

Full Length Article

Hydrogen-to-Ammonia Green Fuel Production via Haber–Bosch Process in a Solar–Wind Poly-Generation System: Design, Intelligent Optimization, and 4E Analysis

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ABSTRACT

Hydrogen offers a pathway to deep decarbonization; however, its storage and transport remain significant barriers for large-scale renewable energy systems. This study proposes a novel hybrid solar-wind poly-generation architecture that couples a two-level thermal cascading structure (supercritical CO₂ Brayton and transcritical CO₂ Rankine cycles) with a continuously operated water electrolyzer–Haber–Bosch ammonia loop, enabling stable renewable-to-hydrogen-to-ammonia conversion without auxiliary heating. This framework provides a high-density and safe long-term energy storage solution. A comprehensive 3E analysis, operational CO₂ emission avoidance assessment, and multi-objective optimization were performed using an ANN-based surrogate method coupled with the NSGA-II algorithm. Exergy and economic analyses identified the solar field as the main source of irreversibility and cost, contributing to 48% and 60.1%, respectively. The surrogate-based optimization reduced computational time by 97.63% relative to direct simulation (≈38 hours to 54 minutes) while maintaining accuracy. Under optimized operating conditions (solar field area of 5624.32 m², compressor pressure ratio of 1.93, solar irradiance of 411.29 W/m², wind speed of 7.98 m/s, and regenerator effectiveness of 0.86), the system achieved an exergy efficiency of 35.86%, ammonia production of 1.09 kg/h, and a payback period of 5.07 years under the adopted economic assumptions. The environmental assessment indicates 167.5 kg/h of CO₂ emissions avoided, corresponding to an emission reduction cost of 4.02 \$/h. A Dubai-based case study demonstrated conceptual feasibility under steady-state conditions. The results highlight the system's theoretical potential as an advanced renewable-to-ammonia platform for high-density energy storage and multi-product output, subject to further dynamic validation and detailed engineering.

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Nomenclature		φ	Maintenance factor
Symbols		Subscripts	
A	Area (m^2)	1,2, ...	State points
$C_{P,wt}$	Power coefficient of wind turbine	a	Anode
e_{CO_2}	Natural gas emission factor (kg/kWh)	act	Actual
ERC_{CO_2}	Emission reduction cost ($\$/h$)	c	Cathode
$\dot{E}x$	Exergy rate (kW)	ch	Chemical
ex	Specific exergy (kJ/kg)	$comp$	Compressor
F	Faraday constant (C/mol)	$cond$	Condenser
G	Solar radiation (W/m^2)	e	Exit
h	Specific enthalpy (kJ/kg)	fw	Freshwater
J	Current density (A/m^2)	HX	Heat exchanger
k	Thermal conductivity (kW/m)	i	Inlet
$\dot{m}$	Mass flow rate (kg/s)	is	Isentropic
P	Pressure (kPa)	ohm	Ohmic
$\dot{Q}$	Heat transfer rate (kW)	ph	Physical
R	Gas constant ($kJ/kg.K$)	PT	Pelton turbine
s	Specific entropy ($kJ/kg.K$)	Reg	Regenerator
T	Temperature ($^{\circ}C$)	tur	Turbine
U	Heat transfer coefficient ($kW/m^2.K$)	wt	Wind turbine
V_w	Average wind speed (m/s)	Abbreviations	
$\dot{W}$	Power rate (kW)	ANN	Artificial neural network
$\dot{Z}$	Cost rate ($\$/h$)	CRF	Capital recovery factor
ΔG	Change in Gibbs free energy (kJ)	HBR	Haber–Bosch reactor
Greek Symbols		NPV	Net present value
ε	Effectiveness	NSGA –II	Non-dominated sorting genetic algorithm II
η	Efficiency	PEME	Proton exchange membrane electrolyzer
ρ	Density	PP	Payback period
λ	Water content	PTCS	Parabolic through solar collector
σ	Spatially resolved ionic conductivity	RO	Reverse osmosis
σ_s	Constant of Stefan and Boltzmann	SCO ₂	Supercritical CO ₂
		TCO ₂	Transcritical CO ₂

1. Introduction

1.1. Preface and background

The global energy sector faces major challenges due to rising energy demand driven by population growth and industrialization [1,2]. Simultaneously, dependence on finite fossil fuel reserves is increasingly unsustainable, while fossil fuel combustion significantly contributes to greenhouse gas emissions, climate change, and environmental degradation [3,4]. Addressing global energy challenges requires a fundamental transition from fossil fuel-based energy generation to renewable sources that offer sustainable availability, reduced environmental impact, and long-term viability [5,6]. Among renewable technologies, solar power stands out due to its vast potential, worldwide accessibility, and scalability across applications ranging from residential systems to utility-scale power plants [7]. Solar installations generally require minimal maintenance, have low operating costs, and produce no direct greenhouse gas emissions, making them a key contributor to global decarbonization efforts [8]. However, solar energy production is intermittent, as it ceases at night and decreases during cloudy conditions. A practical solution to this limitation is hybridization with complementary renewables, such as wind energy, which often generates power during periods of low solar output [9,10]. This combination improves supply stability, increases capacity factors, and supports reliable, sustainable electricity generation [11,12].

Renewable-based poly-generation systems offer an effective solution for meeting diverse energy demands by simultaneously producing electricity, heating, cooling, fuels, and freshwater within a single

integrated framework [13–15]. By cascading energy utilization and recovering waste heat across multiple temperature levels, these systems significantly enhance overall energy and exergy efficiencies [16]. Such integration reduces fuel consumption, emissions, and operating costs while improving flexibility and resilience, making poly-generation a promising pathway for sustainable and high-efficiency energy systems [17].

1.2. Literature review

Recent studies on renewable-based poly-generation systems highlight their promising role in delivering multiple energy products sustainably. Manesh et al. [18] proposed a solar/wind based cogeneration system integrating microbial desalination cell, humidification–dehumidification (HDH), and reverse osmosis (RO) units to simultaneously produce electricity, freshwater, and facilitate wastewater treatment. A hydrogen-fueled internal combustion engine provided backup heat and power, with waste heat recovered via an organic Rankine cycle. Optimization improved energy efficiency and reduced costs. Ismail et al. [19] proposed a hybrid system integrating an organic Rankine cycle (ORC), refrigeration cycle, concentrating solar tower, multi-effect desalination (MED), HDH, and a proton exchange membrane electrolyzer (PEME), simultaneously generating electricity, hydrogen, cooling, and potable water. Through a data-driven optimization and dynamic simulation in San Diego, the system demonstrated high output efficiency, with a reduced payback period of 5.07 years. Wen et al. [20] studied a power-to-hydrogen system integrated with an MED desalination in a multi-generation framework. Their proposed

Table 1

Overview of recent studies on renewable-driven cogeneration systems for hydrogen production and storage.

Ref.	Energy source	Hydrogen production	Hydrogen storage	Productions	Analysis	Optimization procedure
[41]	Geothermal	PEME	Liquid hydrogen	Power, cooling, hydrogen	Energy, exergy, economic	ANN- NSGA-II
[80]	Solar - wind	PEME	Compressed hydrogen gas	Power, hydrogen	Energy, exergy, economic	NSGA-II
[81]	Biomass	PEME	Liquid hydrogen	Power, heating, hydrogen	Energy, exergy, economic, environmental	ANN - grey wolf optimizer
[82]	Solar - wind	PEME	Compressed hydrogen gas	Power, fresh water, hydrogen	Energy, exergy, economic	NSGA-II
[44]	Solar	PEME	Compressed hydrogen gas	Power, fresh water, hydrogen	Energy, exergy, economic	ANN - NSGA-II
[75]	Solar - wind	PEME	Liquid ammonia	Power, cooling, fresh water, hydrogen, ammonia	Energy, exergy,	ANN - NSGA-II
[83]	Biomass - geothermal	PEME	Liquid ammonia	Power, hydrogen, ammonia	Energy, exergy, economic, environmental	ANN - grey wolf optimizer
[84]	Solar	PEME	Liquid ammonia	Power, hydrogen, ammonia	Energy, exergy, economic	-
[85]	Solar - wind	Alkaline electrolyzer	Compressed hydrogen gas	Power, cooling, heating, hydrogen, oxygen, and carbon dioxide	Energy, exergy	-
[86]	Geothermal	PEME	Liquid ammonia	Ammonia, electricity, hot and cold water, oxygen	Energy, exergy, environmental, and economic	-
[87]	Geothermal	PEME	Compressed hydrogen gas	Power, hydrogen, oxygen, cooling	Energy, exergy, economic	NSGA-II
Present study	Solar-wind	PEME	Liquid ammonia	Power, cooling, heating, fresh water, ammonia	Energy, exergy, economic, environmental	ANN- NSGA-II

system utilized hydrogen as an energy carrier within a water-hydrogen nexus, enabling standalone net-zero operation for electricity, potable water, and hydrogen production, while improving efficiency (38.9%) and reducing curtailment through optimal seasonal configuration and dynamic analysis. Wang et al. [16] developed a solar-powered system combining PV/thermal units, absorption refrigeration, PEME, and pumped thermal electricity storage. According to the results, they achieve energy efficiencies of 85.90–88.26% and product costs of 22.21–24.25 USD/GJ. De Rosa and Aliehyaei [21] analyzed a poly-generation system with parabolic trough solar collectors (PTSCs) integrated with thermal energy storage. They reported energy and exergy efficiencies of 12.2% and 4.3%, with PEME as the most efficient subsystem. Alghorayshi et al. [11] developed a hybrid solar-wind multi-generation system using a supercritical CO₂ Brayton cycle, desalination unit, ARC, solar tower with storage, and wind turbines to produce electricity, freshwater, and cooling. The system achieved 57 % energy and 50.1 % exergy efficiency with a 4.2-year payback, demonstrating high performance and sustainability. Therefore, previous research indicates that incorporating waste heat recovery in renewable-based poly-generation systems improves overall performance, enabling the concurrent generation of multiple outputs while supporting sustainable operation and minimizing environmental impacts.

Hydrogen is widely regarded as a clean and versatile energy carrier with strong potential for carbon-free power generation, industrial applications, and large-scale energy storage. In renewable-based poly-generation systems, hydrogen is commonly employed to utilize surplus renewable electricity and enhance operational flexibility. Nevertheless, its widespread deployment is hindered by storage and transportation challenges, primarily arising from its low volumetric energy density [22]. To overcome these limitations, several hydrogen storage strategies have been proposed, with hydrogen carriers receiving increasing attention [23]. Among them, ammonia, produced via the mature Haber–Bosch process, is identified as an effective hydrogen vector due to its high energy density, established infrastructure, and ease of handling, with recent studies focusing on renewable-driven synthesis. Santhappan et al. [24] investigated decentralized green ammonia production by integrating biogas-based power with solar and wind electricity to supply a fully electrified Haber–Bosch reactor (HBR) process, achieving a levelized cost of ammonia of about 740 \$/ton. Their techno-economic analysis showed that biopower mitigates renewable intermittency, and improves overall economic performance compared with solar/wind systems. Campion et al. [25] analyzed off-grid green ammonia synthesis

via a flexible Haber–Bosch loop powered by hybrid renewable systems including the concentrated solar power system. They reported a minimum levelized cost of ammonia of 646 €/t, showing solar cycle becomes dominant with 80% cost reduction, particularly when hydrogen storage or full process flexibility is constrained.

In parallel, emerging CO₂ utilization pathways, including catalytic hydrogenation, photocatalytic reduction, and electrocatalytic processes, have gained attention for converting CO₂ into value-added products such as CO, CH₄, and methanol [26,27]. Their performance depends strongly on catalyst characteristics and operating conditions [28]. However, large-scale integration into energy systems remains limited due to challenges involving efficiency, stability, scalability, and operational uncertainties associated with renewable-based systems [29,30]. Although these technologies show promising environmental and material-level advancements, ammonia synthesis via the Haber–Bosch process continues to be the most mature, reliable, and scalable approach for hydrogen utilization in integrated systems [31].

The supercritical CO₂ (SCO₂) and transcritical CO₂ (TCO₂) cycles have gained considerable attention in recent research owing to their compact design, superior heat transfer properties, and higher cycle efficiency compared to conventional steam-based systems [32,33]. These cycles operate effectively at elevated temperatures and pressures, rendering them highly compatible with renewable thermal sources such as geothermal energy and concentrated solar power systems [34]. Alghorayshi et al. [11] developed a multi-generation system using an SCO₂, desalination unit, absorption chiller, solar tower with storage tank, and wind turbines to produce electricity, freshwater, and cooling. The system achieved 57 % energy and 50.1 % exergy efficiency with a 4.2-year payback, demonstrating high performance and sustainability. Xie and Zheng [35] examined a poly-generation system integrating a cascading TCO₂ cycle with LNG utilization. The optimized design achieved 16.99% exergy efficiency and 0.616-year payback, while delivering outputs of 436 kW of electricity, 251.4 kW of cooling, 3.7 kg/h of H₂, and 0.05 kg/s of potable water.

Enhancing system performance requires optimization to determine the best input configurations [36]. Multi-objective methods, such as non-dominated sorting genetic algorithm II (NSGA-II), efficiently handle competing goals but are computationally intensive [37]. To reduce simulation time, surrogate models and machine learning integration offer fast, accurate approximations of system behavior [38–40]. This methodology has been successfully applied in several studies. For instance, Mehrenjani et al. [41] optimized a geothermal-based

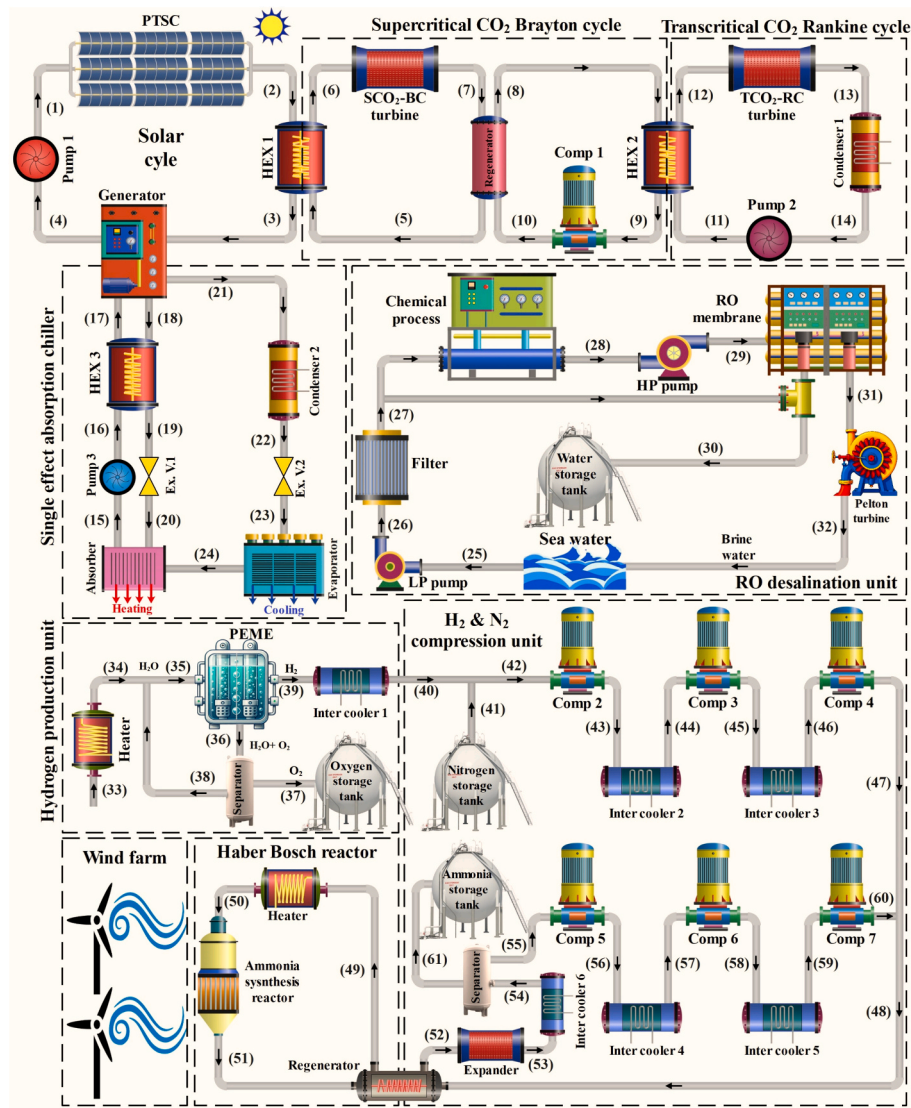


Fig. 1. System configuration of hybrid solar-wind poly-generation system.

cogeneration system for liquefied hydrogen generation using an artificial neural networks (ANN)-assisted NSGA-II framework. This strategy reduced the computational time from 14 hours to 10 minutes. Similarly, Lotfollahi et al. [42] combined ANNs with NSGA-II for multi-criteria optimization of a biomass-based multi-generation system. The study yielded a substantial reduction in optimization time from 32 hours using the developed-MATLAB code to under 5 minutes utilizing the ANN-based optimization.

1.3. Research gap and novelty

Despite the growing interest in renewable-based cogeneration systems for hydrogen production, several critical gaps remain in the existing literature. Most solar-driven hydrogen systems suffer from pronounced intermittency and are often evaluated in isolation, without effective hybridization strategies to ensure continuous operation. Although wind-solar hybrid systems have been proposed, their integration with advanced waste heat recovery technologies and hydrogen valorization pathways remains limited. In particular, the majority of existing studies focus solely on hydrogen production, while overlooking the fundamental challenges associated with hydrogen storage, transportation, and long-term utilization. Moreover, the potential of hydrogen-derived energy carriers, such as ammonia, is rarely explored

within fully integrated poly-generation frameworks. From a systems perspective, insufficient attention has been given to multi-level thermal cascading using high-efficiency CO₂ power cycles, such as SCO₂ and TCO₂ cycles.

This study proposes a novel solar-wind driven poly-generation system integrating hydrogen and ammonia production. A comparative review of recent renewable-based cogeneration systems for hydrogen production and storage is presented in Table 1. The key scientific and technical contributions are summarized as follows:

- o **Integrated hydrogen-ammonia energy pathway:** Unlike most existing studies focusing solely on hydrogen, this work incorporates ammonia synthesis via a Haber-Bosch reactor as a practical hydrogen carrier, enabling high-density, long-term energy storage and improved system flexibility.
- o **Advanced multi-level thermal cascading:** The system uniquely integrates cascaded SCO₂ and TCO₂ power cycles, maximizing waste heat recovery and significantly enhancing overall exergy efficiency compared with single-cycle configurations.
- o **Comprehensive poly-generation framework:** Electricity, cooling, freshwater, hydrogen, and ammonia are simultaneously produced within a unified renewable-driven architecture, improving resource utilization and economic viability.

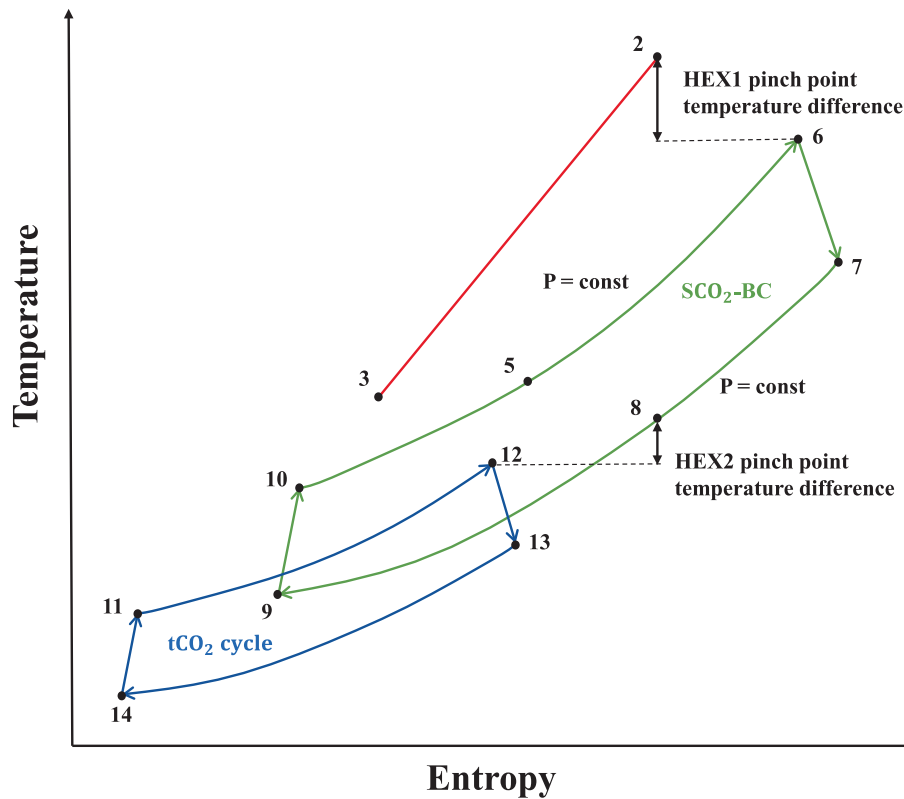


Fig. 2. Qualitative T-S diagram for integrated units.

- o **Hybrid renewable integration to mitigate intermittency:** Solar and wind energy sources are synergistically combined to stabilize power supply and support continuous operation of energy-intensive processes such as electrolysis and ammonia synthesis.
- o **Machine-learning-assisted multi-objective optimization:** A deep-learning-based ANN-NSGA-II framework is developed to optimize thermodynamic and economic objectives with high accuracy and reduced computational effort.
- o **Holistic performance assessment:** The proposed system is evaluated through detailed energy, exergy, economic, and operational environmental analyses, providing a comprehensive assessment of feasibility and sustainability.
- o **Case-study validation for real-world applicability:** To demonstrate the feasibility and practical applicability of the proposed configuration, a comprehensive case study is conducted for Dubai, United Arab Emirates, reflecting realistic climatic and resource conditions.

2. System description

The proposed hybrid poly-generation system (illustrated in Fig. 1) simultaneously produces five high-value products: electricity, freshwater, cooling, heating, and ammonia as a green fuel. It integrates PTSC, a wind farm, SCO_2 and TCO_2 cycles, an ARC, an RO desalination, a PEME unit, and an HBR unit for ammonia synthesis. This configuration enables cascaded renewable energy utilization across multiple temperature levels, maximizing exergy recovery, operational reliability, and overall sustainability.

Thermal energy is harvested via a PTSC field, chosen for its high optical efficiency and outlet temperatures above 600 K, enabling advanced power cycles. Synthetic heat transfer fluid (Therminol VP1) circulates through the loop, reaching about 600 K, and supplies high-grade heat to a SCO_2 cycle via heat exchanger 1 (HEX1). The SCO_2 cycle drives a turbine for electricity generation; its exhaust heat is

cascaded into a TCO_2 cycle for additional power, enhancing exergy utilization. Then, partially cooled Therminol VP1 powers an absorption refrigeration cycle, producing cooling without extra electrical input, broadening applicability in building and industrial refrigeration.

To address the inherent intermittency of solar energy and ensure stable power availability, a wind farm is incorporated into the system. Due to the natural variability and daily limitations of solar radiation, the wind farm is coupled with the solar system to support system operation during periods of low solar irradiance and nighttime hours, thereby ensuring a stable electricity supply for critical electricity-driven subsystems such as the PEME, Haber-Bosch cycle, and the reverse osmosis desalination unit. Wind energy complements solar generation, particularly during nighttime and low-irradiance periods, thereby improving system flexibility and ensuring continuous operation of electricity-dependent subsystems. Furthermore, 30% of the electrical power generated by the SCO_2 cycle and the wind farm is utilized to supply the reverse osmosis desalination unit (points 25–32), which produces freshwater. RO technology is selected due to its commercial maturity, relatively low specific energy consumption, and proven compatibility with renewable energy-driven systems.

Green hydrogen production is achieved using a PEME (points 33–39), which is chosen for its high efficiency, modular design, rapid response to fluctuating power inputs, and suitability for intermittent renewable electricity. The total electrical output of the TCO_2 cycle is directly allocated to the PEME for hydrogen production. The hydrogen produced by the PEME is mixed with nitrogen, and the resulting hydrogen-nitrogen mixture is compressed through a dedicated multi-stage compression train. The high-pressure synthesis gas is then fed into the Haber-Bosch reactor, where ammonia is produced via catalytic synthesis. The high-pressure ammonia stream subsequently expands through an Expander to generate additional electricity, further improving the system's energy efficiency. Finally, ammonia is separated from unreacted hydrogen and nitrogen in a separation unit, while the unreacted gases are recycled through the compression system and mixed

Table 2

Parameters for system formulation [88–92].

Parameter	Value	Parameter	Value
T_0 , (K)	298.15	RO desalination	
P_0 , (bar)	1.013	Pumps and turbine efficiency (%)	85
PTSC		Salinity of product water, (ppm)	450
Single collector length, (m)	12.27	Seawater salinity, (ppm)	35000
Single collector width, (m)	5.76	Membrane recovery ratio,	0.55
Pressure drops in collector, (%)	5	TCO₂ cycle	
Solar intensity, (W/m^2)	500	Pump inlet pressure, (bar)	50.9
Heat loss coefficient in PTSCs, ($W/m^2 \cdot ^\circ C$)	3.82	Pump inlet temperature, ($^\circ C$)	15
Solar collector area, (m^2)	12000	Pinch point temperature of HEX2, ($^\circ C$)	10
Wind farm		Turbine isentropic efficiency	0.85
Efficiency of the turbine, (-)	0.9	Pressure ratio, (-)	3
Average wind speed, (m/s)	4	PEME	
Diameter of the turbine, (m)	44	Operating temperature, (K)	353.15
Power coefficient, (-)	0.55	P_{PEM} (bar)	1.013
SCO₂ cycle		Activation energy for anode, (kJ/mol)	76
Pressure ratio, (-)	3	Faraday constant, (-)	96485
Compressor1 inlet temperature, (K)	305.15	Pre-exponential factor for anode, (A/m^2)	1.7×10^5
Turbine isentropic efficiency (%)	90	Anode water content, (-)	10
Compressor isentropic efficiency (%)	86	Cathode water content, (-)	14
Regenerator effectiveness, (-)	0.8	Pre-exponential factor for cathode, (A/m^2)	4.6×10^3
Compressor1 inlet pressure, (bar)	75	Membrane thickness, (μm)	100
Pinch point temperature of HEX1, ($^\circ C$)	10	Activation energy for cathode (kJ/mol)	18
ARC unit		HBR unit	
Operating temperature of evaporator, ($^\circ C$)	5	Compressor pressure ratio, (-)	5.3
Generator operating temperature, ($^\circ C$)	90	Regenerator effectiveness, (-)	0.9
Condenser2 operating temperature, ($^\circ C$)	35	Feed composition (H_2/N_2 ratio), (-)	3
Absorber operating temperature, ($^\circ C$)	35	Reactor operating pressure, (bar)	150
HEX3 effectiveness, (-)	0.72	Reactor inlet temperature, ($^\circ C$)	450

Table 3

Decision variables for optimization and ANN hyperparameters.

Parameter	Range
Solar radiation (W/m^2)	$300 < G < 900$
Solar collectors' area (m^2)	$5000 < A_{ap} < 15000$
Effectiveness of the SCO ₂ -BC regenerator (-)	$0.7 < \varepsilon_{Reg} < 0.9$
Pressure ratio of SCO ₂ compressor (-)	$1.5 < PR_{SCO_2 comp} < 5$
Wind speed (m/s)	$1 < V_{wind} < 8$

Table 4

ANN hyperparameters and strategy used for training the model.

Parameter	Values	Strategy
Total data	1000	-
Training data	70%	-
Test data	15%	-
Validation data	15%	-
Data sampling method	-	Random generation
Training model	-	Feed forward back propagation
Training function	-	Levenberg-Marquardt back propagation

Table 5

Parameters used in NSGA-II optimization method.

Parameter	Method/Value
Number of variables	5
Maximum generation	100
Crossover fraction	0.8
Mutation fraction	0.1
Population size	200
Selection method	Tournament
Function	1e-4

with the fresh feed, thereby enhancing reactant utilization and reducing overall compression energy demand. The qualitative temperature-entropy (T-S) diagram for the proposed configuration is presented in Fig. 2 to improve the understanding of the system's performance.

3. System mathematical modeling

The thermodynamic system is modeled using an in-house MATLAB code integrated with the CoolProp library to accurately evaluate temperature- and pressure-dependent properties, while sequential subsystem calculations enforce energy, mass, and exergy balances through a modular framework that enables flexible modifications and comprehensive parametric analyses. Baseline operational parameters are provided in Table 2.

Standard thermodynamic assumptions are adopted to enable a tractable and accurate evaluation of the proposed system, including steady-state operation, negligible pressure drops, heat losses, and kinetic and potential energy variations, as well as perfectly insulated boundaries. Since detailed physical design parameters are unavailable at this stage, arbitrary assumptions are avoided to reduce uncertainty. The model nevertheless captures major irreversibility sources through realistic turbomachinery isentropic efficiencies and heat exchanger pinch point constraints. Although these common simplifications may slightly overestimate actual performance, the results provide a reasonable representation of the system's upper-bound performance under idealized operating conditions.

3.1. Mass, energy and exergy balances

The proposed poly-generation system is thermodynamically analyzed in MATLAB using first and second law principles under steady-state mass and energy conservation conditions [43]. The general formulation for the mass balance within a control volume is given as [44]:

$$(1) \sum_i \dot{m}_i - \sum_e \dot{m}_e = \frac{dm_{CV}}{dt}$$

The corresponding energy balance, which accounts for heat transfer, work interactions, and enthalpy variations of the working fluids, is given by [44]:

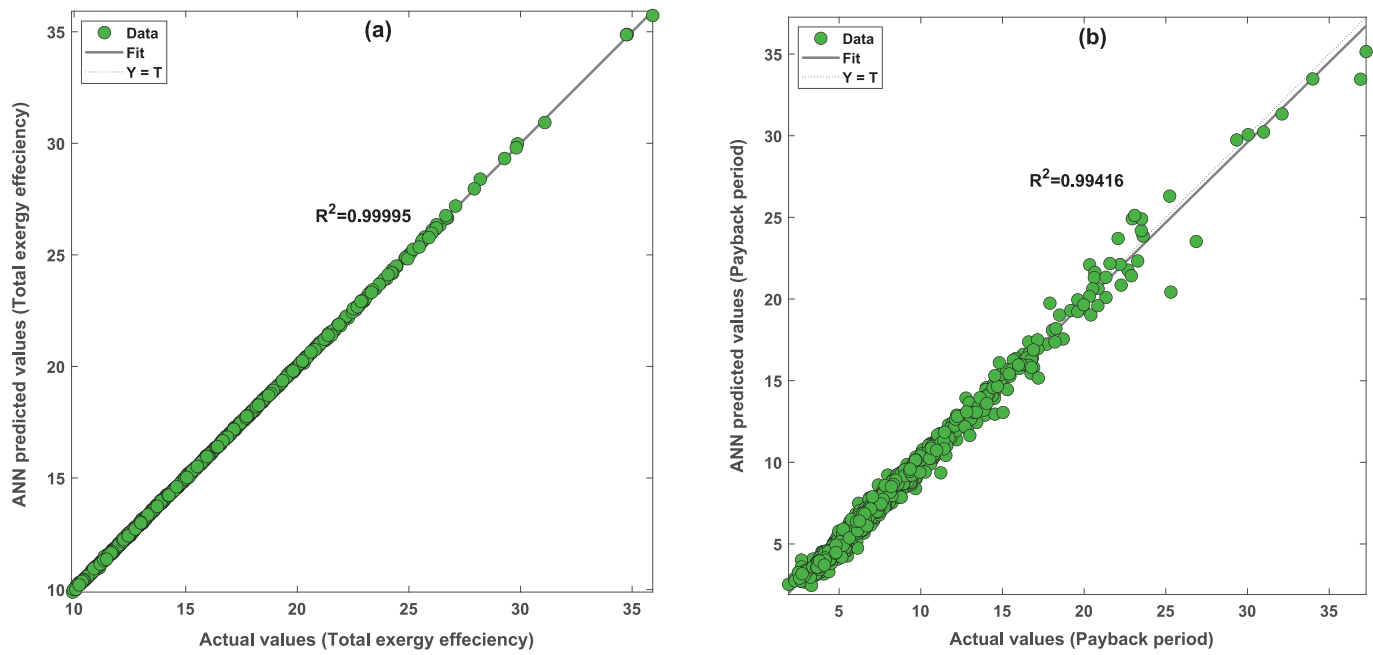
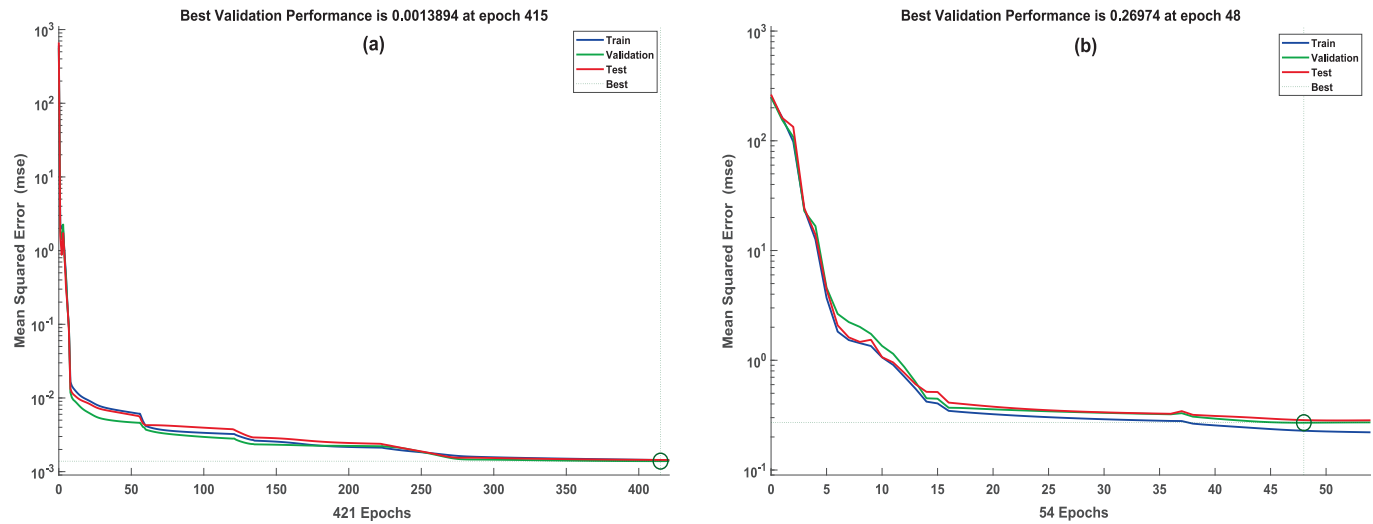
$$(2) \dot{Q} - \dot{W} + \sum_i \dot{m}_i \left(h_i + \frac{V_i^2}{2} + gz_i \right) - \sum_e \dot{m}_e \left(h_e + \frac{V_e^2}{2} + gz_e \right) = \frac{dE_{CV}}{dt}$$

Exergy analysis is conducted to quantify the maximum useful work potential of energy streams and to identify sources of irreversibility within each subsystem. The exergy balance is expressed as [44]:

$$(3) \dot{E}x_Q + \sum_i \dot{m}_i ex_i = \dot{E}x_W + \sum_e \dot{m}_e ex_e + \dot{E}x_D$$

$$(4) \dot{E}x_Q = \left(1 - \frac{T_0}{T} \right) \dot{Q}$$

$$(5) \dot{E}x_W = \dot{W}$$

Fig. 3. ANN validation using R^2 -score evaluation metric.Fig. 4. MSE error metric of ANN for the objective functions: a) $\eta_{ex,tot}$, b) payback period.

The overall exergy of a fluid stream comprises physical and chemical exergy. The physical exergy is determined by:

$$(6) \quad ex_{ph} = h - h_0 - T_0(s - s_0)$$

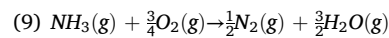
where, h and s are the stream's enthalpy and entropy, and h_0 , s_0 , and T_0 represent the properties at the reference (dead) state. Chemical exergy, relevant for species such as hydrogen, is evaluated as:

$$(7) \quad ex_{ch} = \sum x_k ex_{ch,k}^0 + RT_0 \sum x_k \ln(x_k)$$

Finally, the overall exergy efficiency of the integrated poly-generation system is expressed as:

$$(8) \quad \eta_{ex,tot} = \frac{\dot{W}_{grid} + \dot{E}x_{Ammonia} + \dot{E}x_{fw} + \dot{E}x_{cooling} + \dot{E}x_{heating}}{\dot{E}x_{wt} + \dot{E}x_{solar}}$$

In this study, overall exergy efficiency is defined as the ratio of useful exergy outputs (including electricity, cooling, heating, freshwater, and ammonia) to renewable input exergy from solar radiation and wind energy, ensuring consistent evaluation and comparability with existing renewable multi-generation systems. The chemical exergy of ammonia is calculated assuming its utilization as a carbon-free fuel in direct combustion or ammonia fuel cells, based on the reference reaction of complete oxidation to nitrogen and water vapor.



The standard chemical exergy of NH_3 is calculated using the formula:

$$(10) \quad \bar{e}_{NH_3}^{ch,0} = \Delta_f G_{NH_3}^0 + \frac{3}{4}\bar{e}_{O_2}^{ch,0} - \frac{1}{2}\bar{e}_{N_2}^{ch,0} - \frac{3}{2}\bar{e}_{H_2O}^{ch,0}$$

• Parabolic through solar collectors (PTSCs)

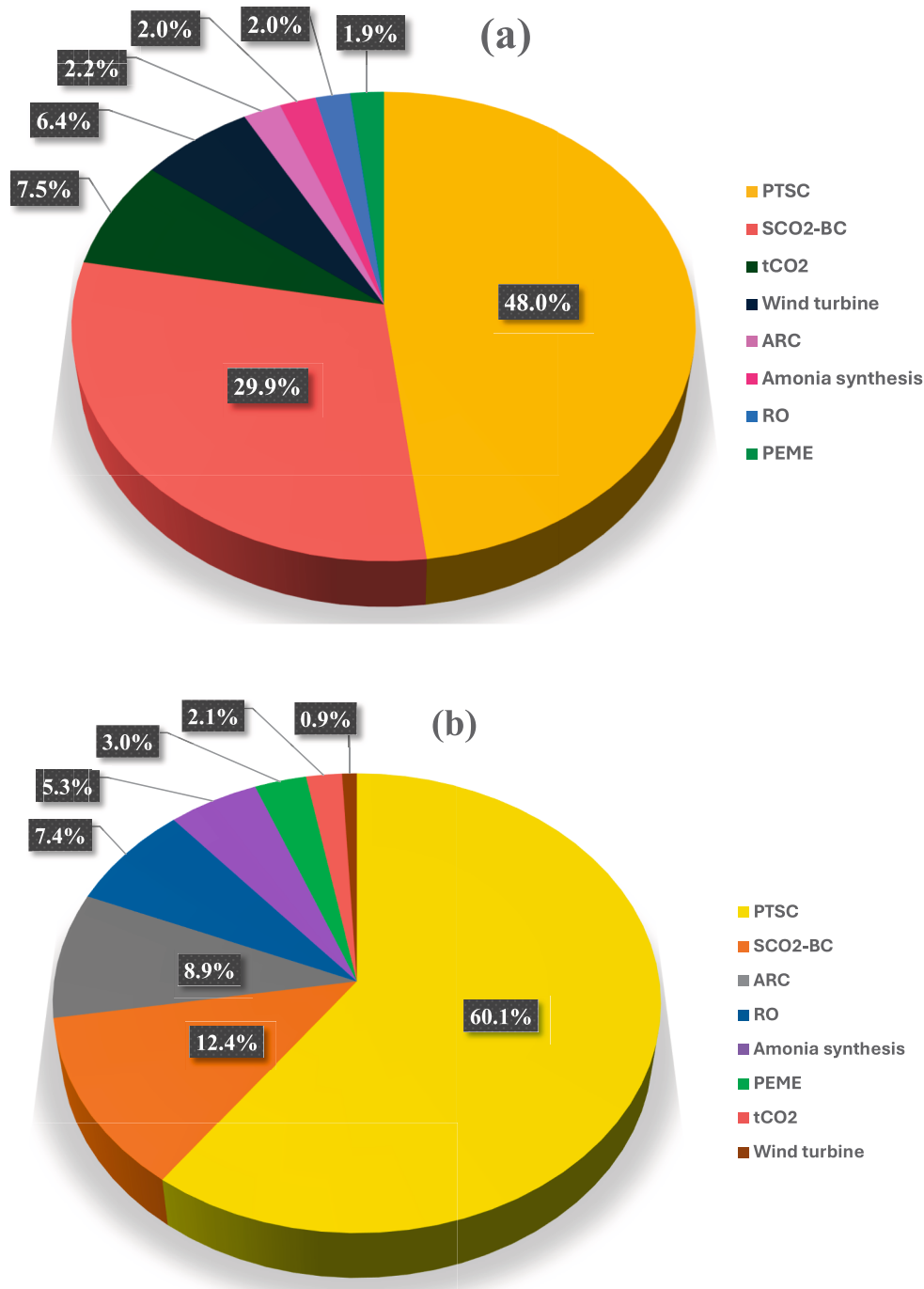


Fig. 5. Breakdown of (a) exergy destruction and (b) subsystem cost rates.

PTSCs are mature concentrating solar technologies that use curved mirrors to heat transfer fluids, such as Therminol VP1 or molten salts, to 600–650 K [45]. Their high thermal output supports advanced cycles including SCO₂ Brayton and TCO₂ Rankine systems. Owing to their modularity, scalability, and low thermal losses, PTSCs integrate effectively into multi-generation systems while supporting thermal energy storage, reducing fossil fuel dependence, and advancing net-zero emission objectives. The governing equations for PTSC modeling are summarized in Table S1 [46,47].

• Wind turbine

A wind turbine transforms the kinetic energy of moving air into

electrical energy, and its output, denoted as $\dot{W}_{wt}$, can be estimated using the wind speed and turbine characteristics. The generated power is calculated as [48–52]:

$$(11) \quad \dot{W}_{wt} = \frac{1}{2} \eta_{wt} \rho_{air} A_{wt} C_{p,wt} (V_{wind})^3$$

Here, η_{wt} is the turbine efficiency, ρ_{air} is air density, A_{wt} is the rotor swept area, $C_{p,wt}$ is the power coefficient, and V_{wind} is the wind velocity. This formulation accounts for both aerodynamic and conversion-related losses in the energy transformation process. The input energy to the wind turbine ($\dot{W}_{wt,i}$) is defined in this study as the effective extractable wind energy, which represents the portion of the wind's kinetic energy

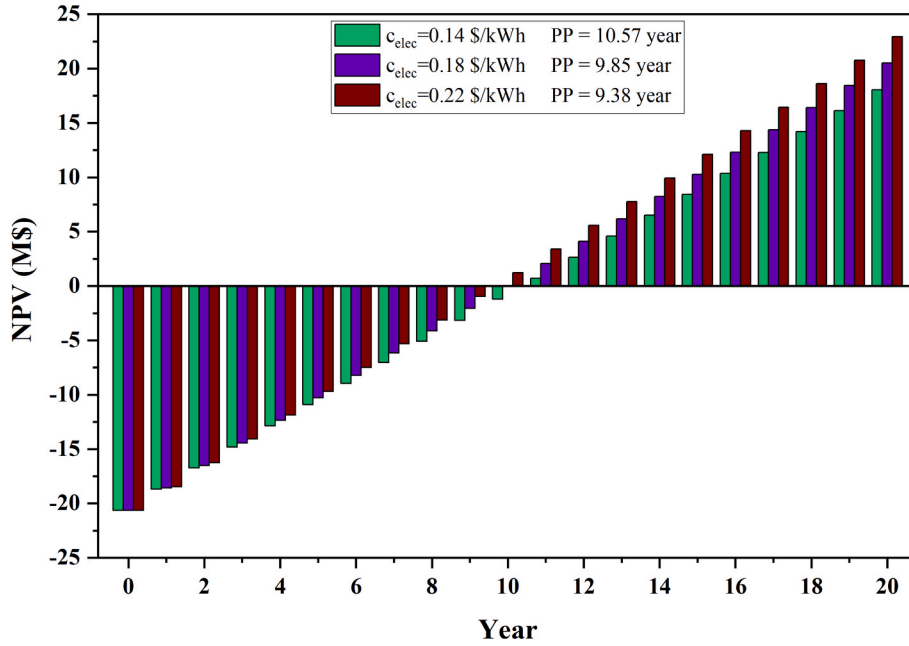


Fig. 6. NPV estimation at various electricity selling prices.

that can be theoretically captured by the turbine. Accordingly, it is given by [48–52]:

$$(12) \dot{W}_{wt,i} = \frac{1}{2} \rho_{air} A_{wt} C_{P,wt} (V_{wind})^3$$

It should be noted that this formulation represents a system-level modeling approximation widely used in literature, where only the extractable portion of wind energy is considered in the energy balance.

From an exergy perspective, the useful exergy of the wind, $\dot{E}x_{wt}$, is directly proportional to the wind's kinetic energy [48–53]:

$$(13) \dot{E}x_{wt} = \frac{1}{2} \rho_{air} A_{wt} (V_{wind})^3$$

Exergy destruction due to inefficiencies in energy conversion is given by [48–53]:

$$(14) \dot{E}x_{D,wt} = \left(\frac{1}{C_{P,wt}} - 1 \right) \dot{W}_{wt}$$

• SCO₂ Brayton cycle

The SCO₂ Brayton cycle is a high-efficiency power generation cycle that operates with carbon dioxide above its critical point, typically at approximately pressure of 7.38 MPa and temperature of 31.1 °C. The cycle compresses CO₂ in the compressor, heats it using high-temperature heat sources such as parabolic through solar collectors, and expands it through a turbine to produce electricity. The work of the compressor and turbine can be expressed as follows [54]:

$$(15) \dot{W}_{SCO_2,comp} = \dot{m}_{CO_2} \times (h_{10} - h_9)$$

$$(16) \dot{W}_{SCO_2,tur} = \dot{m}_{CO_2} \times (h_6 - h_7)$$

$$(17) \dot{W}_{net,SCO_2} = \dot{W}_{SCO_2,tur} - \dot{W}_{SCO_2,comp}$$

A regenerator is utilized to recover turbine exhaust heat and improve cycle efficiency, with its performance assessed using the effectiveness–NTU approach to determine outlet temperatures and optimize thermal energy recovery [54]:

$$(18) \varepsilon = \frac{\dot{Q}_{act}}{\dot{Q}_{max}}$$

here, $\dot{Q}_{act}$ represents the actual heat transfer rate occurring in the regenerator, while $\dot{Q}_{max}$ defines the maximum theoretical heat transfer achievable.

• Transcritical CO₂ Rankine cycle

The TCO₂ Rankine cycle operates in both supercritical and subcritical regions, enhancing thermal efficiency for moderate heat-source applications. Benefiting from CO₂'s high density and low viscosity, the cycle enables compact equipment design and reduced pumping work compared to conventional ORCs. The turbine output power can be expressed as: [33]

$$(19) \dot{W}_{TCO_2,tur} = \dot{m}_{CO_2} (h_{12} - h_{13})$$

The pump work is calculated by:

$$(20) \dot{W}_{TCO_2,pump} = \dot{m}_{CO_2} (h_{14} - h_{11})$$

The net power output is:

$$(21) \dot{W}_{net,TCO_2} = \dot{W}_{TCO_2,tur} - \dot{W}_{TCO_2,pump}$$

• Absorption refrigeration cycle

A single-effect LiBr–H₂O absorption refrigeration cycle is commonly employed for cooling and air-conditioning, particularly when powered by low-grade thermal sources such as solar heat or industrial waste heat. In this system, water serves as the refrigerant and lithium bromide as the absorbent. The cycle proceeds through four main stages: evaporation (producing cooling via low-pressure vaporization), absorption (vapor absorption by concentrated LiBr solution with heat rejection), generation (thermal separation of refrigerant vapor to reconcentrate the absorbent), and condensation (vapor liquefaction and return to the evaporator via an expansion valve) [55]. The performance of the system is quantified by the coefficient of performance (COP), which for a single-effect cycle is given as [55]:

$$(22) COP = \frac{\dot{Q}_{evap}}{\dot{Q}_{gen} + \dot{W}_p}$$

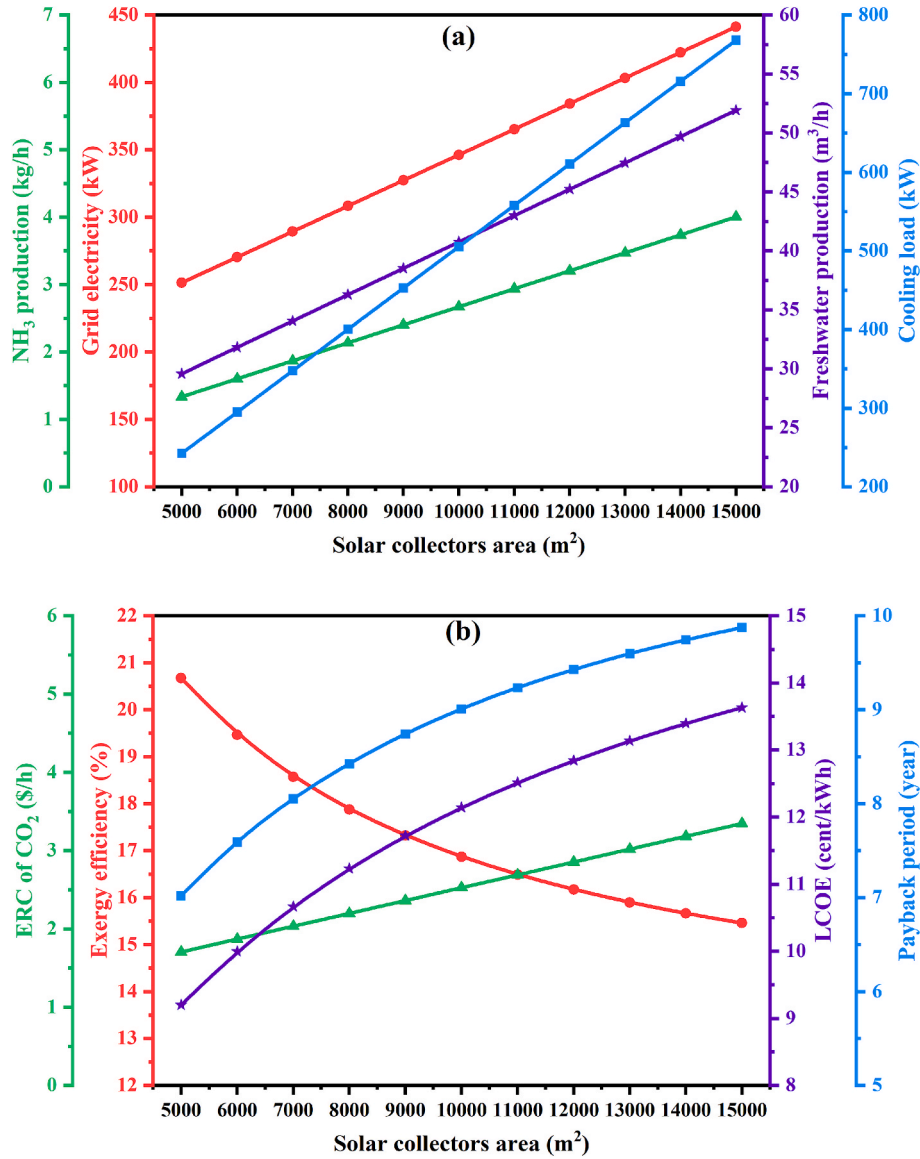


Fig. 7. Impact of varying the solar collector's area on system output.

where, $\dot{Q}_{evap}$ is the cooling capacity, $\dot{Q}_{gen}$ is the heat input to the generator, and $\dot{W}_p$ is the pump work. The overall mass and energy balance across the generator and absorber can be written as:

$$(23) \dot{m}_{sol,i}h_{sol,i} + \dot{Q}_{gen} = \dot{m}_{sol,e}h_{sol,e} + \dot{m}_{ref}h_{ref}$$

$$(24) \dot{m}_{ref}h_{ref} + \dot{m}_{sol,i}h_{sol,i} = \dot{m}_{sol,e}h_{sol,e} + \dot{Q}_{abs}$$

where, $\dot{m}$ and h denote the mass flow rate and enthalpy of refrigerant/solution streams, respectively.

• Reverse osmosis desalination unit

Reverse osmosis desalination is a membrane-driven separation technique used to extract dissolved salts and contaminants from seawater. This process involves applying a pressure exceeding the natural osmotic pressure, enabling water molecules to pass through a semi-permeable membrane while effectively retaining the majority of salts and impurities in the concentrated brine stream. The feed seawater mass flow rate ($\dot{m}_f$) is related to the product water mass flow rate ($\dot{m}_p$) and the recovery ratio (R_r) as [46,56]:

$$(25) \dot{m}_f = \dot{m}_p / R_r$$

The brine mass flow rate ($\dot{m}_b$) is determined from the difference between the feed and product streams [46,56]:

$$(26) \dot{m}_b = \dot{m}_f - \dot{m}_p$$

The mass fraction of salt in the brine ($y_{s,b}$) can be expressed as [46,56]:

$$(27) y_{s,b} = \frac{y_{s,f} - R_r y_{s,RO}}{1 - R_r}$$

here, $y_{s,f}$ is the feed salt mass fraction, and $y_{s,RO}$ represents the salt concentration in the permeate.

• Hydrogen production unit

The hydrogen production unit employs a PEME to generate hydrogen and oxygen from water via electrochemical reactions separated by a proton-conducting membrane. Operating at moderate temperatures, the PEME offers high efficiency, rapid dynamic response, and a compact

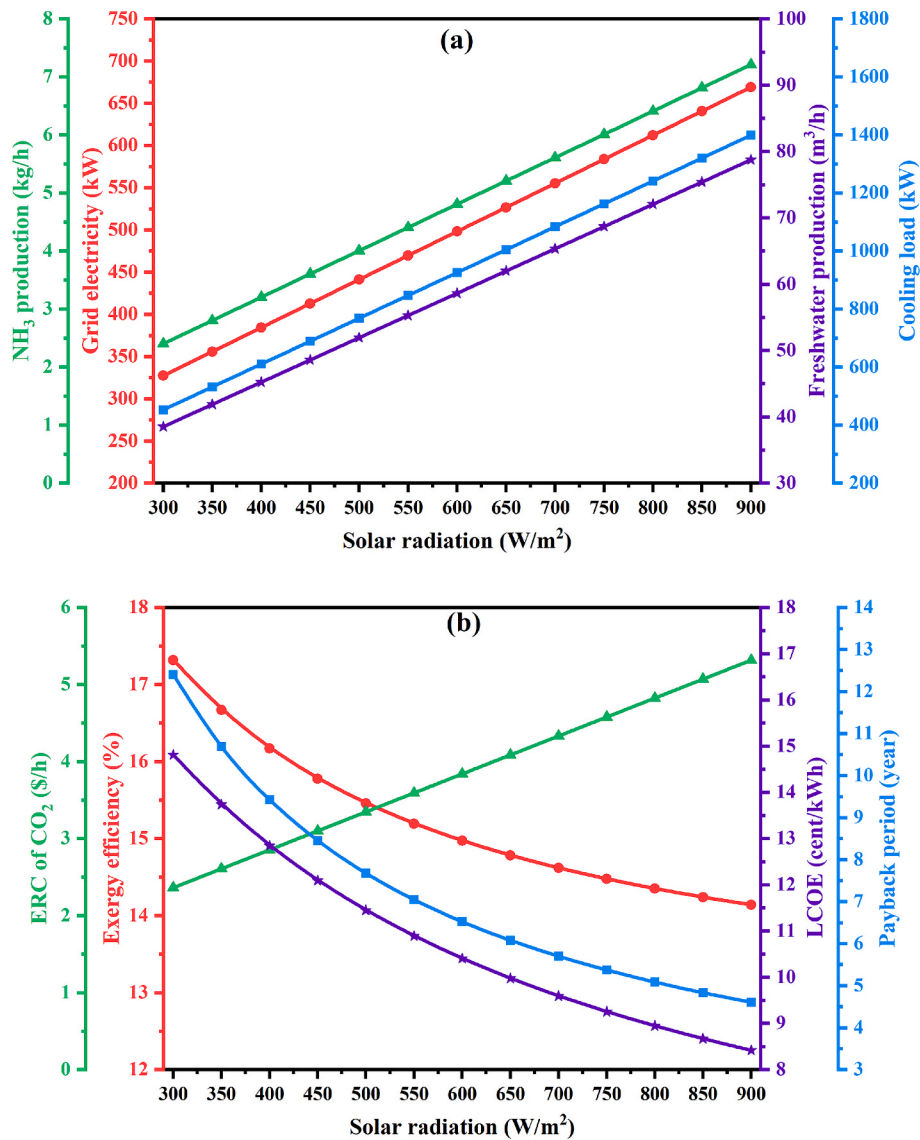


Fig. 8. Impact of varying the solar radiation on system output.

design, making it particularly suitable for seamless integration with renewable energy sources. Its ability to produce high-purity hydrogen without alkaline solutions further enhances operational safety and environmental compatibility [57–59]. The governing equations for the PEME model are presented in Table S2.

• Ammonia synthesis unit

In this study, the HBR is employed as the primary unit for ammonia production due to its industrial reliability, high efficiency, and well-established technology for converting hydrogen into a stable chemical energy carrier. Ammonia serves as an efficient hydrogen storage medium, making the HBR a critical component of integrated renewable-based energy systems. In this conceptual study, nitrogen for the Haber–Bosch synthesis loop was assumed to be externally supplied, and the Air Separation Unit (ASU) was not explicitly modeled to maintain focus on thermodynamic integration and renewable energy cascading. Consequently, the reported exergy efficiency and economic results may be moderately optimistic due to the exclusion of ASU power consumption and capital costs. To improve thermal efficiency, a steady-state counter-current regenerator with 0.9 effectiveness recovers sensible heat from the reactor effluent to preheat the incoming feed stream,

representing realistic industrial heat recovery performance.

$$(28) \quad \dot{Q} = \dot{m}_h c_{p,h} (T_{h,in} - T_{h,out}) = \dot{m}_c c_{p,c} (T_{c,in} - T_{c,out})$$

and the effectiveness relation is expressed as:

$$(29) \quad \varepsilon_{HBR} = \frac{C_h (T_{h,in} - T_{h,out})}{C_{min} (T_{h,in} - T_{h,out})} = \frac{C_c (T_{c,out} - T_{c,in})}{C_{min} (T_{h,in} - T_{h,out})}$$

here, C denotes the heat capacity rate, with the subscripts h and c representing hot and cold streams, respectively, and C_{min} indicates the smaller of the two capacity rates. Heat losses to the environment are neglected, and the specific heats of the gas streams are assumed constant over the operating temperature range. Ammonia synthesis occurs through the catalytic reaction of nitrogen and hydrogen under high-pressure and high-temperature conditions, facilitated by an iron-based catalyst:



A stoichiometric nitrogen–hydrogen mixture (1:3 molar ratio) is

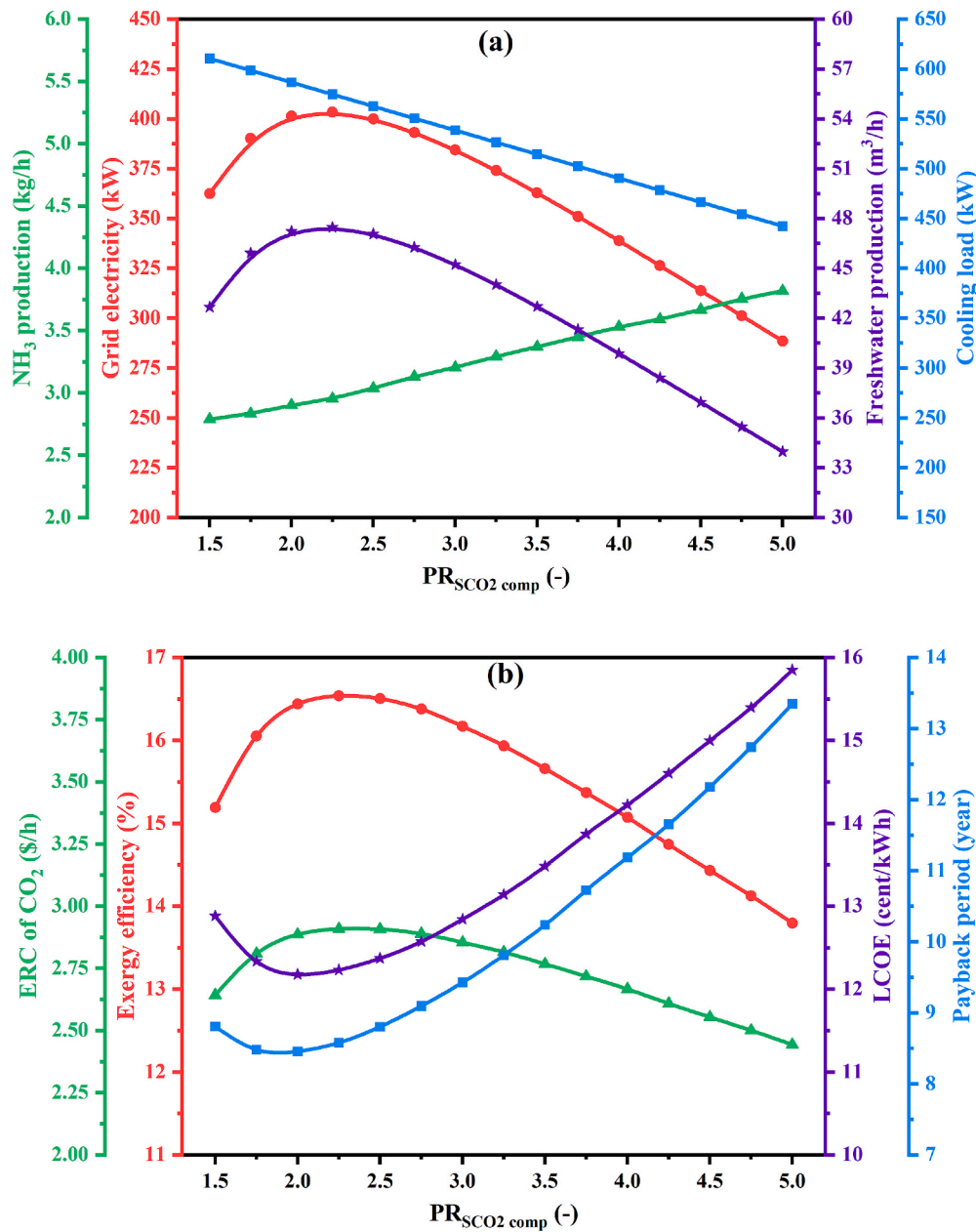


Fig. 9. Impact of varying the pressure ratio of SCO₂ compressor on system output.

compressed in three stages to 150 bar and preheated to approximately 450 °C via a regenerative heat exchanger prior to entering the Haber-Bosch reactor. These conditions correspond to the typical industrial operating range for conventional iron-based catalysts, representing a practical trade-off between thermodynamic equilibrium constraints and reaction kinetics. Industrial Haber-Bosch reactors generally achieve a single-pass ammonia conversion of 15–25% due to equilibrium limitations, with higher overall plant conversions realized through recycle loops. In this system-level analysis, a single-pass conversion of 20% is adopted to implicitly reflect equilibrium limitations while circumventing the complexity of detailed recycling loop modeling.

To more accurately represent the reaction behavior inside the catalytic reactor, the ammonia synthesis rate is modeled using a pressure-dependent kinetic expression commonly applied to iron-based catalysts [60]:

$$(31) \quad r_{NH_3} = r_{forward} - r_{backward} = \frac{\frac{2f}{\rho_{cat}} k_1 \left(P_{N_2} P_{H_2}^3 \frac{k_{-1} P_{NH_3}^2}{k_1 P_{NH_3}} \right)}{P_{H_2}^{1.5} P_{NH_3}}$$

Here, r_{NH_3} is the ammonia formation rate ($kmol/(kg_{cat} \cdot h)$). Moreover, P_{H_2} , P_{N_2} , and P_{NH_3} are partial pressures of hydrogen, nitrogen, and ammonia, respectively. Additionally, f is a correcting factor of 4.75, and ρ_{cat} is the catalyst bulk density which assumed as 2200 kg/m³. Furthermore, k_1 and k_{-1} are rate constants which are calculated via the Arrhenius equation, as shown here [60]:

$$(32) \quad k_1 = 17,900 e^{\left(\frac{-87090}{RT} \right)}$$

$$(33) \quad k_{-1} = 2.75 \times 10^{16} e^{\left(\frac{-198464}{RT} \right)}$$

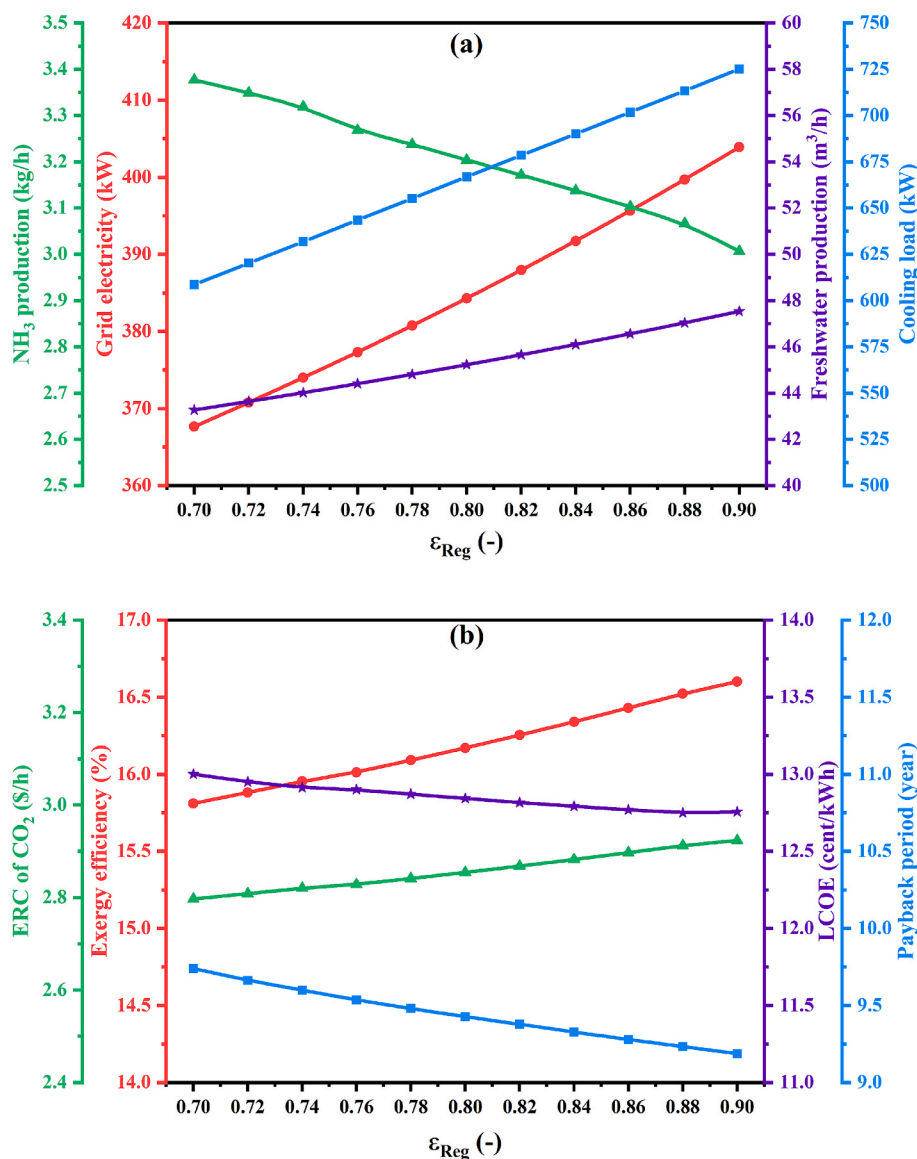


Fig. 10. Impact of varying the effectiveness of the SCO₂-BC regenerator on system output.

where, R is the universal gas constant and T is the reactor temperature in Kelvin. The Haber–Bosch reactor is modeled as a steady-state, adiabatic system using established kinetic correlations for iron-based catalysts under industrial conditions (400–500 °C, 100–300 bar). Species mass balances determine outlet composition based on reaction kinetics and catalyst loading. Multistage compression, regenerative heat recovery, and catalytic conversion enhance thermal energy utilization for renewable ammonia production. Recycling and separation processes are not explicitly modeled but are represented through conversion constraints and thermodynamic balances, while high-pressure stream expansion is treated as an idealized energy recovery process.

It is important to emphasize that the high-pressure ammonia expansion process is modeled as an idealized energy recovery step within the system-level thermodynamic framework. The expander is included to represent the potential for useful work extraction during pressure reduction, without incorporating detailed turbomachinery design constraints or phase-dependent performance analysis. Real-gas effects, non-ideal mixture behavior, and possible phase transition phenomena that may occur during expansion from high-pressure conditions (≈ 150 bar) to near-ambient pressure are not explicitly considered in this study. Therefore, the expander should be interpreted as a

thermodynamic modeling approximation used for overall system integration and performance evaluation, consistent with the conceptual nature of the present work.

3.2. Economic and financial analysis

The economic assessment evaluates system viability by analyzing capital costs, operational expenses, and revenue streams to identify cost-effective configurations and support decisions on sizing, integration, and energy management. Component cost rates are based on investment data from [Tables S3 and S4](#), while the capital recovery factor (CRF) converts initial investments into equivalent annual costs [61].

$$(34) \text{ CRF} = \frac{i(1+i)^N}{(1+i)^N - 1}$$

where, i is the interest rate and N is the project lifetime in years. To integrate system efficiency with financial considerations, the total annualized cost of the integrated system is calculated using the following relation [61]:

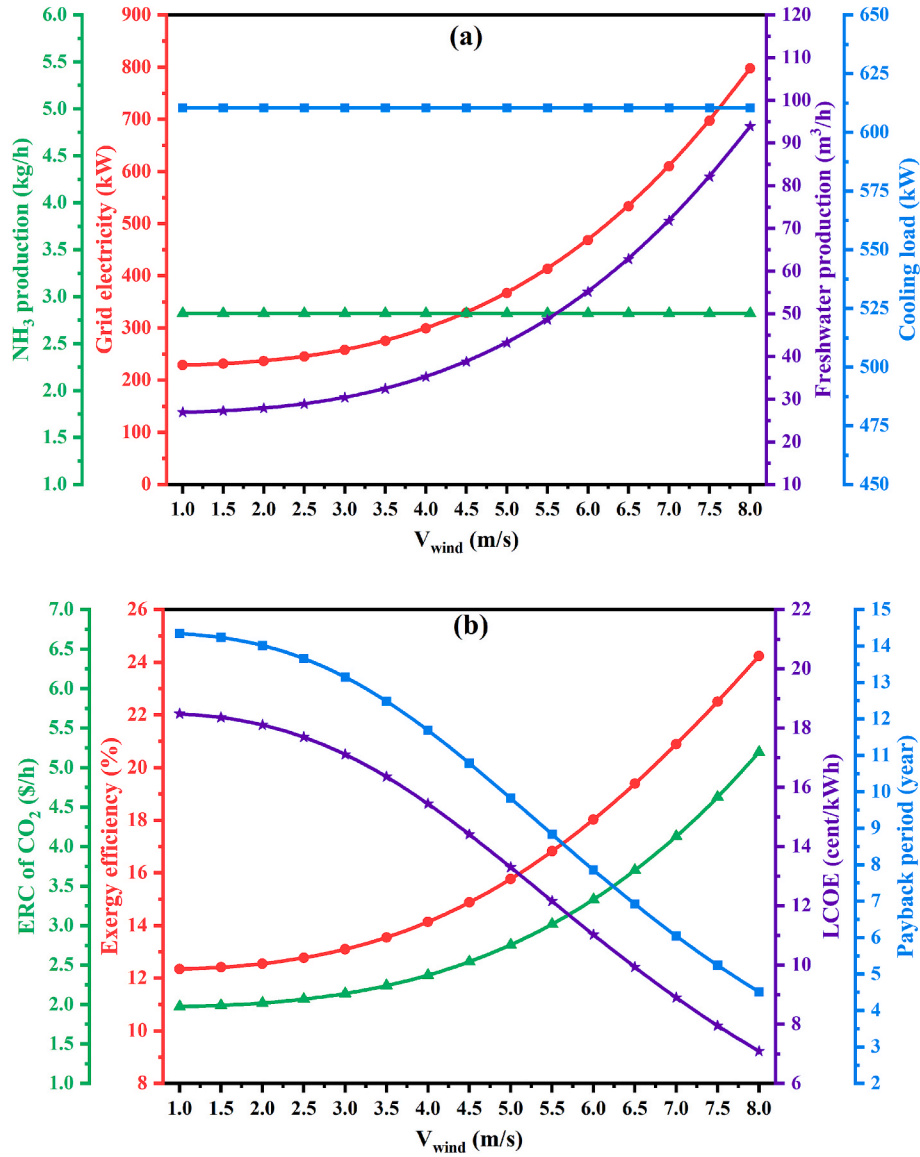


Fig. 11. Impact of varying the wind speed on system output.

$$(35) \dot{Z}_{tot} = \frac{CRF \times \varphi \times \sum Z_k}{t_{hour}}$$

here, φ represents any applicable scaling or operational factors, Z_k denotes the cost of individual components, and t_{hour} is the total operating hours. Since the cost functions listed in Table S3 are based on data from previous years, the corresponding cost functions are updated using the chemical engineering plant cost index (CEPCI) as follows [42]:

$$(36) \dot{Z}_{2023} = \dot{Z}_{CEPCI_{ref}} \frac{CEPCI_{2023}}{CEPCI_{ref}}$$

where, $CEPCI_{2023}$ and $CEPCI_{ref}$ are the CEPCI for January 2023 ($CEPCI_{2023} = 802.6$) and the reference year, respectively.

The economic feasibility of the proposed system is evaluated using the net present value (NPV) method, which determines profitability by discounting future cash flows over the system lifetime. The payback period is reached when NPV becomes zero, indicating full recovery of the initial investment, while a positive NPV thereafter confirms economic viability and profitable returns [62].

$$(37) NPV_t = (-FC \times IF_0 \times RDF_0) \times \sum_{i=1}^N (AS \times IF_i \times RDF_i)$$

Within this framework, several parameters are considered. AS denotes the annual financial savings obtained from system operation. IF_i represents the annual inflation or escalation rate of costs, reflecting the expected increase in prices over time. RDF_i is the relevant discount factor, which adjusts future cash flows to account for the time value of money, ensuring that future gains are measured in terms of present-day worth. In addition, TFC corresponds to the total fixed costs that are assumed to remain constant throughout the operational period. Finally, N represents the expected lifetime of the system, which is considered to be 20 years.

$$(38) TFC = DC - IC$$

$$(39) AS = AI - OC$$

$$(40) IF_i = (1 + \frac{R}{100})^{-i}$$

$$(41) RDF_i = (1 + \frac{RIR}{100})^{-i}$$

$$(42) RIR = DR - R$$

here, DC and IC represent direct and indirect costs, respectively. The calculation of direct and indirect costs is tabulated in Table S5. Also, AI represents the total annual revenue generated by the proposed system. R

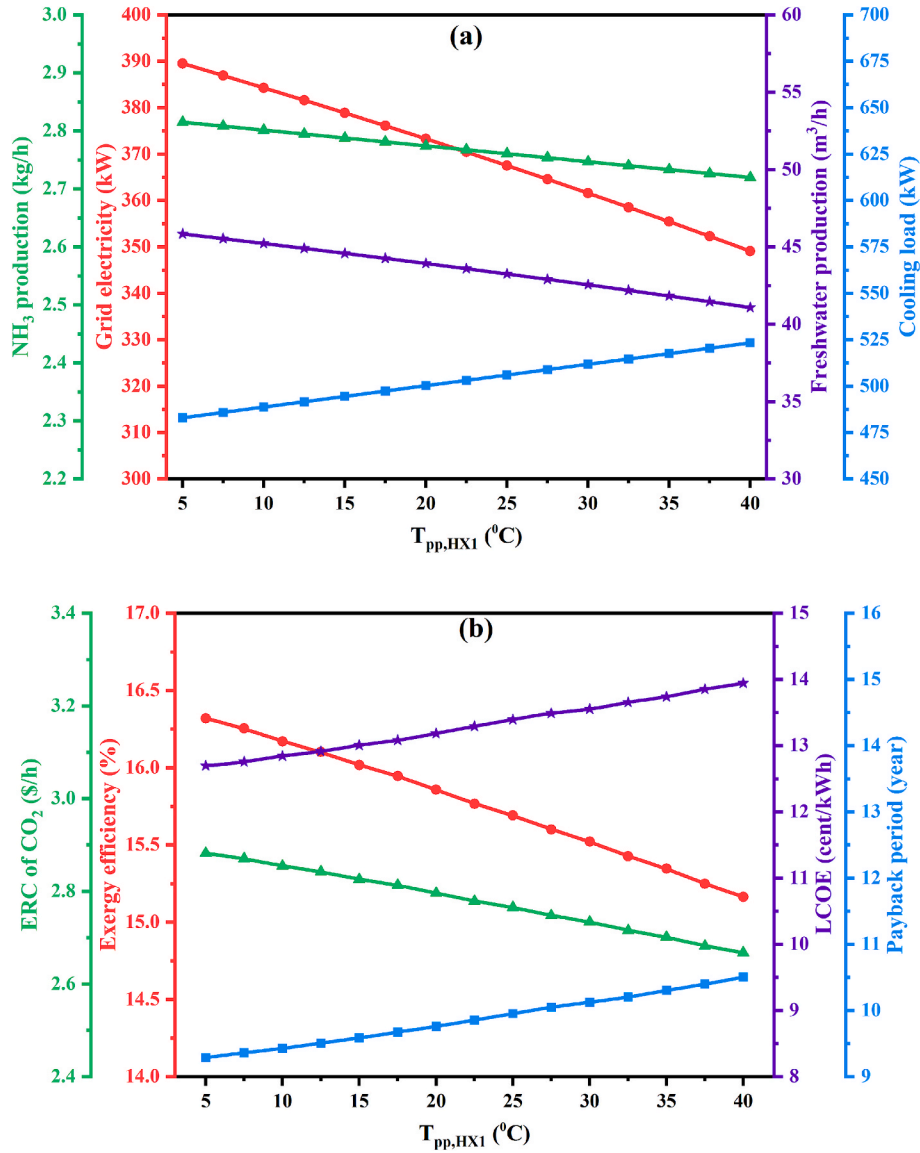


Fig. 12. Impact of varying the HEX1 pinch point temperature difference on system output.

denotes the inflation rate, assumed to be 5%, RIR refers to the real interest rate, and DR indicates the discount rate, which is taken as 8%. Furthermore, i represents the specific year within the operational lifetime of the system. No government subsidies, financial incentives, or carbon credit revenues were considered in economic analysis. Therefore, the reported payback period reflects the intrinsic techno-economic performance of the proposed system based solely on product revenues [63,64].

The levelized cost of electricity (LCOE) is a comparative indicator used to assess energy generation systems by relating annualized operational costs of all power-producing components to total electricity output, which can be mathematically expressed as [65,66]:

$$(43) \text{ LCOE} = \frac{\text{CRF} \cdot Z_{\text{investment}} + Z_{\text{O\&M}}}{\text{PG}_{\text{net}}}$$

where, $Z_{\text{investment}}$ is the investment cost, $Z_{\text{O\&M}}$ is the annual operating and maintenance costs, and PG_{net} denotes for the annual net power generation by the power plant.

3.3. Operational CO_2 emission avoidance

Solar and wind-based renewable systems provide significant environmental benefits through sustainable operation and minimal ecological impact. Unlike fossil fuel technologies, they generate electricity without greenhouse gas emissions or harmful pollutants, reducing air and water contamination while conserving finite natural resources. Their adoption supports climate change mitigation and the transition toward sustainable energy infrastructure [67]. The environmental impact of the suggested configuration can be quantified in terms of hourly reductions in CO_2 emissions. This is calculated by comparing the net electricity output of the system to a conventional natural gas-fired plant using the relationship:

$$(44) \Delta \dot{m}_{\text{CO}_2} = \dot{W}_{\text{net}} \times e_{\text{CO}_2}$$

here, e_{CO_2} denotes the emission factor for natural gas that is $0.18 \text{ kgCO}_2/\text{kWh}$. Furthermore, the economic benefits of reducing CO_2 emissions are evaluated through the emission reduction cost (ERC), defined as:

$$(45) \text{ERC}_{\text{CO}_2} = \Delta \dot{m}_{\text{CO}_2} \times C_{\text{CO}_2}$$

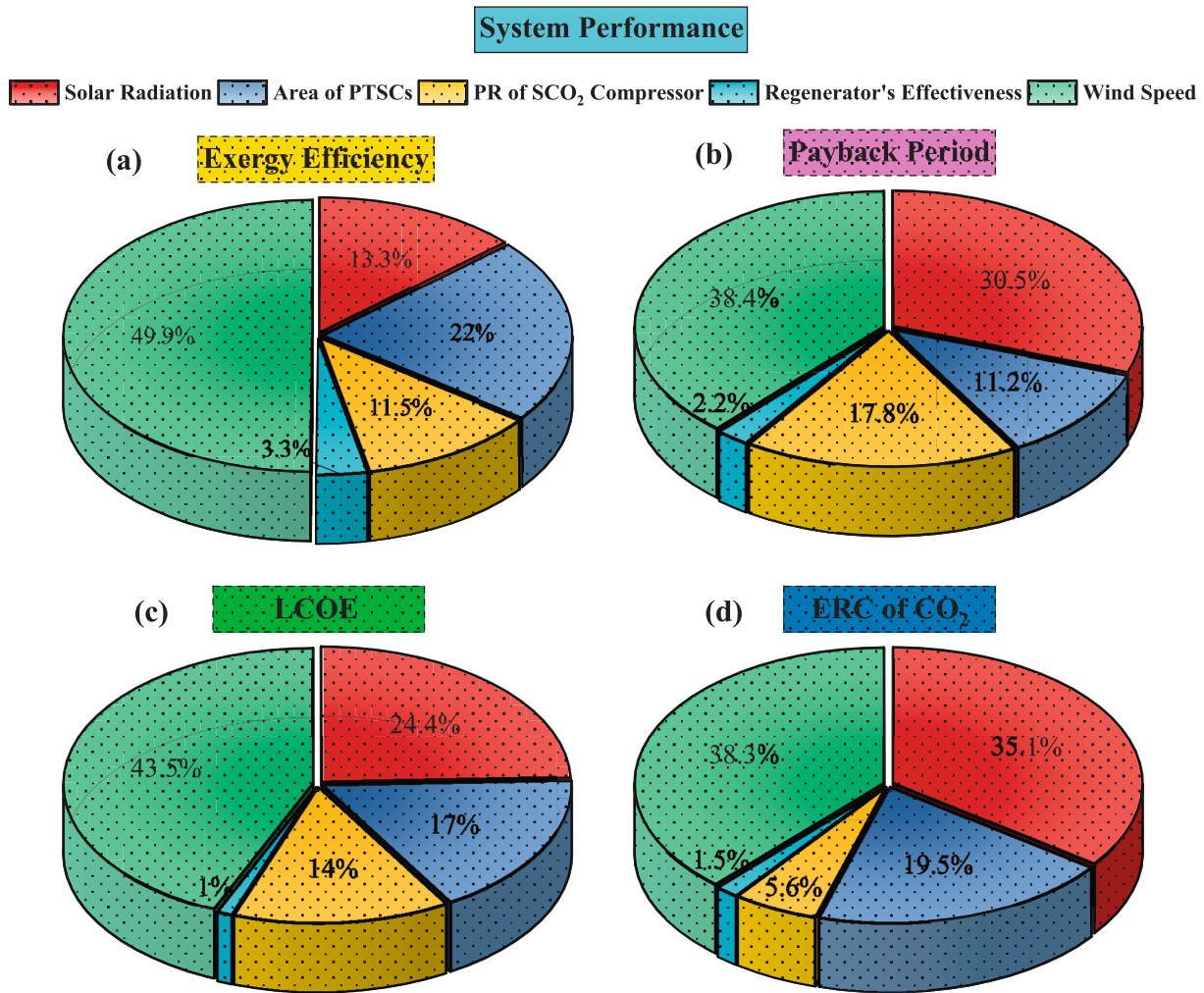


Fig. 13. Sensitivity analysis of the main parameters on the system performance metrics.

In this equation, C_{CO_2} represents the economic cost of CO₂ emissions, set at 0.024 USD/kg. In this study, the environmental dimension of the 4E analysis focuses on the operational environmental benefits associated with renewable energy utilization. The environmental performance is quantified by estimating the amount of CO₂ emissions avoided when the net electricity output of the proposed poly-generation system displaces electricity that would otherwise be generated by a conventional natural-gas-fired power plant. This approach is commonly employed in thermodynamic and techno-economic studies of renewable energy systems to evaluate operational emission reductions.

4. Machine learning-based optimization procedure

Optimization plays a central role in the design and operation of modern energy systems, particularly in complex poly-generation configurations where multiple conflicting objectives must be addressed simultaneously [68]. In this study, the optimization problem is explicitly formulated with two primary objective functions: maximizing the total exergy efficiency ($\eta_{ex,tot}$) and minimizing the system payback period (PP). The problem is solved subject to thermodynamic and operational constraints, including bounds on decision variables, energy and mass balances, component performance limits, and realistic environmental conditions (solar irradiance and wind speed).

For the proposed hybrid renewable poly-generation system, the NSGA-II algorithm was selected for multi-objective optimization due to its efficacy in handling conflicting goals. To mitigate the high

computational cost of direct optimization of the full MATLAB system model, attributable to its high dimensionality and complex subsystem interactions, a surrogate modeling approach was adopted. Specifically, an ANN was trained to reliably estimate system performance across diverse operating conditions. The NSGA-II algorithm was subsequently applied to the ANN surrogate, significantly reducing computational time while maintaining predictive accuracy. Table 3 provides a detailed specification of key decision variables ranges, and Table 4 shows the ANN hyperparameters and strategy used for training the model.

A feed-forward ANN is developed to approximate the system response. The ANN architecture consists of six hidden layers with ten neurons in each layer, employing nonlinear activation functions to capture complex input-output relationships. Prior to training, all input and output data are normalized to improve convergence stability and prediction accuracy. The network is trained using the Levenberg-Marquardt back-propagation algorithm, which combines the advantages of gradient descent and Gauss-Newton methods to achieve fast convergence and high accuracy. During training, model performance is continuously evaluated using the validation dataset to prevent overfitting and ensure generalization capability [69,70].

The surrogate-based optimization reduced computational time by 97.63% relative to direct simulation (from approximately 38 hours to 54 minutes) while preserving prediction accuracy. This integrated machine learning and optimization framework ensures both high-performance system design and computational efficiency. The parameters used in NSGA-II optimization method are listed in Table 5.

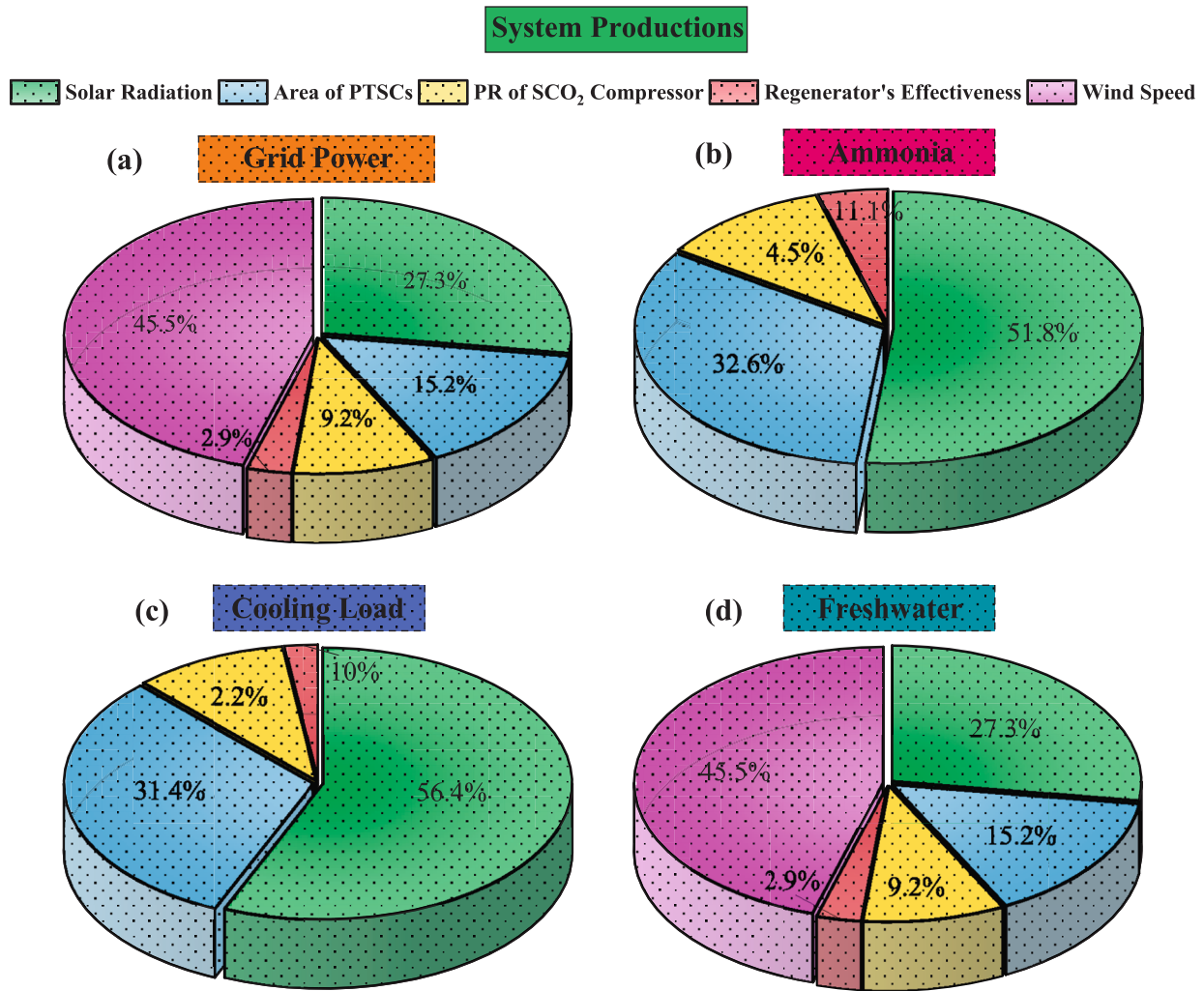


Fig. 14. Sensitivity analysis of the main parameters on system productions.

5. System verification

Given the novelty of the suggested system design, no fully comparable reference study exists for validating the entire configuration. Therefore, the accuracy and reliability of the model are ensured through step-by-step verification of each subsystem against credible experimental or well-established numerical references. This validation approach is a conventional and widely accepted methodology in the thermodynamic simulation of novel energy systems to ensure the fundamental reliability of the overall conceptual model.

• PTSC validation

The PTSC model was validated against experimental data from Al-Suliman et al. [71], under the actual operating conditions. The collector geometry consisted of a single module with a length of 12.27 m, and a width of 5.76 m. Thermal parameters included a heat-loss coefficient of $3.82 \text{ W/m}^2\cdot^\circ\text{C}$ and an internal receiver heat-transfer coefficient of $300 \text{ W/m}^2\cdot^\circ\text{C}$. Optical properties were defined by an interception factor of 0.95, mirror reflectance of 0.94, and receiver absorptivity of 0.96. As shown in Fig. S1(a), the predicted thermal output closely matches the experimental measurements, confirming that the model accurately captures the optical and thermal behavior of the PTSC.

• PEME validation

The PEME model was validated against the experimental results of Ioroi et al. [72]. The validation uses the same electrochemical conditions, including operating temperature of 353.15 K, membrane thickness of 100 μm , Faraday constant of 96485 C/mol, and the corresponding pre-exponential factors and activation energies. Fig. S1(b) illustrates that the predicted cell voltage matches the reference results across the examined current-density range with less than 1.6% deviation.

• SCO₂ cycle validation

The supercritical CO₂ cycle was validated using data reported by Wang et al. [73]. The adopted boundary conditions include a compressor inlet temperature of 305.15 K, compressor inlet pressure of 75 bar, pressure ratio of 3, and component isentropic efficiencies from Table 1. As presented in Table S6, model predictions for thermal efficiency, exergy efficiency, and net output power deviate by less than 2%, confirming the robustness of the SCO₂ cycle simulation.

• ARC unit validation

The absorption refrigeration cycle was verified using the experimental data of Maryami et al. [74]. The model applies to the same operating conditions, including evaporator temperature of 5 $^\circ\text{C}$, generator temperature of 90 $^\circ\text{C}$, and HEX effectiveness of 0.72. Table S7 shows the comparison of cooling capacity, COP, absorber heat load, and mass-flow ratio. The close correspondence between the present results

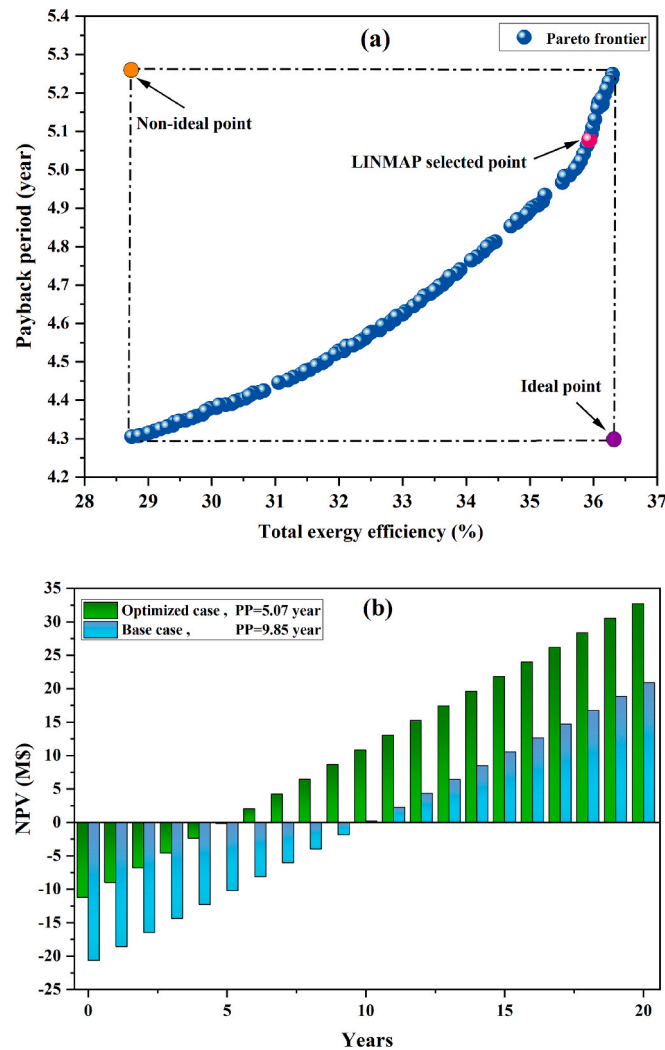


Fig. 15. (a) Pareto frontier of the multi-objective optimization (a) and (b) 20-year variation of NPV for base and optimized cases.

Table 6

System results under optimized configuration.

Parameter	Value
Decision variable	
$G(W/m^2)$	411.29
$A_{ap}(m^2)$	5624.32
$PR_{SCO_2,comp}(-)$	1.93
$\epsilon_{Reg}(-)$	0.86
$V_{wind}(m/s)$	7.98
Outputs	
$\dot{W}_{Grid}(kW)$	674.17
$\dot{Q}_{cooling}(kW)$	224.54
$\dot{m}_{fw}(m^3/h)$	79.33
$\dot{m}_{H_2}(kg/h)$	0.95
$\dot{m}_{NH_3}(kg/h)$	1.09
$ERC_{CO_2}(\$/h)$	4.02
$\Delta m_{CO_2}(kg/h)$	167.5
$\dot{Z}_{tot}(\$/h)$	72.18
$LCOE(cent/kWh)$	4.21
Objectives	
$\eta_{ex,tot}(\%)$	35.86
$PP(year)$	5.07

and those in literature, with only minor discrepancies, demonstrates the robustness and reliability of the proposed model.

• Ammonia synthesis reactor validation

The ammonia synthesis reactor model was benchmarked against the experimental and numerical results reported by Ahbabi et al. [75], with a comparison presented in Table S8. The model applies the same operating conditions, including reactor inlet temperature of 450°C, H_2/N_2 feed ratio of 3, and regenerator effectiveness of 0.9. The close agreement across key parameters, including reactor pressure, exergy destruction, and ammonia production rate, confirms the model's accuracy and robustness, validating its suitability for subsequent system analyses.

To reduce computational cost, an ANN surrogate model was coupled with the NSGA-II algorithm. A dataset of 1000 samples was generated and randomly split into training (70%), validation (15%), and testing (15%) sets. In machine learning and regression analysis, the coefficient of determination (R^2) was used as the primary goodness-of-fit metric; values near 1 indicate strong predictive accuracy, whereas values near 0 reflect weak explanatory power. In this study, the R^2 indicators for the trained ANN models are shown in Fig. 3 for exergy efficiency and payback period. The results demonstrate exceptional agreement between predicted and actual values, with R^2 exceeding 0.9999 for total exergy efficiency and 0.9941 for payback period. These outcomes confirm the robustness of the developed ANN models and their effectiveness in delivering accurate and reliable predictions for both thermodynamic and economic parameters of the proposed system.

Additionally, as illustrated in Fig. 4, the mean squared error (MSE) for training, validation, and test datasets demonstrates a concurrent decline across all three generated networks as training progresses through successive epochs. Once an optimal iteration is achieved, the training process is halted to mitigate the risk of overfitting. Extending the number of iterations beyond this critical threshold fails to enhance predictive accuracy, as the ANN has already assimilated the salient patterns within the data. Beyond this point, the model begins to fit noise or random fluctuations in the training data, which results in decreased performance on the validation set.

6. Result and discussion

This section presents the evaluation of the proposed system under baseline conditions through comprehensive techno-economic and operational CO_2 emission through avoidance analyses, followed by an extensive parametric investigation of key design and operational variables. The system is subsequently optimized to maximize efficiency and minimize payback period, and a case study is performed to assess its operational applicability under steady-state and various climatic conditions.

6.1. Base system results

This subsection outlines the simulation consequences of the introduced configuration under baseline operating parameters, encompassing products, exergy destruction, and associated cost rates. In this regard, the stream data for the proposed system at base conditions are reported in Table S9 and Table S10. Table S11 offers an exhaustive overview of the system's output and key performance indicators. The system demonstrates the ability to concurrently yield 384.28 kW of grid-compatible electricity, 610.47 kW cooling load, 45.22 m^3/h of potable water, 2.82 kg/h of hydrogen, and 3.2 kg/h of ammonia. Additionally, the system attains an exergy efficiency of 16.17% with a payback period of 5.89 years.

Fig. 5(a) illustrates the distribution of exergy destruction among subsystems under baseline conditions, showing that the PTSCs and SCO_2 subsystems dominate with contributions of 48% and 29.9%, respectively. The high irreversibility in the PTSC primarily arises from optical losses, including limited mirror reflectivity, tracking errors, shading, and absorber inefficiencies, along with temperature mismatches during heat transfer, environmental thermal losses, and the inherently low exergy-to-energy ratio of solar radiation, all of which increase entropy

Table 7

Comparison of system performance metrics and system productions in different studies.

Ref.	Energy source	Exergy efficiency (%)	Total cost rate (\$/h)	Generated power (kW)	Generated cooling (kW)	Produced freshwater (m ³ /h)	Produced ammonia (kg/h)
[75]	Solar-wind	44.69	-	13,200	3,400	13.07	583.2
[93]	Solar-wind	21.25%	114.46	1,390	1375.9	69.9	-
[7]	Solar	43.09	-	913.95	6.25	122.58	13.93
[94]	Solar-wind	27.37	96.2	597.49	-	70.31	-
This study	Solar-wind	35.86	72.18	674.17	224.54	79.33	1.09

generation and reduce useful exergy output. Moreover, Fig. 5(b) presents the subsystem cost rates, revealing that the PTSC and SCO₂ subsystems contribute the highest economic burdens at 60.1% and 12.4%, respectively. The PTSC field dominates the total cost rate due to its capital-intensive nature, requiring extensive collector arrays, tracking systems, absorb tubes, support structures, and piping networks, along with significant capital recovery and maintenance costs associated with its large thermal capacity.

Fig. 6 presents the estimated NPV and payback period of the proposed system under three different electricity selling prices. As electricity prices rise, the system earns greater income from exporting power to the grid, which enhances cash flow and speeds up the recovery of the initial investment. Consequently, higher electricity prices lead to increased NPV and reduced payback period. In particular, the payback period decreases from 10.57 years at 0.14 \$/kWh to 9.38 years at 0.22 \$/kWh, emphasizing the significant role of regional electricity pricing in determining financial feasibility.

6.2. Parametric analysis

This subsection presents a comprehensive energetic, exergetic, economic, and environmental parametric analysis to evaluate the effects of key system parameters on electricity, ammonia, freshwater, and cooling outputs, while identifying trade-offs and optimal conditions for enhanced efficiency, cost-effectiveness, and environmental performance.

• Influence of solar collector area

Fig. 7(a) illustrates the effect of solar collector area on system performance within the steady-state framework. Increasing the collector area enhances solar energy absorption and heat transfer to the SCO₂ Brayton cycle, raising turbine output and increasing power generation by about 189.9 kW. The additional thermal input also strengthens waste heat recovery in the TCO₂ cycle, leading to higher electricity availability for downstream processes. As a result, hydrogen and freshwater production increase by approximately 199.6% and 75.5%, respectively, while cooling capacity rises from 242.51 to 768.17 kW. Ammonia production correspondingly increases from 1.32 to 3.99 kg/h due to full hydrogen utilization. These gains are accompanied by trade-offs. Larger collector areas elevate operating temperatures, increasing entropy generation and reducing exergy efficiency by about 5.22%. In addition, higher capital and maintenance requirements increase the LCOE (9.19–13.63 cent/kWh) and extend the payback period. These results represent indicative steady-state trends, emphasizing the need for balanced design optimization.

• Influence of solar radiation

Fig. 8(a) illustrates the influence of solar radiation intensity on system performance under steady-state conditions. Increasing solar input enhances thermal energy absorption in the parabolic trough collectors, raising the outlet temperature of Therminol VP1 and improving heat transfer to the SCO₂ cycle. This results in higher turbine output and

increased electricity generation, which, within the present conceptual framework, supports greater hydrogen and freshwater production via the PEME and RO units. Accordingly, hydrogen, ammonia, and freshwater outputs increase by approximately 4.24 kg/h, 4.81 kg/h, and 40.22 m³/h, respectively, while cooling capacity rises by nearly 946.2 kW due to additional low-grade heat availability. Despite these gains, higher solar radiation introduces thermodynamic and economic trade-offs. Elevated operating temperatures increase irreversibility, reducing exergy efficiency by about 3.17%. Economically, LCOE decreases by 6.4 cent/kWh and the payback period shortens by approximately 7.8 years, reflecting improved energy yield under the adopted assumptions. Overall, these results represent steady-state performance trends and should be interpreted as indicative of system behavior rather than predictive of real-time operation under fluctuating solar conditions.

• Influence of supercritical CO₂ compressor pressure ratio

Fig. 9(a) presents the influence of the SCO₂ compressor pressure ratio on system performance under steady-state assumptions. Increasing the pressure ratio from low to moderate values enhances heat source utilization and cycle efficiency, leading to a rise in net power output from 362.46 kW to 403.26 kW. Beyond an optimal value of approximately 2.25, further increases result in declining performance, with power output dropping to 288.55 kW due to increased compression work and degraded heat transfer in the regenerator and cooler. Freshwater production follows a similar trend, reflecting its dependence on electricity generation. In contrast, hydrogen and ammonia production increase by about 0.91 kg/h and 1.03 kg/h, respectively, while cooling capacity decreases by approximately 27.55% due to reduced low-grade heat availability. Fig. 9(b) indicates that exergy efficiency exhibits a similar non-monotonic behavior. Economically, higher pressure ratios increase system costs, raising LCOE by about 2.97 cent/kWh and extending the payback period from 8.8 to 13.34 years. These results highlight an optimal operating region within the modeled framework, representing steady-state performance trends rather than real-time operational behavior.

• Influence of effectiveness of the SCO₂ regenerator

The effectiveness of the SCO₂ regenerator plays a critical role in internal heat recovery under steady-state conditions. As shown in Fig. 10 (a), increasing effectiveness enhances thermal energy recuperation from the turbine exhaust, reducing external heat demand and slightly increasing turbine work. Consequently, grid power increases by approximately 36.26 kW, while freshwater production rises by about 9.87% due to greater electricity availability for desalination. In contrast, hydrogen and ammonia production decrease by roughly 10.3% and 11.07%, respectively, as higher internal heat recovery reduces the thermal input to the TCO₂ cycle, limiting power supplied to the PEME. Fig. 10(b) indicates a modest improvement in exergy efficiency (≈0.79%) due to reduced irreversibility in the heat exchange process. Economically, enhanced regenerator performance slightly increases capital and maintenance requirements; however, LCOE decreases by about 1.93%, and the payback period shortens from 9.74 to 9.18 years.

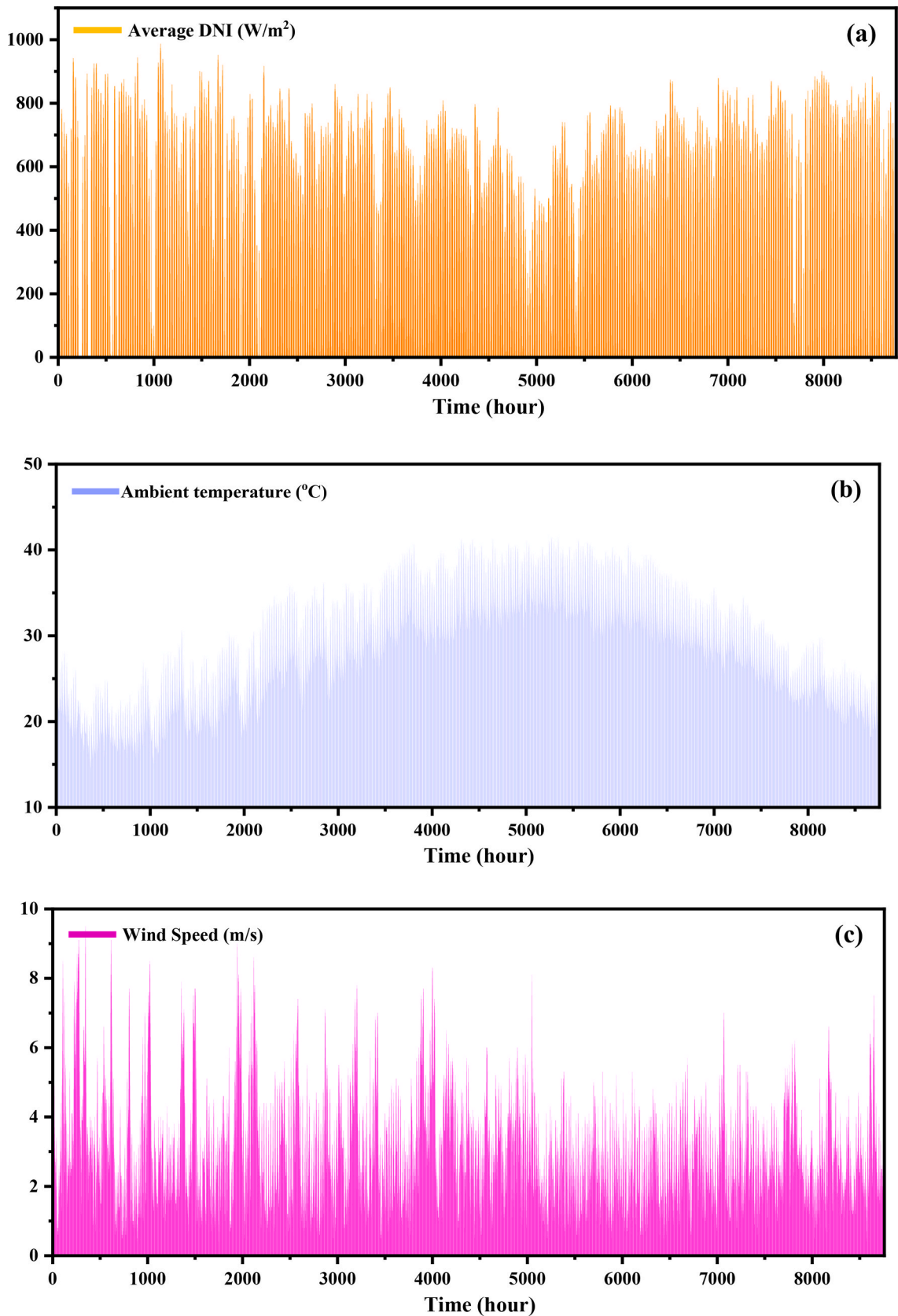


Fig. 16. Hourly meteorological data for case study of Dubai city.

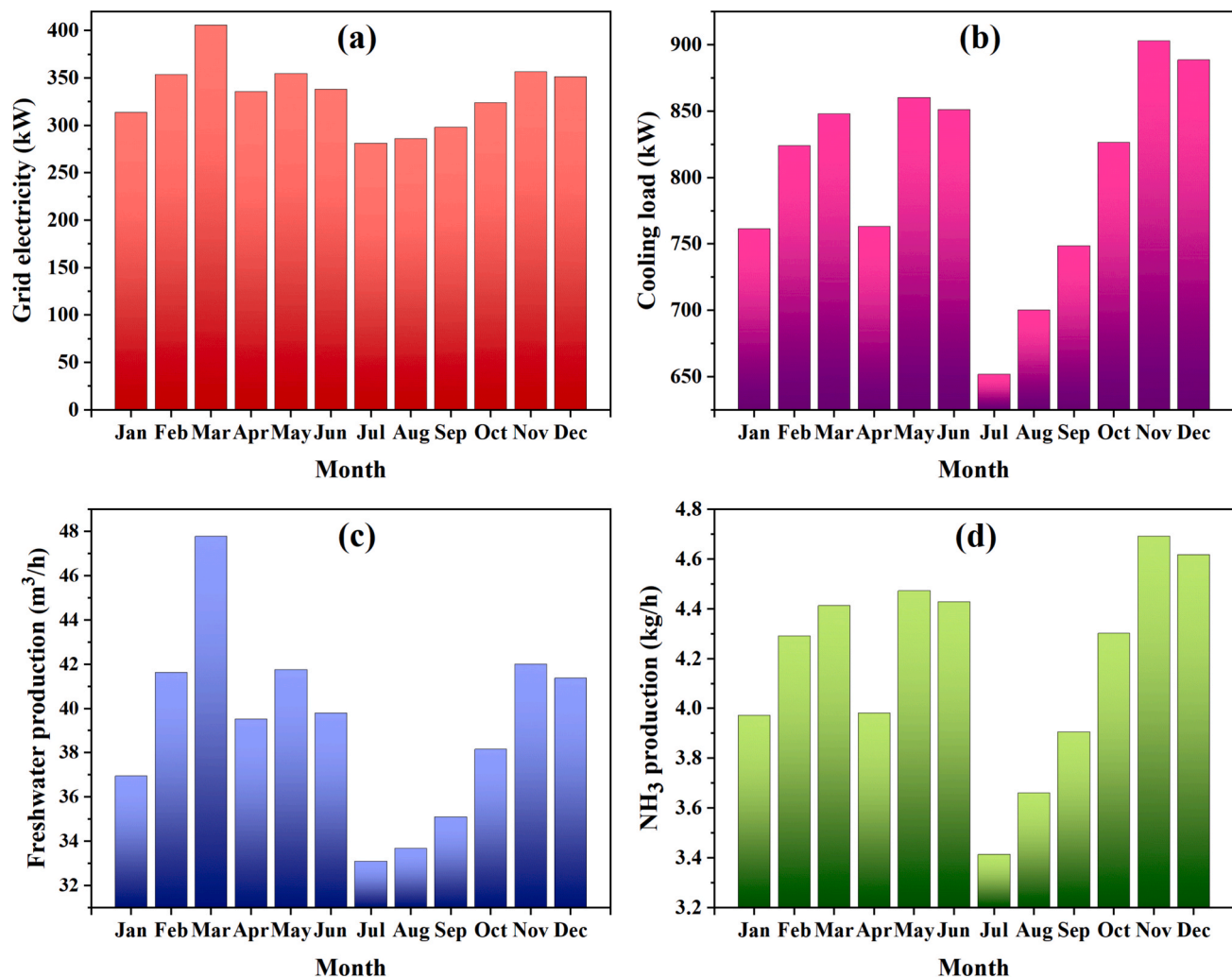


Fig. 17. Monthly average production rates for case study of Dubai city.

The ERC also declines by 0.126 \$/h. These results reflect steady-state performance trade-offs within the modeled system and should be interpreted as indicative trends rather than operational predictions.

• Influence of the wind speed

Fig. 11(a) illustrates the influence of wind speed on system performance within the steady-state modeling framework. Due to the cubic relationship between wind velocity and power output, increasing wind speed leads to a substantial rise in electricity generation, with grid power increasing by approximately 569 kW. This additional electricity enhances freshwater production, reaching nearly 93.88 m³/h, as the reverse osmosis unit benefits directly from increased electrical input. In contrast, hydrogen production and cooling capacity remain essentially unchanged, as they depend on the TCO₂ cycle and thermal subsystems, which are not influenced by wind conditions. As shown in Fig. 11(b), higher wind speeds improve exergy efficiency by about 11.89%, reflecting more effective utilization of renewable energy. Economically, system costs increase by approximately 12.1 \$/h due to larger equipment capacity; however, the overall impact remains favorable, with LCOE decreasing by 11.38% and the payback period shortening from 14.34 to 4.51 years. These results represent steady-state performance trends and should be interpreted as indicative of system behavior rather than real-time operational performance under variable wind conditions.

• Influence of HEX1 pinch point temperature

Fig. 12 presents the effect of the HEX1 pinch point temperature difference on system performance under steady-state conditions. Increasing the pinch point temperature reduces heat transfer from the hot stream to downstream subsystems, leading to lower thermal input to the SCO₂ and TCO₂ cycles. As a result, grid electricity, hydrogen, and ammonia production decrease by approximately 40.43 kW, 0.096 kg/h, and 0.108 kg/h, respectively. In contrast, the higher outlet temperature of the hot stream increases the cooling load in the ARC unit by about 39.8 kW. From a thermodynamic and economic perspective (Fig. 12(b)), reduced heat recovery leads to a 1.16% decline in overall exergy efficiency. The payback period increases by approximately 1.22 years, while LCOE rises by about 1.25 cent/kWh due to reduced power generation relative to system costs. These results highlight the sensitivity of system performance to heat exchanger design parameters and should be interpreted as steady-state performance trends within the conceptual modeling framework, rather than direct indicators of real operating conditions.

6.3. Sensitivity analysis

In this study, a local one factor at a time (OFAT) sensitivity analysis was performed by independently perturbing each parameter around its optimized value and quantifying the resulting normalized changes in system outputs, providing a computationally efficient diagnostic assessment of dominant design and economic drivers. The sensitivity of the system's performance and production rates to variations in key input

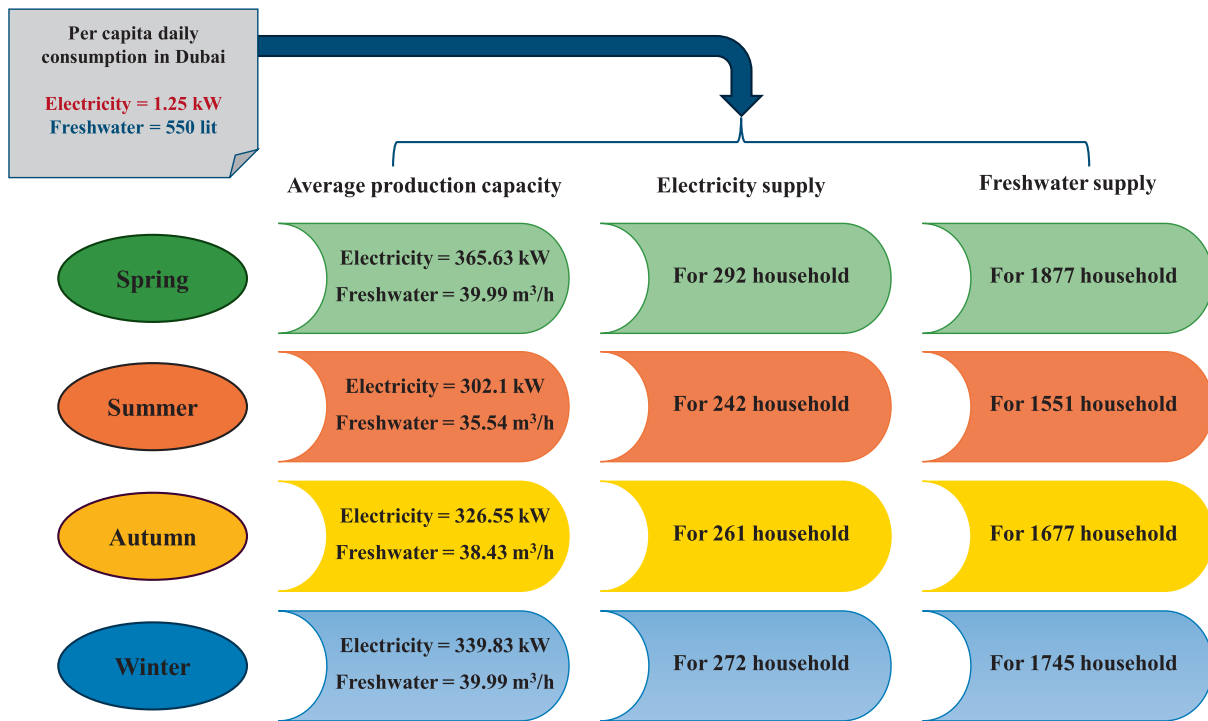


Fig. 18. Estimated number of households supplied with electricity and freshwater under varying seasonal conditions.

parameters is illustrated in Figs. 13 and Fig. 14. By varying the main parameters within a normalized range, percentage contribution of each factor to the variance of the results was determined. It should be emphasized that the OFAT approach provides a local deterministic sensitivity assessment and does not account for potential nonlinear interactions between parameters or probabilistic uncertainty in the system outputs; therefore, the results should not be interpreted as a global sensitivity or robustness analysis.

Fig. 13 identifies wind speed as the dominant parameter influencing system performance under steady-state conditions, contributing 49.87% to exergy efficiency sensitivity and 43.53% to LCOE variation. This reflects the strong dependence of overall system behavior on wind resource availability within the modeled framework. Solar radiation intensity and collector area also play significant roles, particularly in ERC and payback period, with solar radiation accounting for 35.08% of ERC variation. In contrast, parameters such as compressor pressure ratio and regenerator effectiveness have comparatively smaller impacts on high-level metrics, indicating that renewable inputs primarily govern system performance trends in this conceptual analysis.

Fig. 14 shows the sensitivity of system outputs to key operating parameters under the steady-state modeling framework. Ammonia and cooling production are mainly governed by solar-related variables, with solar radiation and solar field area contributing over 80% of their sensitivity due to their direct link to the solar-thermal and Haber-Bosch pathways. In contrast, wind speed dominates grid power and freshwater production, accounting for 45.45% sensitivity in each case through wind-driven electricity supply. Wind speed has no influence on ammonia and cooling outputs, confirming their dependence on the solar-thermal subsystem and indicating a clear sensitivity separation between system pathways.

6.4. Optimization results

A hybrid optimization framework integrating ANN with the NSGA-II algorithm was developed to identify optimal operating conditions for the proposed energy system. This approach significantly reduces computational time compared with conventional optimization

techniques while efficiently solving complex nonlinear optimization problems. The methodology focuses on two major performance indicators: total exergy efficiency and payback period, representing the thermodynamic and economic aspects of system performance. The optimization process aims to determine the ideal operating point that simultaneously maximizes exergy efficiency and minimizes the payback period. Consequently, the proposed framework provides an effective and modern strategy for achieving both technical efficiency and economic feasibility in advanced energy system conceptual design and analysis.

The LINMAP decision-making method was applied to identify the optimal solution by minimizing the distance between Pareto-optimal points and the ideal reference point. Fig. 15(a) illustrates the Pareto frontier representing the trade-off between exergy efficiency and payback period, while Table 6 presents the optimized decision variables and corresponding outputs, demonstrating the enhanced system performance achieved under optimal operating conditions. It is important to note that the ammonia production rate obtained in this study reflects the scale of a decentralized, renewable-driven poly-generation system rather than large-scale industrial production. In this context, ammonia serves primarily as a chemical energy carrier and storage medium, enabling energy flexibility and sector coupling, rather than being intended for bulk industrial supply.

Fig. 15(b) compares the economic performance of the reference and optimized systems at an electricity price of 0.18 \$/kWh. The optimized configuration significantly improves financial performance, reducing the payback period by 48.53% from 9.85 to 5.07 years. Additionally, the 20-year NPV increases by 56.68%, rising from 20.89 million USD to 32.73 million USD. These results demonstrate enhanced investment recovery and long-term profitability under optimized conditions. The reported payback period should be considered an indicative techno-economic metric within the adopted steady-state modeling framework. While direct, indirect, and contingency costs were incorporated, the first-of-a-kind integrated architecture introduces additional uncertainties associated with system integration, commissioning, control infrastructure, scale-up, and site-specific financial conditions. Sensitivity analysis further demonstrates that the payback period is highly

dependent on cost escalation assumptions, indicating that the economic findings are preliminary and scenario-dependent rather than investment-grade.

All simulations and optimizations were executed on an Intel® Core™ i7 (2.3 GHz) processor with 16 GB RAM. To reduce computational cost, an ANN-based surrogate model was employed, requiring approximately 46 minutes for data generation and training and about 8 minutes for NSGA-II optimization. This approach represents a drastic efficiency improvement compared to the estimated 38 hours required for conventional direct optimization (97.63% improvement), significantly lowering computational cost without sacrificing predictive accuracy.

To further interpret the obtained performance, the optimized system results are benchmarked against similar renewable-based multi-generation systems, as presented in Table 7. The comparison indicates that the achieved exergy efficiency of 35.86% is competitive and within the upper range of reported values. This performance can be primarily attributed to the effective integration of multi-level waste heat recovery, where thermal energy from high-temperature streams is progressively utilized in cascaded SCO_2 and TCO_2 cycles. This approach improves thermal matching between system components, reduces irreversibility, and enhances overall exergy utilization. In contrast, systems with limited or single-level heat recovery exhibit higher exergy losses due to inefficient heat utilization. Furthermore, although the inclusion of ammonia synthesis introduces additional thermodynamic losses, it enables energy storage and multi-functionality, providing a balanced trade-off between efficiency and system flexibility.

6.5. Case study

A case study was conducted in Dubai, United Arab Emirates (UAE), to assess the conceptual applicability of the proposed system under steady-state conditions. While the region has traditionally depended on fossil fuels, the UAE has increasingly invested in renewable energy technologies to promote sustainability and reduce environmental impacts. Dubai was selected because of its exceptionally high solar irradiance and moderate wind potential, which together provide favorable conditions for integrated solar–wind systems and support reliable energy generation during periods of reduced solar availability. Fig. 16 presents Dubai's hourly solar irradiance, wind speed, and ambient temperature data obtained from the national solar radiation database NSRDB [76] in 2019.

According to Fig. 17, the performance assessment of the proposed case study reveals clear seasonal variations in the production of electricity, potable water, cooling load, and ammonia. The analysis indicates that the highest outputs of electricity and freshwater occurred in March, with maximum values of 406.1 kW and 47.78 m³/h, respectively. This peak performance during early spring can be attributed to favorable solar irradiance levels and moderate ambient conditions, which enhance the efficiency of both power generation and desalination subsystems. In contrast, the system demonstrates its maximum cooling and ammonia production in November, reaching 903 kW of cooling capacity and 4.69 kg/h of ammonia. It is important to note that hydrogen-to-ammonia subsystem production is primarily supported by the electricity generated in the TCO_2 cycle, which is driven by the solar thermal subsystem through a cascading heat recovery process. Therefore, ammonia generation depends not only on solar irradiance but also on thermal recovery efficiency and system operating conditions. Consequently, peak ammonia production may not coincide directly with maximum solar intensity. Furthermore, ammonia acts as a long-term energy carrier, enabling temporal decoupling between production and demand. Seasonal variations in production can therefore be effectively managed through storage strategies, and the economic analysis is based on annualized production, consistent with standard practices in renewable energy system evaluation. These findings highlight the complementary nature of the multi-generation system, where different products reach their peak values in different months of the year.

Fig. 18 presents the results of estimating the number of households that can be supplied with electricity and freshwater by the proposed system under different seasonal conditions. Based on official statistics, the average daily per capita consumption of electricity and freshwater in Dubai is 1.25 kW and 550 liters per household, respectively. The results indicate that the proposed system achieves its highest performance in the spring, during which it is capable of supplying electricity to approximately 292 households and freshwater to about 1,877 households.

7. Conclusion

This study proposed and analyzed a novel poly-generation system with the conceptual capability of delivering multiple energy and utility outputs, including electricity, freshwater, cooling, heating, and ammonia, under steady state operating conditions. A key feature of the system is the integration of a hydrogen-to-ammonia pathway, which enables efficient and safe long-term storage of green hydrogen produced from renewable sources. The configuration design integrates PTSCs, a wind farm, SCO_2 , TCO_2 , an ARC, an RO desalination unit, hydrogen production unit, and ammonia synthesis unit. A comprehensive 3E analysis and operational CO_2 emission avoidance was carried out, while system optimization was performed using the NSGA-II algorithm. To mitigate the high computational demand of multi-criteria optimization, an ANN-based surrogate model was developed, which significantly reduced optimization time while maintaining predictive accuracy.

The results represent a theoretical benchmark for this class of systems, establishing thermodynamic and economic feasibility at the conceptual level. Exergy analysis showed that the PTSCs and the SCO_2 cycle were the primary sources of irreversibility, contributing 48% and 29.2% of total exergy destruction, respectively, and also represented the most cost-intensive components of the system. Parametric studies revealed the strong influence of solar collector area and solar radiation intensity on system outputs. For instance, increasing the PTSC area grid electricity, ammonia production, and freshwater generation by 189.88 kW, 199.6%, and 75.5%, respectively, though it also raised the LCOE from 9.19 cent/kWh to 13.63 cent/kWh. Similarly, rising solar radiation nearly doubled power generation ($\approx 104\%$) and tripled cooling capacity (from 452.77 to 1,398.97 kW), underscoring the sensitivity of system performance to solar availability. The multi-objective optimization yielded an optimal configuration achieved 0.98 kg/h of ammonia, 35.86% exergy efficiency, and a payback period of 5.07 years, indicating theoretical techno-economic feasibility under steady-state assumptions. Based on the parametric sensitivity analysis, it varies within a range of approximately 4.51–14.34 years, depending on key operating and design parameters. This confirms that the economic performance exhibits moderate sensitivity to system configuration and resource availability, and should therefore be interpreted as an indicative techno-economic range rather than a deterministic value. The results indicated peak electricity (406.1 kW) and freshwater production (47.78 m³/h) in March, while maximum cooling and ammonia outputs occur in November, reaching 903 kW and 4.69 kg/h, respectively. These results should be interpreted as conceptual performance targets under steady-state conditions rather than guaranteed real-world operation, as dynamic behavior, control requirements, and renewable intermittency effects are not captured in the present model.

This study expands the discussion to better position ammonia-based storage within the broader hydrogen storage landscape, considering recent studies on hybrid storage portfolios such as Liang et al. [77]. Ammonia is identified as a strategic solution for long-term, high-density, and transportable energy storage in export-oriented renewable systems. Its advantages are supported by system-level, economic, and industrial perspectives, highlighting compatibility with integrated poly-generation systems, existing Haber–Bosch infrastructure, and potential integration within hybrid storage frameworks. Beyond the specific case study, the results suggest that, from a thermodynamic and

economic perspective, coupling renewable energy with hydrogen–ammonia pathways offer a conceptually scalable and flexible approach to long-duration energy storage and multi-sector energy production. However, practical scalability and flexibility must be confirmed through transient simulations and hardware-in-the-loop testing. The ANN-assisted optimization framework demonstrates an efficient method for exploring the large design space of such integrated systems at the conceptual stage and can be extended to more detailed design phases.

8. Considerations and suggestions for future research

This study is based on steady-state thermodynamic modeling and does not account for transient effects, dynamic control behavior, or component inertia. The economic analysis uses conservative cost estimates but excludes integration, commissioning, and risk contingencies. Therefore, the results represent theoretical upper-bound performance of renewable-driven Haber–Bosch facility demonstrating conceptual feasibility rather than expected real-world operation, highlighting the need for important real-world considerations such as transient operation, renewable intermittency, dynamic process control, catalyst degradation, operational flexibility, and infrastructure-scale integration require further investigation through dynamic and pilot-scale studies. Recent studies, such as Bi et al. [78] and Liu et al. [79], indicate that transient thermal and electrochemical behaviors significantly affect efficiency, temperature distribution, and degradation in key components. Therefore, future work should incorporate dynamic modeling and transient analyses to improve operational realism. The proposed system benefits from renewable hybridization and integrated hydrogen–ammonia storage, enabling temporal decoupling between generation and demand. Additionally, advances in SCO_2 cycles and modular ammonia synthesis enhance operational flexibility, startup capability, and part-load performance.

From an environmental perspective, it is explicitly emphasized that this study does not include a full life cycle assessment. The environmental evaluation is limited to operational-phase CO_2 emission avoidance, which only accounts for direct emissions reduction during system operation. It does not consider upstream and downstream environmental burdens, including raw material extraction, manufacturing of system components (e.g., solar collectors, wind turbines, electrolyzers, and chemical reactors), transportation, construction activities, maintenance, and end-of-life dismantling or recycling processes. Therefore, while the present results provide useful insight into operational environmental performance, they do not represent the total environmental footprint of the system. Consequently, future studies are strongly recommended to perform a comprehensive cradle-to-grave life cycle assessment in order to fully evaluate the environmental sustainability, resource intensity, and potential trade-offs of the proposed configuration.

Future studies should incorporate probabilistic techno-economic analysis and global sensitivity methodologies, such as Monte Carlo simulation, stochastic modeling, or variance-based sensitivity analysis, to better quantify uncertainty propagation and parameter interactions in large-scale renewable–ammonia systems. Furthermore, future research should emphasize advanced dynamic and optimization-based control frameworks to enhance power management, subsystem stability, and coordinated operation under fluctuating renewable conditions. Finally, integrating thermal energy storage and battery systems can mitigate renewable intermittency, enable continuous operation, improve capacity factor, and increase the reliability and stability of ammonia production.

CRediT authorship contribution statement

Omar J. Alkhatib: Validation, Methodology, Conceptualization. **Ali Basem:** Investigation, Formal analysis. **Hyder H. Abed Balla:** Investigation, Data curation. **Mohana Alanazi:** Validation, Data curation.

Ibrahim Albaijan: Data curation, Conceptualization. **Hind Albalawi:** Writing – review & editing, Resources, Investigation. **H.Elhosiny Ali:** Writing – original draft, Project administration, Formal analysis. **Zuhair Jastaneyah:** Writing – review & editing, Writing – original draft, Resources. **Yasser Fouad:** Validation, Supervision, Methodology, Funding acquisition. **Ibrahim Mahariq:** Writing – review & editing, Supervision, Formal analysis.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.fuel.2026.140153>.

Data availability

The authors do not have permission to share data.

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