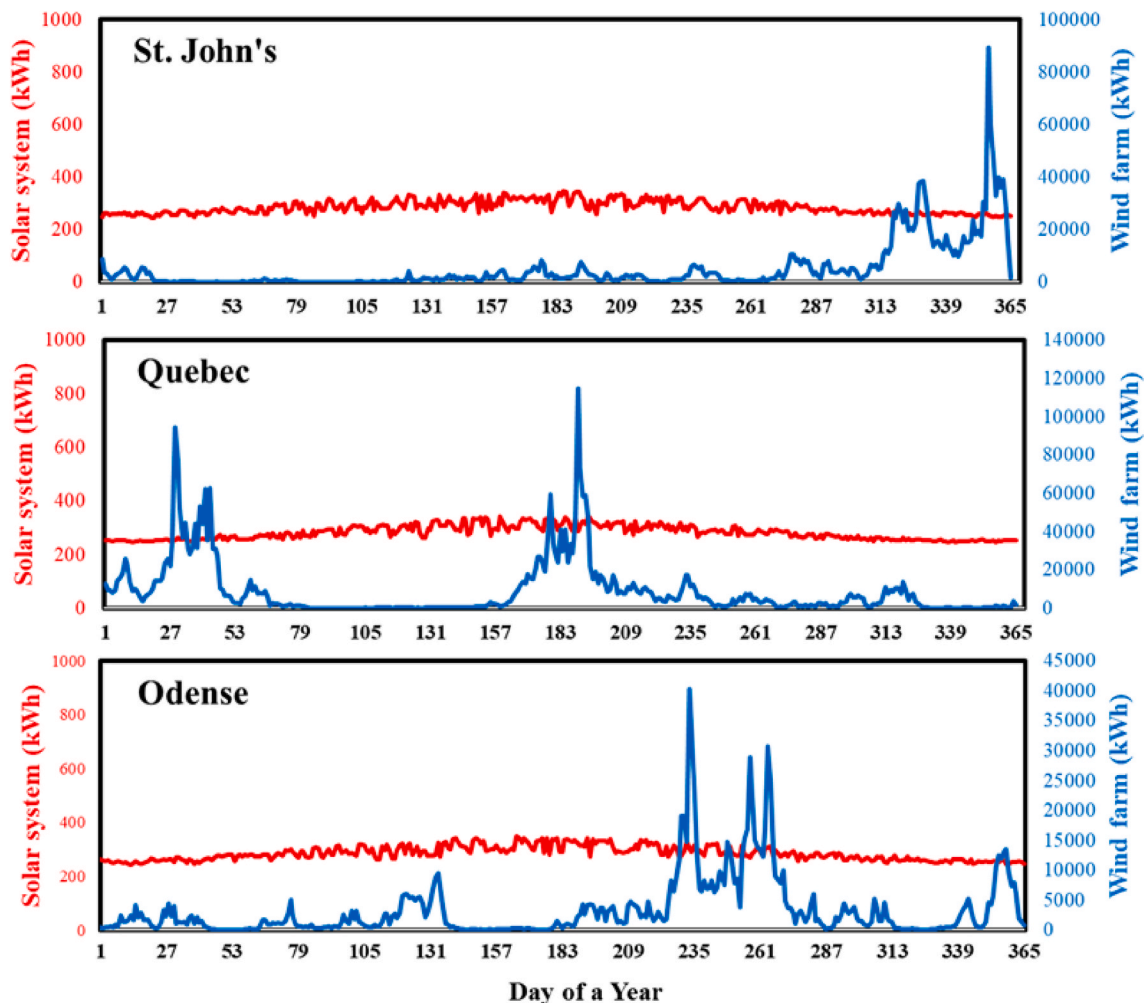


Fig. 14. Daily wind-solar electricity generation patterns in St. John's, Quebec, and Odense.

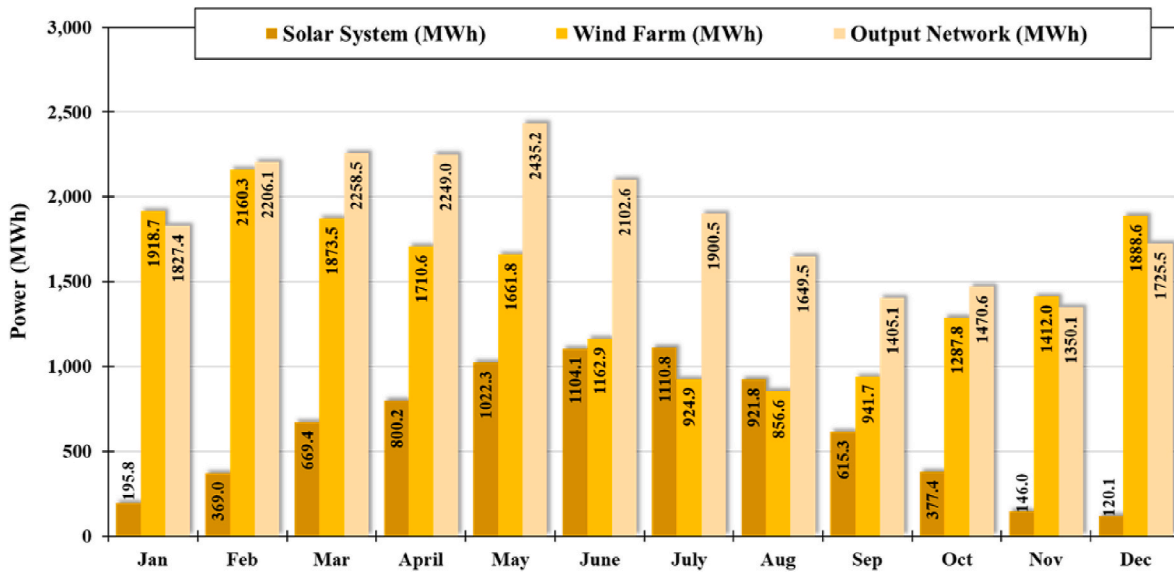


Fig. 15. Monthly variation of solar, wind, and Network generation in Quebec.

month where solar approaches parity is June, yet wind still supplies more than 200 MWh extra. This dominance of wind results in consistently high net output, peaking at 2453 MWh in May, when wind and solar jointly contribute. Remarkably, during transitional and winter months when solar is minimal, wind alone sustains strong output, ensuring reliability. Quebec exemplifies a wind-driven hybrid model where wind compensates for solar intermittency, delivering two to six times more power than solar in most months, and enables year-round grid stability without heavy reliance on energy storage.

Fig. 16 demonstrates the monthly variation in exergy efficiency with and without wind farm integration in Quebec, highlighting the critical role of wind energy in improving overall system performance. Without the wind farm, exergy efficiency remains below 22 % year-round, with a minimum of 7.17 % in December and a peak of 21.87 % in July. In contrast, when the wind farm is included, efficiency significantly increases, reaching 82.89 % in January, 79.84 % in March, and peaking at 89.36 % in December, representing an improvement of more than 70 percentage points in some months. This drastic enhancement is directly linked to the substantial contribution of wind energy during periods of

low solar availability, particularly in winter. The added wind capacity not only compensates for solar intermittency but also increases electricity output, enabling the system to operate closer to its optimal potential. These results confirm that wind integration greatly enhances the energy conversion effectiveness of the plant, making the hybrid system far more efficient, resilient, and sustainable across all seasons.

Fig. 17 shows the monthly variation in cost rate (\$/h) for the power plant with and without wind farm integration. The results clearly indicate that incorporating the wind farm, modeled with 24 optimally operating turbines, leads to a noticeable increase in cost rate across all months due to added investment, maintenance, and operational costs. Without the wind farm, the cost rate remains relatively stable, ranging from \$129.91/h to \$144.52/h throughout the year. In contrast, with the wind farm included, the cost rate rises significantly, peaking at \$408.52/h in February and \$370.06/h in December, which are over 3 times higher than the corresponding values without wind. This increase reflects the financial impact of integrating wind energy infrastructure. However, as highlighted in earlier analyses, this added cost coincides with substantial gains in exergy efficiency, renewable electricity output,

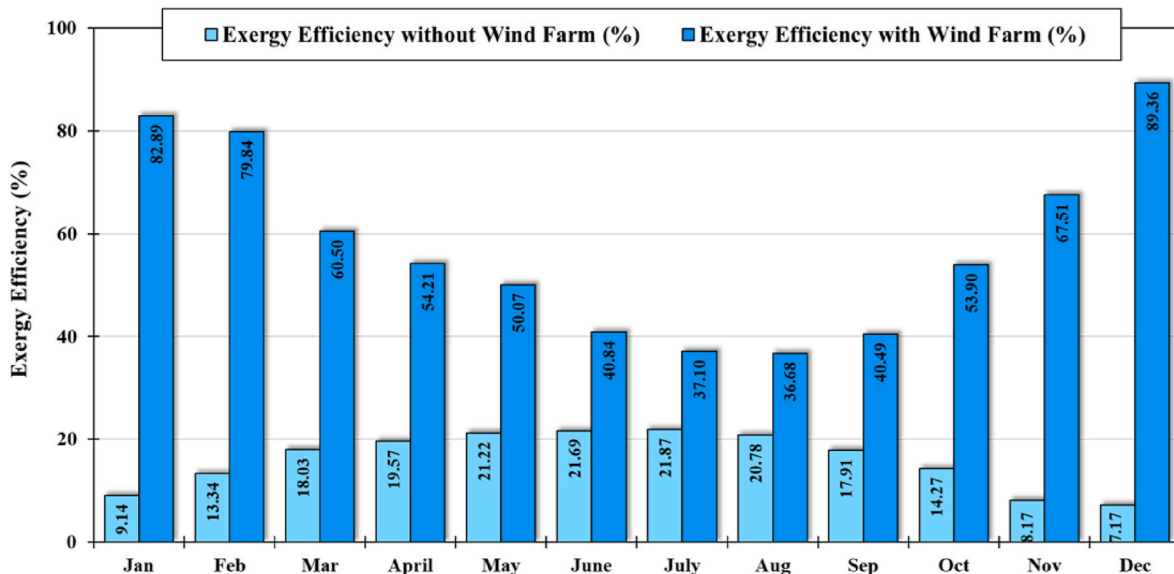


Fig. 16. Monthly variation of exergy efficiency with and without wind farm integration in Quebec.

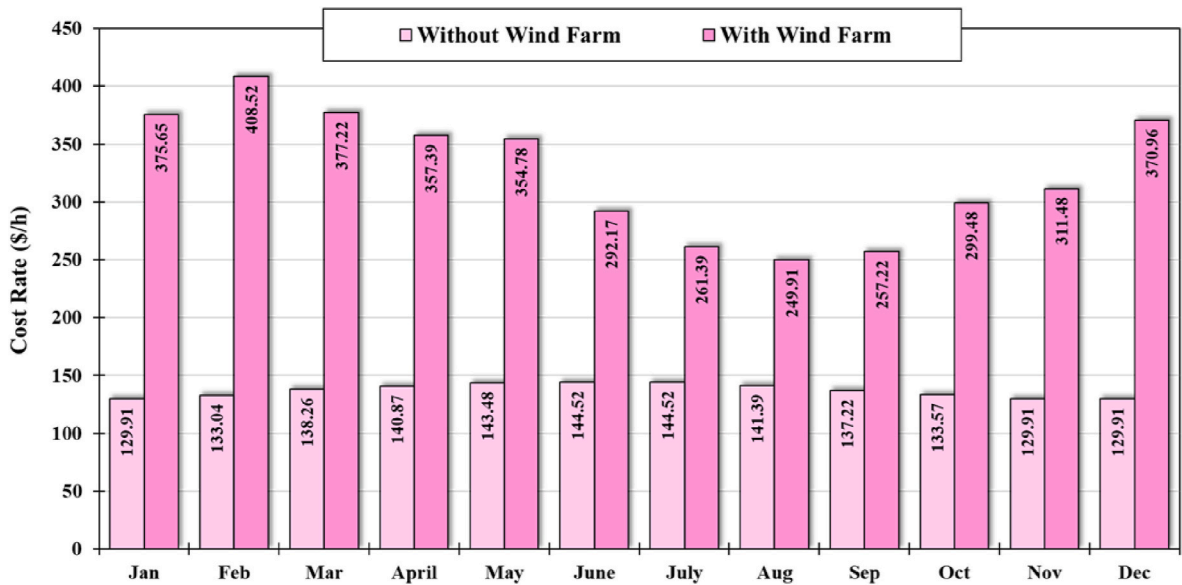


Fig. 17. Monthly variation of cost rate with and without wind farm integration in Quebec.

and environmental sustainability. Therefore, while the upfront cost rate is higher, the integration of wind farms enhances long-term system resilience and reduces fossil fuel dependence, making it a strategic investment in sustainable power generation.

Fig. 18 presents the hourly power generation of the solar and wind systems in Quebec across four seasons, demonstrating their

complementary behavior and seasonal variability. Solar generation in all seasons follows the expected daylight curve, with peaks between 5000 and 7000 kWh in summer (around 13:00) and 3000–4500 kWh in spring and autumn, while dropping below 2500 kWh in winter. In contrast, wind generation exhibits broader temporal coverage and seasonal dominance. The wind farm reaches its highest peak in spring, with

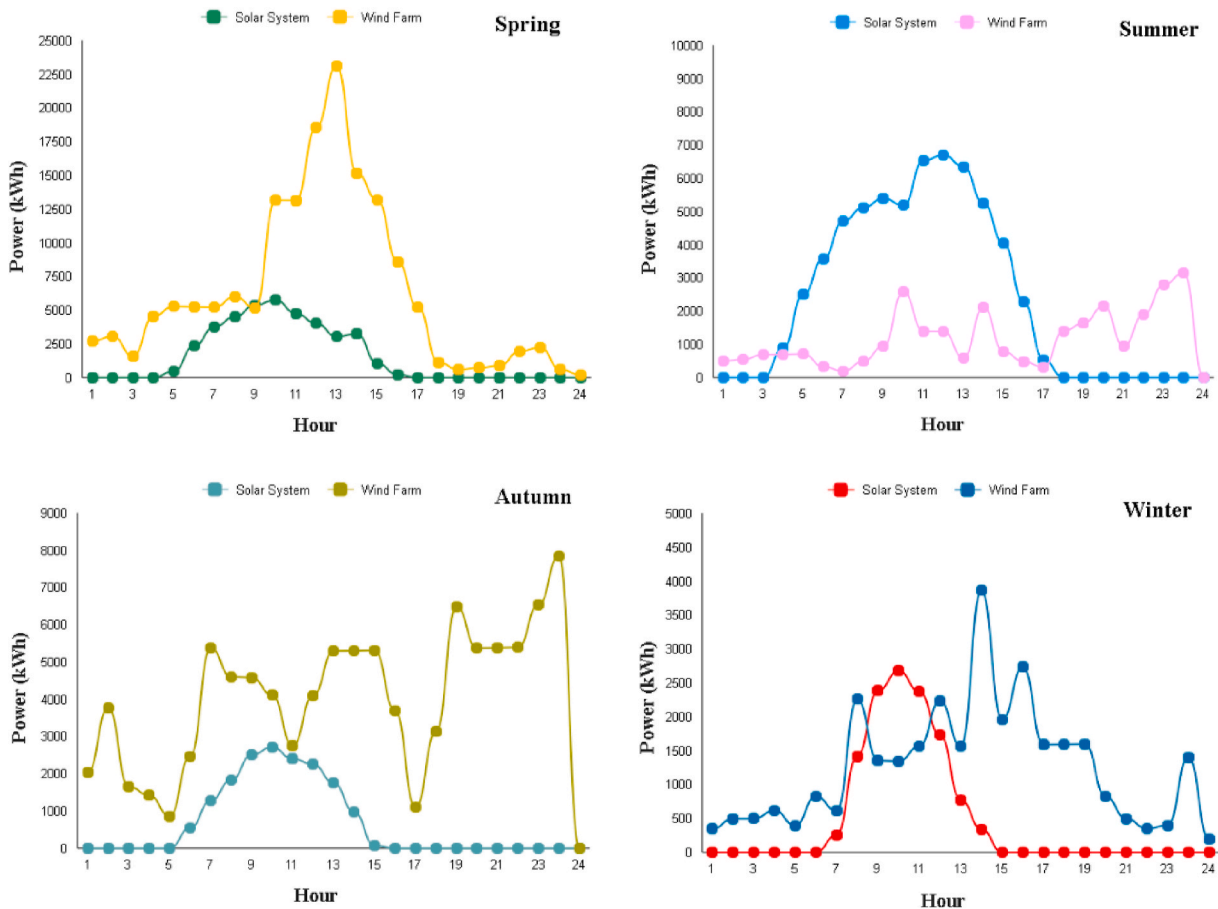


Fig. 18. Hourly power generation of solar and wind systems in Quebec across four seasons.

output exceeding 24,000 kWh at 14:00, more than 3.5 times the concurrent solar peak. In autumn, wind power peaks at nearly 8500 kWh at 23:00, while solar remains below 4000 kWh at its midday maximum. During winter, when solar production barely reaches 2500 kWh, wind generation exceeds 4000 kWh in multiple early afternoon hours, peaking at 4500 kWh around 14:00. In summer, although solar dominates midday with peaks above 7000 kWh, wind still contributes consistently during off-peak hours, particularly between 1:00 and 7:00 and again from 18:00 to midnight, filling in critical gaps. These patterns confirm that wind generation not only extends the coverage beyond solar hours but also provides notably higher output in the non-summer months, effectively compensating for solar shortfalls and ensuring round-the-clock energy availability.

5.8. Environmental analysis

Quebec City has been identified as the optimal site for deploying the proposed hybrid power plant, based on its high renewable energy potential and significant environmental impact reduction, as illustrated in Fig. 19. The system's monthly electricity production varies from 1350 MWh in October to a peak of 2426 MWh in May, directly influencing the associated CO₂ emissions. Traditional fossil fuel-based power plants emit approximately 0.204 tons of CO₂ per MWh, which would result in over 494 tons of CO₂ in May alone. The proposed system offsets these emissions by utilizing wind and solar energy, substantially lowering environmental burdens. With a carbon cost of \$24 per ton, this translates into a potential monthly savings of up to \$11,856, contributing to a cumulative reduction of over \$120,000 annually in externalized carbon costs.

In addition to emissions and cost avoidance, the system's monthly land use requirements, ranging from 1.3 ha in November to 2.5 ha in May, are comparatively low, given the scale of energy production. More importantly, this infrastructure supports green space integration, offering co-benefits such as heat mitigation, air quality improvement, and

potential carbon sequestration. The integration of clean generation with low-emission outcomes aligns with the paper's overarching aim of delivering resilient, efficient, and environmentally sustainable hybrid systems. By significantly reducing CO₂ emissions and associated costs while maintaining high energy output, the proposed system not only meets energy demands but also advances broader environmental and climate goals.

5.9. Hybrid optimization using artificial intelligence

To enhance the robustness and predictive accuracy of system optimization, this section proposes a hybrid AI-based framework that integrates a machine learning prediction model with a metaheuristic optimization algorithm. This forward-looking approach leverages the capabilities of artificial intelligence to address the limitations of traditional techniques such as RSM. While RSM is useful for exploring design spaces, it relies on low-order polynomial regression, which can struggle to capture complex, nonlinear interactions and high-dimensional variable relationships. In contrast, machine learning models like AdaBoost offer greater flexibility and precision in modeling intricate, nonlinear patterns within large datasets. PSO is employed as an advanced optimization tool capable of efficiently identifying global optima in complex, multidimensional search spaces.

A critical component of this hybrid approach is data preprocessing, which ensures that the input dataset is clean, consistent, and suitable for both prediction and optimization tasks. Key preprocessing operations include handling missing values, removing duplicates, correcting inconsistencies, detecting and managing outliers, and applying feature scaling and normalization. These steps directly affect model reliability and optimization performance, especially in data-driven environments (Hassan et al., 2023).

The proposed AI-based procedure comprises the following sequential steps:

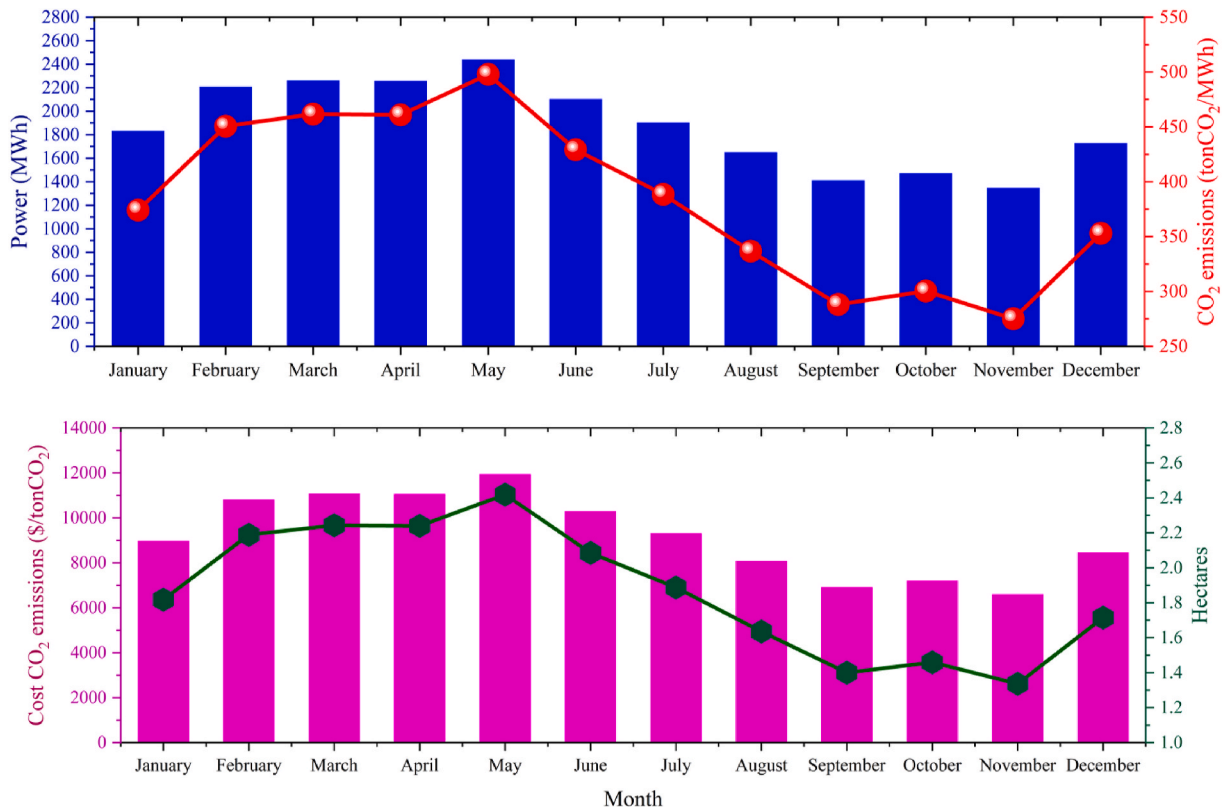


Fig. 19. Environmental and economic impact of the hybrid system in Quebec.

- Generation of approximately 2500 simulation records using EES.
- Preprocessing of the dataset to prepare it for machine learning modeling.
- Prediction of additional data points using the AdaBoost regression algorithm to expand and refine the dataset.
- Optimization of the system using PSO to identify optimal configurations based on exergy efficiency and cost objectives.

This methodology forms the foundation for re-optimizing the system and enables a direct comparison with the RSM-based results presented earlier, providing insights into the benefits of adopting AI for multi-objective engineering problems.

To validate the robustness of the proposed AI-based optimization framework, it is essential to examine the distribution characteristics of the input data before preprocessing. Fig. 20 displays the distribution plots of the two objective functions, log-transformed exergy efficiency (Fig. 20a) and log-transformed cost rate (Fig. 20b), before preprocessing. The exergy efficiency data exhibits an approximately normal distribution with a symmetric, bell-shaped curve, suggesting that the log transformation was effective in stabilizing variance and improving normality. The mode of the distribution lies between 3.6 and 3.7, indicating that the majority of log-transformed exergy efficiency values fall within this narrow range, with moderate variance and no apparent extreme outliers.

In contrast, the distribution of the log-transformed cost rate reveals a tight clustering between 5.8 and 7.2, with a peak frequency around 6.5 to 7.0, suggesting a low-variance distribution. However, the histogram shows a slight right-skew, indicating the presence of a long tail toward higher cost values. Although the log transformation improves the overall distribution shape, residual skewness suggests that additional preprocessing steps, such as outlier detection, normalization, and standardization, may be necessary to ensure data quality and enhance model performance. These distributional insights reinforce the importance of thorough preprocessing to support accurate machine learning prediction

and efficient optimization.

Fig. 21 presents box plots of four selected features, number of heliostats, number of wind turbines, pressure ratio, and T10 ($^{\circ}\text{C}$), before preprocessing, offering insights into their distributions and variability. Among them, the number of heliostats shows the widest spread, ranging from 300 to 500, with a median of 401.5, indicating high variability and the likely need for normalization. The number of wind turbines also displays a notable spread (10–39.99, median 25.55), suggesting moderate variance. In contrast, the pressure ratio (4.01–12, median 8.03) and T10 (30.01 $^{\circ}\text{C}$ –49.99 $^{\circ}\text{C}$, median 39.76 $^{\circ}\text{C}$) exhibit more compact distributions. No extreme outliers are evident in any of the features; however, due to the varying scales, particularly between heliostat counts and pressure ratios, further preprocessing, including feature scaling or standardization, is recommended to ensure consistent model performance.

Fig. 22 shows the correlation matrix of key features, which is an essential tool for evaluating relationships between variables, identifying multicollinearity, and selecting relevant inputs for modeling. The matrix presents correlation coefficients ranging from -1 to 1 , where positive values indicate direct relationships and negative values indicate inverse ones. Among all features, the number of wind turbines has the strongest positive correlation with exergy efficiency (0.78), while the number of heliostats shows a moderate negative correlation (-0.27), suggesting that increasing heliostat count may reduce system efficiency. For the cost rate, the number of wind turbines again appears as the most influential variable (0.22), followed closely by gas turbine (0.20) and compressor efficiency (0.25). The two objective functions, exergy efficiency and cost rate, are also moderately correlated with each other (0.22), indicating a partial trade-off. Most other variables show weak correlations with both objectives, emphasizing that a few core features play dominant roles in performance prediction and optimization.

Fig. 23 presents scatter plots with regression lines assessing how five key features, number of heliostats, number of wind turbines, pressure ratio, T10 ($^{\circ}\text{C}$), and P8 (kPa), influence the objective functions: Exergy Efficiency (%) and Cost Rate (\$/h). The number of wind turbines shows a strong positive linear trend with exergy efficiency; as turbine count increases from 10 to 40, efficiency rises from below 30 % to over 55 %, confirming its critical role in performance enhancement. Conversely, the number of heliostats shows a mild negative trend, with exergy efficiency dropping gradually from above 40 % to near 35 % as the count increases from 300 to 500. This suggests that larger heliostat fields may introduce higher losses or diminishing returns in exergy gains.

For cost rate, wind turbines exhibit a slight positive trend, cost increases from approximately \$400/h to \$600/h across the turbine range, indicating the financial trade-off for higher efficiency. In contrast, heliostats show little to no clear relationship with cost rate, as data points remain broadly scattered around the mean. The other parameters, pressure ratio, T10, and P8, exhibit nearly horizontal regression lines in both exergy efficiency and cost rate plots. This implies minimal direct influence, with efficiency variations of less than 5 % and cost changes of less than \$50/h across their respective ranges. These results quantitatively confirm that the number of wind turbines is the most influential parameter, while others contribute only marginally within the explored design space.

The Williams plots in Fig. 24 provide a robust visual assessment of the AdaBoost regression model's reliability before and after preprocessing. In Fig. 24a, before preprocessing, approximately 30 red squares (suspected data) and 2 purple triangles (out-of-leverage points) fall beyond the standardized residual bounds of ± 3 and the leverage threshold of 0.008. These data points represent roughly 1.3 % of the total dataset and indicate potential outliers or influential observations that could distort the regression model. Several other data points also cluster near the ± 2 residual limits, suggesting a high variance in prediction accuracy and a lack of robustness in the initial model. The triangular spread further reflects non-uniform influence distribution, confirming the need for data transformation and noise reduction.

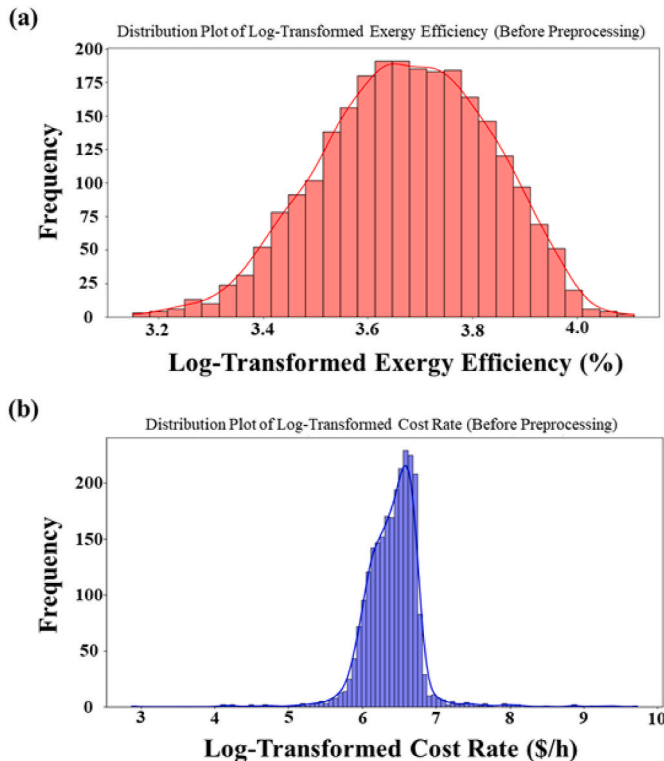


Fig. 20. Distribution of log-transformed exergy efficiency and cost rate before preprocessing.

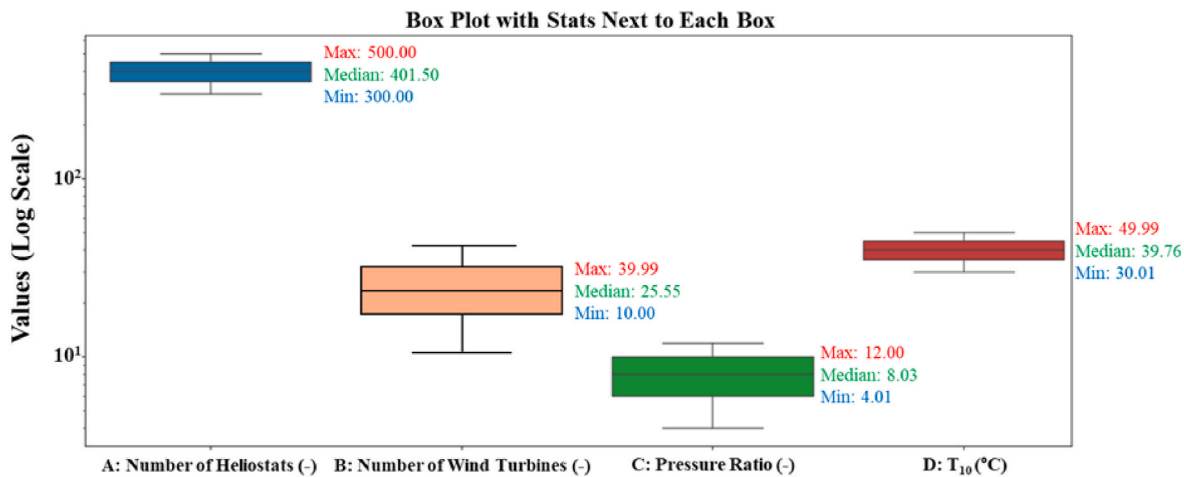


Fig. 21. Box plots of key features before preprocessing.

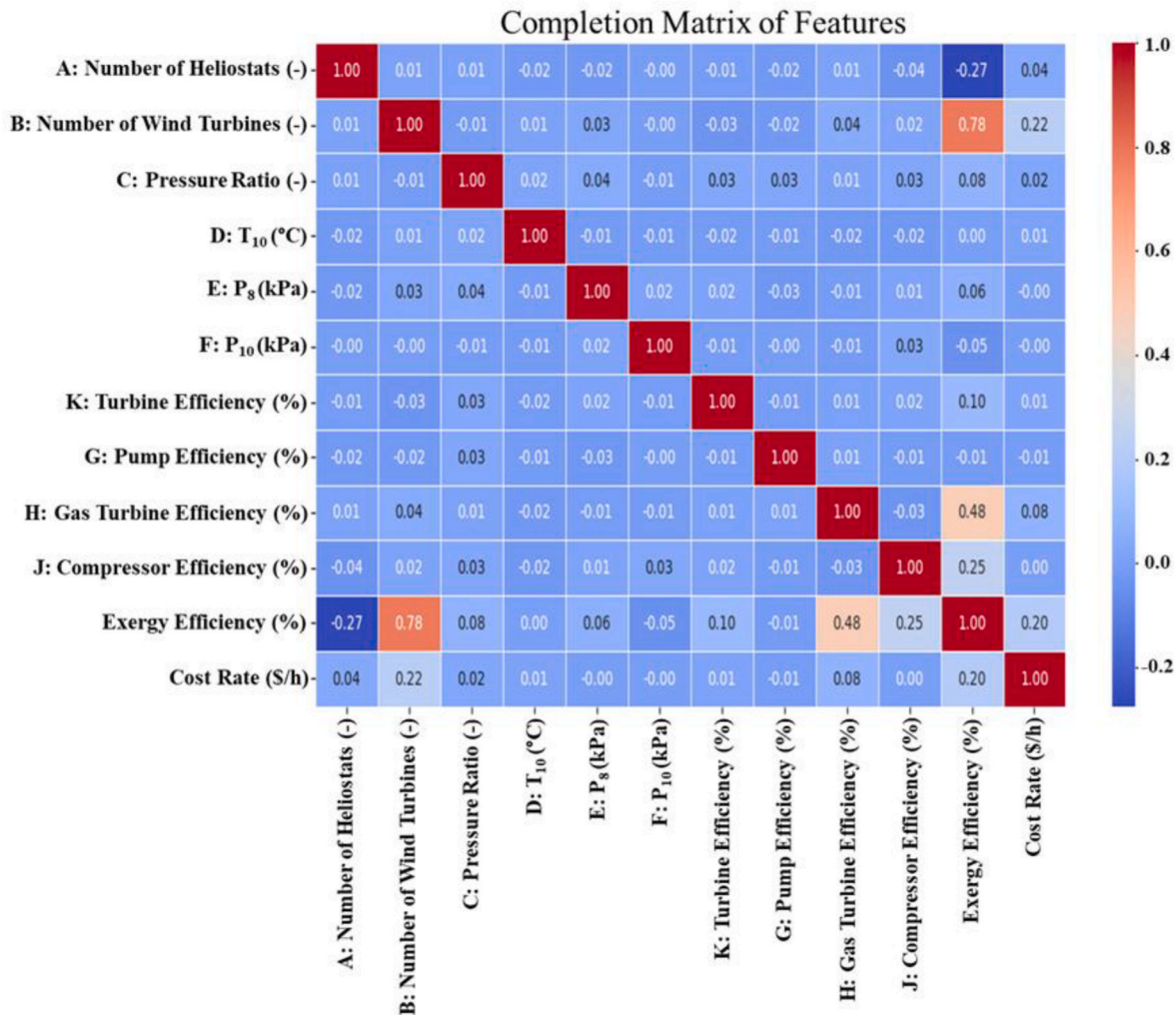


Fig. 22. Correlation matrix of features and objectives.

After preprocessing, Fig. 24b shows a substantial improvement. All data points fall within the standardized residual range of ± 3 and remain below the new leverage threshold of approximately 0.065. The distribution becomes compact, with over 95 % of the data centralized around zero residuals and leverage values between 0.02 and 0.05, indicating

homogeneity in influence and prediction accuracy. This transformation eliminates the previously identified outliers and stabilizes the model's behavior, confirming the success of preprocessing techniques such as outlier removal, normalization, and feature standardization. Consequently, the regression model becomes more reliable and generalizable,

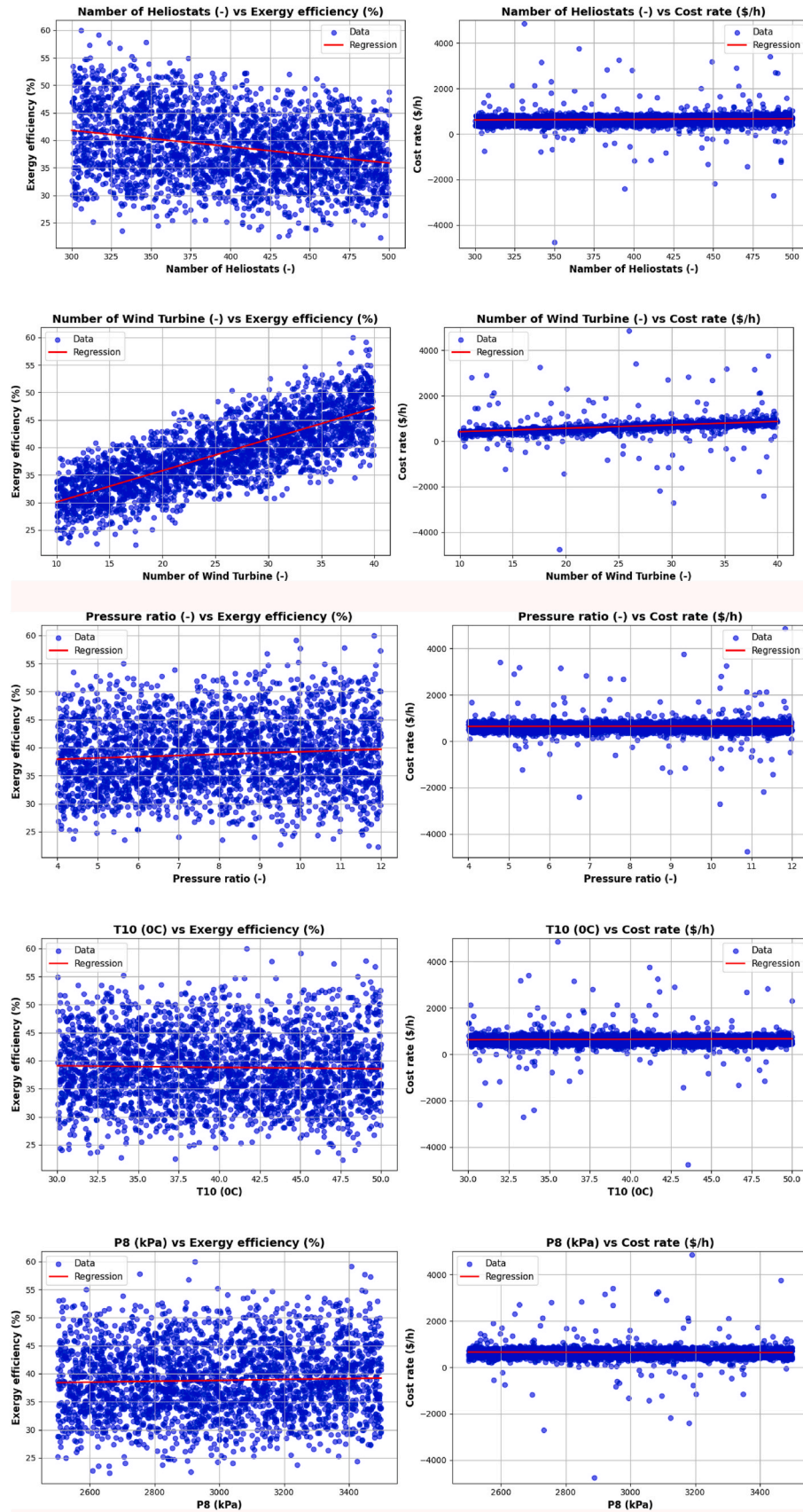


Fig. 23. Selected Design Features vs. Energy Efficiency and Cost Rate with Regression Lines.

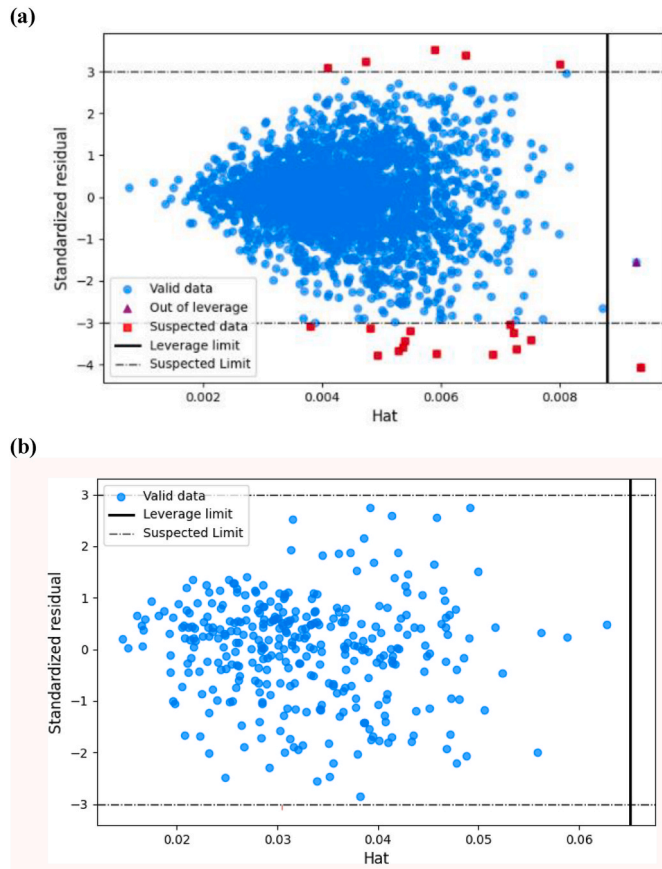


Fig. 24. Williams plot before and after preprocessing using AdaBoost regression model.

especially in multi-objective optimization tasks like those addressed in this study.

The feature importance analysis in Fig. 25 reveals key insights into the factors influencing both exergy efficiency and cost rate after preprocessing. For exergy efficiency (a), gas turbine efficiency stands out with the highest importance (~ 0.42), followed by compressor efficiency (~ 0.27). These two features collectively contribute nearly 70 % of the model's predictive capability for exergy performance. While pump and turbine efficiencies also play a role, their influence is much smaller. Other parameters, including pressure ratio, temperature (T10), and pressure inputs (P8, P10), show minimal or negligible importance. Interestingly, although the number of wind turbines and heliostats contributes marginally, they are not the primary drivers of thermodynamic efficiency, indicating that enhancing component-level efficiencies offers greater leverage for exergy optimization.

In contrast, the cost rate model (b) identifies the number of wind turbines as the most influential feature (~ 0.27), reflecting the capital and operational cost impact of wind energy infrastructure. This is followed by compressor (~ 0.22) and gas turbine efficiencies (~ 0.19), suggesting that boosting component performance can also yield economic benefits. Temperature and pressure variables (T10, P8, P10) show moderate relevance, unlike in the exergy model. These findings demonstrate a divergence in feature significance across objectives, where thermodynamic performance hinges on equipment efficiencies, cost minimization is more sensitive to system scales (wind turbines), and a mix of efficiency and operational variables.

Using the PSO algorithm, the optimal results are summarized in Table 11, providing a clear comparison between the RSM-based method. While the RSM approach yields a higher exergy efficiency (45.9 %), the AI-driven method significantly reduces the cost rate to \$211.2/h, a

63.38 % improvement. This trade-off highlights the distinct strengths of each method: RSM is more suitable when thermodynamic performance is the priority, whereas AI offers superior economic efficiency. Notably, the AI method reduces the number of wind turbines by 54.17 % and increases the number of heliostats by 48.04 %, indicating a strategic shift toward solar utilization for cost reduction. Other changes include a 45.63 % increase in P10 and a 12.63 % rise in pressure ratio, both contributing to system cost-efficiency. While there is a 28.08 % drop in exergy efficiency using AI, the cost savings make it a compelling choice when operational affordability outweighs peak performance. Ultimately, the selection between the two methods depends on project goals: energy performance (RSM) or economic feasibility (AI).

Fig. 26 shows the convergence behavior of the PSO algorithm for both objective functions. In Fig. 26a, exergy efficiency starts at 32.94 % and remains constant for the first 50 iterations before gradually increasing to 32.96 %, stabilizing after iteration 100, indicating a slow and limited improvement in energy performance. Conversely, Fig. 26b demonstrates a sharper decline in cost rate, starting above \$700/h and reducing in distinct steps to \$211.2/h by iteration 175, with major drops occurring in the first 50 and between iterations 125–175. This contrast reveals that PSO effectively minimizes cost with greater sensitivity, while efficiency gains are marginal and slower, reinforcing PSO's strength in cost-driven optimizations.

5.10. Scalability and modularity design

A critical advantage of the proposed hybrid solar-wind multi-generation system lies in its inherent modular design, providing substantial flexibility to adapt to varying energy demands and geographical conditions. The system was designed from the outset with industrial-scale feasibility in mind, ensuring that each module, from energy generation to water and hydrogen production, can be economically and technically scaled up to meet large-scale demands in industrial or urban precincts. By independently scaling key components such as heliostat fields, wind turbines, and the integrated thermodynamic cycles, the system can effectively address diverse scenarios, from small-scale residential communities to large industrial complexes. For instance, in regions with higher solar irradiance but limited land availability, selectively scaling the heliostat count and optimizing receiver efficiency could maximize solar utilization while minimizing land use. Conversely, in windy regions with ample open space, expanding wind turbine capacity would deliver greater power output and improved system resilience. The independence of subsystems, such as RO desalination, PEME, and absorption chillers, further supports selective enhancement of specific outputs, making the system adaptable to customized end-user needs without redesigning the entire infrastructure.

The integration of advanced AI-based optimization ensures that the system remains efficient at different scales, identifying optimal configurations dynamically as demands evolve. The capability to incrementally scale up or replicate system modules offers economic advantages by reducing initial capital risk and allowing incremental investment aligned with growth in energy demand. The modular approach also supports phased implementation, enabling continuous technological improvements to be incorporated over the project's lifespan, significantly enhancing long-term operational efficiency and sustainability. Future integration of smart control systems and IoT-enabled predictive maintenance can further improve modular scalability, allowing real-time monitoring and dynamic adjustments of individual modules to optimize performance. Thus, this hybrid system can meet current energy transition challenges and provide a robust and future-proof infrastructure capable of seamlessly adapting to evolving technological advancements and environmental targets.

5.11. Comparison with previous systems

The proposed hybrid solar-wind multi-generation system

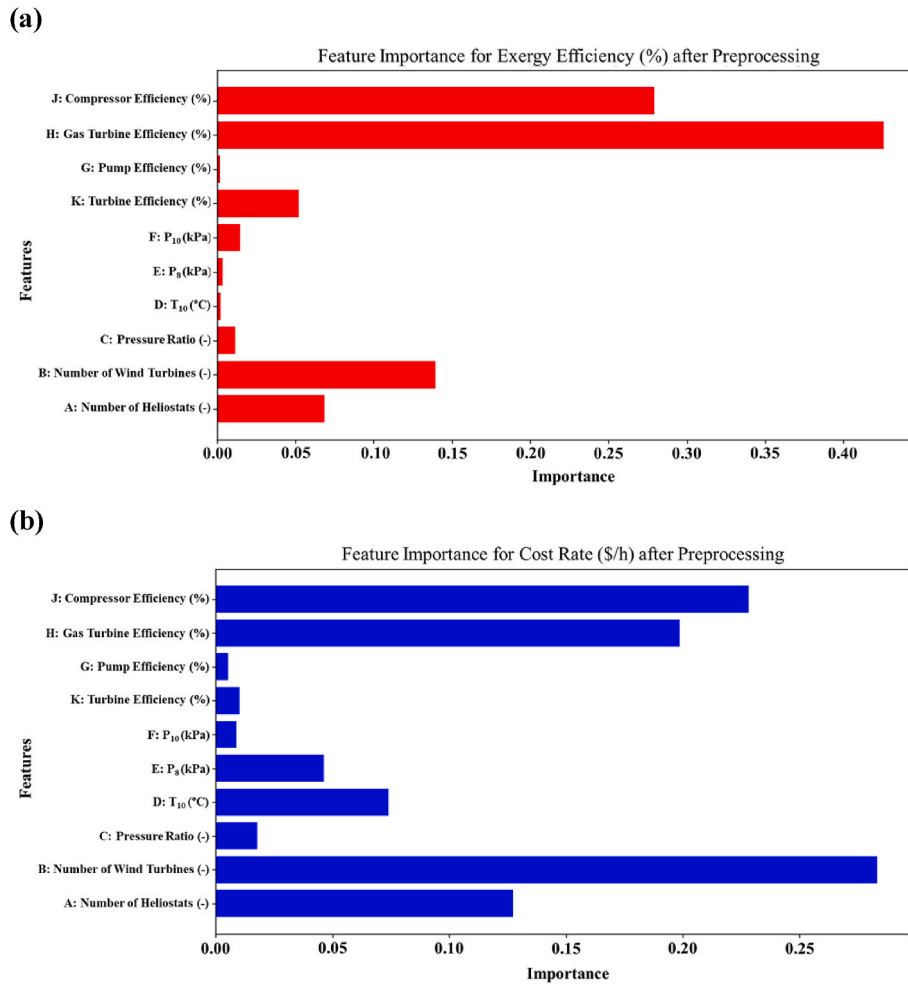


Fig. 25. Feature importance for exergy efficiency (a) and cost rate (b) after preprocessing.

Table 11
Comparison of optimal results from RSM and AI-Based optimization.

Feature	Unit	Optimal Values (RSM)	Optimal Values (AI)	Variation (%)
Number of Heliostats	–	306	453	48.04
Number of Wind Turbines	–	24	11	54.17
Pressure ratio	–	8.71	9.81	12.63
T_{10}	°C	40.24	49.93	24.08
P_8	kPa	3035.65	3154.88	3.93
P_{10}	kPa	99.35	144.68	45.63
Pump Efficiency	%	0.83	0.79	–4.82
Gas turbine Efficiency	%	0.82	0.79	–3.66
Compressor Efficiency	%	0.89	0.93	4.49
Number of Heliostats	–	0.85	0.83	–3.35
Exergy Efficiency	%	45.8	32.93	–28.10
Cost Rate	\$/h	576.76	211.2	63.38

demonstrates advancements over previous configurations, particularly in optimizing the critical trade-off between exergy efficiency, cost-effectiveness, and environmental performance. Table 12 summarizes the comparative performance of the proposed hybrid system against previously developed multi-generation configurations, highlighting differences in optimization methods, cost rates, exergy efficiencies, and CO₂ reduction capabilities.

Table 12 highlights that the current system achieves superior exergy efficiency (45.8 %) using the RSM approach, surpassing the hybrid wind-gas turbine configuration at 36.95 % (Rahman et al., 2025), and the gas turbine system integrating heat recovery and hydrogen blending at 42.73 % (IEA, 2023). Furthermore, the AI-enhanced optimization dramatically reduces the cost rate to \$211.2/h, providing a substantial economic advantage over high-cost systems like the hybrid solar-biomass-wind ammonia system (Attílio et al., 2024), which operates at \$5616/h, and the gas turbine system at \$1514/h (IEA, 2023). This illustrates that the current system's sophisticated optimization strategy effectively balances operational expenditure and performance.

Moreover, the present system provides an environmental benefit by reducing CO₂ emissions by 4616.4 tons annually, outperforming notable configurations such as the gas turbine system (1896 tons/year) (IEA, 2023) and the solar-hydrogen-desalination hybrid (23.3 tons/year) (Mohtasim et al., 2025). Although the hybrid wind-gas turbine configuration exhibits higher total annual CO₂ reduction (10,416 tons/year), its associated operational cost remains substantially higher (\$446.04/h), reinforcing the present system's strong value proposition (Rahman et al., 2025). Hence, the developed solar-wind hybrid configuration, bolstered by advanced optimization techniques, offers an exemplary integrated solution, effectively navigating the complexities of enhancing exergy performance, achieving substantial economic efficiency, and delivering meaningful reductions in environmental impacts compared to previously studied systems.

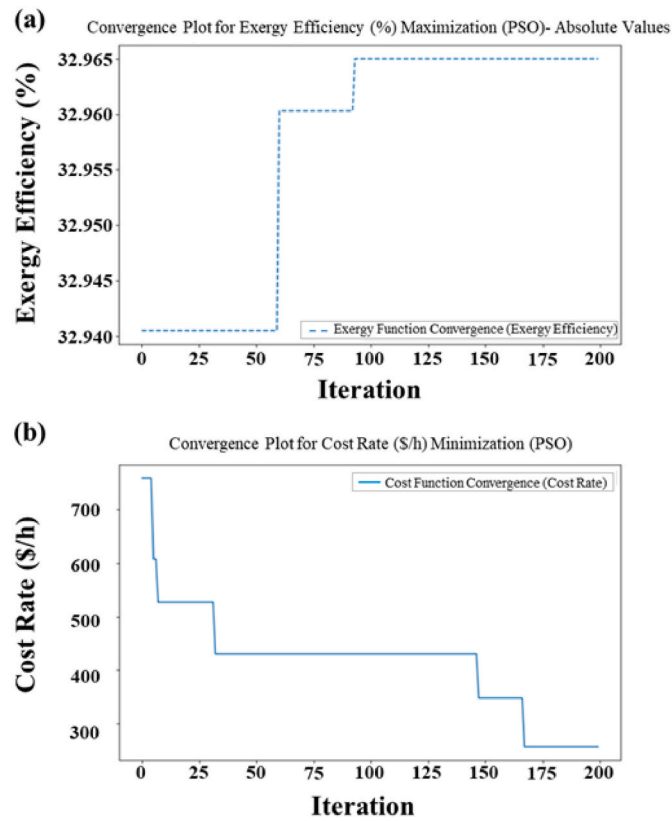


Fig. 26. Convergence plots of PSO for (a) exergy efficiency and (b) cost rate.

6. Limitations and future directions

This study proposes an integrated hybrid solar-wind multi-generation system for producing electricity, hydrogen, oxygen, cooling, and

freshwater. Through combined thermodynamic, economic, and climate-based analysis, it demonstrates adaptability and efficiency across varied environments. While the results are promising, the following limitations highlight areas for future refinement. This section acknowledges methodological and modeling constraints. The reliance on simplified thermodynamic assumptions, such as steady-state operation, idealized turbine efficiencies, negligible pressure drops, and omission of kinetic and potential energy changes, represents a limitation that might underpredict real-world losses and operational complexities. Moreover, the economic assessment's use of standardized component-costing methods potentially overlooks region-specific financial factors such as fluctuating market prices, local subsidies, or installation and maintenance variations. The exclusion of hydrogen compression energy requirements also likely underestimates the system's total energy consumption, thus overestimating net efficiency. These modeling simplifications, necessary to achieve computational efficiency and analytical clarity, introduce uncertainties that could influence system performance predictions, particularly during real-world implementation under dynamically variable environmental conditions.

To overcome these limitations and enhance predictive accuracy, future research should pursue advanced dynamic modeling approaches, incorporating transient simulation tools and analyses to capture real-time operational behaviors and more accurately represent the interactions between integrated subsystems. Although this study used Meteororm 8.0 datasets (Meteotest, 2020), which provide Typical Meteorological Year (TMY)-style synthetic data, they may not fully reflect the frequency or severity of rare weather events. Therefore, future work should incorporate climate projection models such as those from the Coupled Model Intercomparison Project Phase 6 (CMIP6) (Eyring et al., 2016) or downscaled regional forecasts to address extreme weather variability and long-term climate impacts. Incorporating real-world performance data through pilot-scale installations would further calibrate and validate these models, significantly enhancing the practical applicability and reliability of predictions. Future economic assessments should also consider broader lifecycle cost analyses, accounting explicitly for local market conditions, carbon pricing scenarios, and emerging advancements. Finally, developing an AI-driven digital

Table 12
Comparative performance of the proposed system and previous multi-generation systems.

Ref	System Description	Optimization Method	Cost Rate (\$/h)	Exergy Efficiency (%)	CO ₂ Reduction (tons/year)
Current Study	Hybrid solar-wind multi-generation system	Multi-objective (Cost & Exergy Efficiency) using RSM & PSO + AdaBoost	576.76 (RSM) & 211.2 (AI)	45.8 (RSM) & 32.93 (AI)	4616.4
Manesh et al. (2025)	Hybrid solar-biomass-wind ammonia & power production	Multi-objective optimization (energy efficiency, cost, environmental impact) using the dragonfly algorithm	5616	38.53	N/A
Bedakhanian et al. (2025)	Hybrid wind-solar with a flat plate collector & PEME	Multi-objective (Cost Rate & Exergy Efficiency) using Nelder-Mead	25.48	13.35	N/A
Zoghi et al. (2025a)	CAES with solar, biomass, geothermal & wind for hydrogen production	4E (energy, exergy, exergy-economic, and environmental) analysis with design optimization	49.34	28.62	N/A
Zoghi et al. (2025b)	Hydrogen production with renewable-powered PEME	4E (energy, exergy, exergy-economic, and environmental) parametric design optimization	23.37	13.39 (biomass) & 7.53 (geothermal)	N/A
Zuo et al. (2025)	Hybrid solar-wind with SCO ₂ & ORC cycles	Hybrid Machine Learning-based multi-objective optimization	96.2	27.37	N/A
Rong et al. (2024)	Solar-wind integrated cooling, heating & power with hydrogen storage	ANN + NSGA-II	7.969	19.98	N/A
Mobayen et al. (2025)	Hybrid wind-gas turbine system with PEME	Multi-objective (Cost & Exergy Efficiency) using ANN	446.04	36.95	10,416
Li et al. (2024)	Gas turbine system with heat recovery & hydrogen blending	Multi-objective (Cost & Exergy Efficiency) using mathematical modeling	1514	42.73	1896
Sami et al. (2024)	Solar-hydrogen-desalination hybrid	Multi-objective optimization (cost rate, exergy efficiency & net output power) using TOPSIS	6.08	26.3	23.3
Nikitin et al. (2023)	Dynamic multi-generation system with TES & hydrogen storage	Energy simulation based multi-objective (energy, exergy, economic & environmental)	N/A	27.07	20.34
Cai et al. (2022)	PEM fuel cell-based hybrid cogeneration heat & power	Multi-objective (energy, exergy, environment & economy)	N/A	58.04	N/A

twin of the multi-generation system could enable real-time optimization, predictive maintenance, and continuous learning from operational feedback, substantially improving decision-making capabilities and system robustness in diverse environmental and economic contexts.

7. Conclusions

This study tackled the challenge of developing climate-resilient, cost-effective multi-generation energy systems to generate electricity, cooling, hydrogen, and freshwater. While previous research typically examined isolated subsystems or region-specific configurations, this work introduced a fully integrated solar-wind multi-generation system that unifies modified Brayton and Rankine cycles, thermoelectric generation, RO desalination, PEME, and absorption cooling through integrated thermal energy recovery. To address performance trade-offs and support deployment, the system was optimized using a dual-stage approach combining RSM for initial exploration with AdaBoost-enhanced PSO for refined thermoeconomic analysis. This integration, alongside climatic validation across eight global cities, supports a scalable solution to diverse real-world energy demands.

Some of the key findings are as follows:

- **Thermoeconomic Gains:** RSM achieved 45.8 % exergy efficiency at a cost rate of \$576.76/h; AI optimization reduced cost to \$211.2/h with 32.93 % efficiency.
- **Environmental Benefits:** The system cut annual CO₂ emissions by 4616.4 tons.
- **AI Advantage:** The AI-optimized system reduced the cost rate by 63.38 % compared to RSM, confirming PSO's effectiveness as a robust tool for economic optimization where cost is prioritized over maximum efficiency.
- **Climate Adaptability:** Solar input dominated in hot-dry climates, while wind ensured reliability in cold regions.
- **Design Insights:** Compressor and gas turbine efficiencies had the highest impact on system performance.
- **Scalability and Generalizability:** The system is modular and adaptable across global climate zones and load profiles. This integrated AI-driven optimization strategy is also generalizable to other complex engineering systems with nonlinear, multi-objective challenges.

CRedit authorship contribution statement

Ehsanolah Assareh: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Nima Izadyar:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Conceptualization. **Emad Tandis:** Writing – review & editing, Visualization, Supervision, Software, Methodology. **Mehdi Khiadani:** Writing – review & editing, Validation, Formal analysis. **Amir shahavand:** Resources, Investigation, Data curation. **Neha Agarwal:** Software, Formal analysis, Data curation. **Arian Gerami:** Visualization, Investigation, Data curation. **Ahmed Rezk:** Writing – review & editing, Validation, Resources. **Minkyu Kim:** Writing – review & editing, Supervision, Methodology. **Reza Kord:** Software, Investigation, Formal analysis. **Tahereh Pirhoushyaran:** Visualization, Validation, Data curation. **Mehdi Hosseinzadeh:** Validation, Software. **Saleh Mobayen:** Writing – review & editing, Supervision, Conceptualization.

Declaration of generative AI

During the preparation of this work, the authors used an OpenAI tool to enhance language and readability. After using the tool, the authors reviewed and edited the content as needed. They take full responsibility for the final content of the publication. The authors highlight that AI's role was to assist in refining the text and language, and not to replace

any critical tasks of the authors.

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. System Simulation Pseudocode

Appendix A provides pseudocode to show the procedure used to simulate the performance of the hybrid multi-generation system. The model integrates four key subsystems, Brayton cycle, Steam Rankine Cycle (SRC), Reverse Osmosis (RO), and Proton Exchange Membrane Electrolyzer (PEME), to calculate the system's overall cost rate and exergy efficiency. Input parameters are processed through thermodynamic calculations to evaluate energy balances, water and gas outputs, and associated performance metrics. The detailed pseudocode outlines the sequential flow of the simulation process from design input to final performance evaluation.

Input: Design parameters (e.g., number of heliostats, wind turbines, pressures, efficiencies)

Output: Performance metrics (cost rate, exergy efficiency, net outputs)

1. Initialize input variables from the design matrix
2. Simulate thermodynamic subsystems:
 - a. Brayton cycle → power output
 - b. Steam Rankine Cycle (SRC) → power recovery
 - c. Reverse Osmosis (RO) → freshwater output
 - d. Proton Exchange Membrane Electrolyzer (PEME) → hydrogen and oxygen generation
3. Calculate energy and exergy balances
4. Estimate cost rate and exergy efficiency
5. Return system outputs for the given input

Appendix B. Ant Colony Optimization Pseudocode

Appendix B outlines the pseudocode for the Ant Colony Optimization (ACO) algorithm used to optimize the design parameters of the hybrid multi-generation system. The ACO algorithm is a nature-inspired metaheuristic that mimics the foraging behavior of ants to find optimal or near-optimal solutions. In this context, ACO aims to minimize the cost rate and maximize exergy efficiency by iteratively exploring design configurations within defined parameter bounds. The algorithm guides solution construction through probabilistic decision-making based on pheromone trails, updated based on the performance of each solution.

Input: Objective functions (minimum cost rate, maximum exergy efficiency), parameter bounds.

Output: Optimized design parameters.

1. Initialize pheromones on each design variable
2. For each iteration:
 - a. For each ant
 - i. Construct a solution based on pheromone probability
 - ii. Evaluate the solution using system simulation
 - b. Update the best solution if the current is better
 - c. Update pheromones based on performance
3. Return the best-found design and corresponding objective values

Data availability

Data will be made available on request.

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