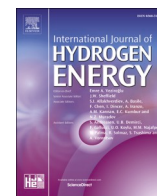




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Green liquefied hydrogen production with multi energy generation by solar–wind cogeneration system incorporating HTCORCs and PEME–Claude cycle: Techno economic environmental analysis and ANN-assisted optimization

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ABSTRACT

This study proposes an integrated renewable energy-driven cogeneration system designed to deliver multiple outputs, including liquefied hydrogen, electricity, heating, cooling, and desalinated water. The configuration combines solar and wind resources with cascaded organic Rankine cycles, a proton exchange membrane electrolyzer, absorption-based cooling with hydrogen liquefaction and desalination units. Multi-stage thermal coupling within the Rankine subsystems improves recovery of energy across different temperature levels, while low-grade heat is utilized for cooling without additional power demand. Excess renewable electricity is converted into hydrogen to improve system flexibility and mitigate intermittency issues. Performance is assessed using combined thermodynamic, economic, and environmental metrics, including net present value and payback time. A machine-learning-assisted optimization framework is applied to efficiently obtain optimal operating conditions targeting high exergy efficiency and reduced cost. Optimal results indicate hydrogen production of 15.61 kg/h, exergy efficiency of 29.92%, and a payback period of 3.89 years.

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1. Introduction

1.1. Background and motivation

The global energy sector is undergoing a fundamental transition in response to increasing energy demand, population growth, industrial development, and the urgent need to mitigate greenhouse-gas emissions [1]. Although fossil fuels continue to supply a considerable proportion of global energy demand, their extensive consumption is associated with climate change, atmospheric pollution, depletion of finite resources, and long-term energy-security concerns [2,3]. Renewable energy technologies offer a viable pathway to meet future energy needs while reducing environmental burdens [4]. Among renewable options, solar and wind energy stand out due to their abundance and technological maturity [5–7]. They can supply large amounts of electricity without direct emissions. However, their intermittent nature creates challenges for reliable and continuous energy supply [8–10]. Hybrid energy systems that integrate solar and wind resources provide an effective solution to this issue. Their complementary generation patterns improve system reliability and reduce reliance on storage and backup fuels [11,12]. Furthermore, hybrid systems enable advanced poly-generation applications, allowing the simultaneous production of electricity, heat, cooling, freshwater, and hydrogen [13]. This integrated approach supports the development of resilient, efficient, and sustainable energy infrastructures. These advantages have motivated increasing research efforts toward integrated renewable multigeneration systems capable of simultaneously improving energy efficiency, operational flexibility, and sustainability.

Building upon these developments, renewable multigeneration systems have emerged as one of the most promising approaches for simultaneously satisfying diverse energy demands while maximizing the utilization of renewable resources. The escalating global demand for energy, combined with the increasing need for electricity, heating, cooling, freshwater, and clean fuels, poses a significant challenge for sustainable and reliable power generation [14,15]. Renewable-based cogeneration systems provide an effective solution by simultaneously addressing these diverse energy needs [16]. They achieve this through the integrated production of multiple energy carriers from renewable resources. By employing advanced thermodynamic cycles alongside waste heat recovery strategies, these systems efficiently utilize both high- and low-grade energy streams [17,18]. This approach enhances overall system efficiency while minimizing exergy losses. The multi-output configuration further optimizes energy use and delivers economic benefits through the co-generation of electricity, thermal energy, cooling, hydrogen, and freshwater [19,20]. Consequently, renewable-based multi-generation systems offer a practical, cost-effective, and environmentally sustainable strategy for meeting the heterogeneous energy demands of modern society. They also provide improved operational reliability and lower lifecycle costs compared to conventional single-output renewable or fossil-fuel-based power plants [21]. Accordingly, extensive research has focused on developing and improving renewable-based multigeneration configurations with enhanced thermodynamic, economic, and environmental performance.

1.2. Literature review

In recent years, numerous studies have explored renewable-based cogeneration systems to enhance energy efficiency and sustainability. Chen et al. [22] developed a hydrogen-oriented solar-driven system integrating thermochemical water splitting and chemical-looping oxygen removal, achieving improved solar utilization and exergy performance through effective waste heat recovery. Similarly, Singh et al. [23] proposed a solar-powered cogeneration system coupled with a fuel cell to address intermittency, employing parabolic trough collectors and dual Rankine cycles to co-produce power, cooling, heating, and freshwater, with an exergy efficiency of 31.69% and a total cost rate of 87.2

\$/h. Waste heat recovery has also been widely investigated. Asadi et al. [24] integrated an organic Rankine cycle (ORC) with distributed multi-effect distillation, achieving a payback period of 1.62 years along with improvements in energy and exergy efficiencies. Moradi et al. [25] conducted a 4E assessment of a solar-driven multi-generation system incorporating hydrogen, ammonia, and methane production, reporting energy and exergy efficiencies of 53.5% and 50.7%, respectively. More recently, Bakircioğlu and Yilmaz [26] proposed a renewable-driven cogeneration system integrating a double-flash ORC, desalination unit, and proton exchange membrane electrolyzer (PEME). Their optimized design achieved an overall efficiency of 39.1% and a net power output of 15.64 MW, demonstrating the effectiveness of optimization-based renewable multigeneration systems. Furthermore, Zheng et al. [27] developed a solar-assisted Brayton-based cogeneration system integrating power generation, desalination, and hydrogen production. Their results showed that increasing the pressure ratio improved exergy efficiency from 28.4% to 34.7%.

Among the various technologies employed in these integrated systems, high-temperature cascaded organic Rankine cycles (HTCORCs) have attracted considerable attention because of their capability to maximize thermal energy utilization through multi-level heat recovery. HTCORCs are highly effective for enhancing the efficiency of renewable-based cogeneration systems [28]. Their cascaded structure allows sequential utilization of residual heat from high-temperature sources, maximizing energy extraction and improving exergy efficiency. The top cycle operates at elevated temperatures to capture the majority of thermal energy, while subsequent lower-temperature cycles recover remaining heat to produce additional electricity [29]. This configuration increases power output per unit of thermal input and enables seamless integration with other energy carriers, such as cooling, freshwater, or hydrogen, making HTCORCs particularly suitable for versatile, high-performance hybrid systems.

Another key aspect of renewable multigeneration systems is the efficient production, storage, and utilization of hydrogen as a clean energy carrier. Hydrogen production is a key element in solar-wind cogeneration systems, enabling conversion of surplus renewable electricity into a clean and storable energy carrier [30,31]. This helps mitigate the mismatch between intermittent generation and variable demand [32]. PEMEs are widely used due to their high efficiency, compactness, and fast dynamic response under fluctuating solar and wind inputs [33]. However, hydrogen storage is limited by its low volumetric energy density in gaseous form, making large-scale application challenging [34]. Cryogenic liquefaction, particularly via the Claude cycle, significantly increases storage density and improves transportability [35,36]. Integrating hydrogen production and liquefaction within renewable cogeneration systems enhances thermodynamic synergy and system flexibility. Despite these advantages, most existing studies focus on isolated subsystems, while fully integrated multi-product systems combining power, hydrogen, liquefaction, and other outputs remain insufficiently investigated, indicating a need for comprehensive system-level optimization.

Besides advances in system configuration, intelligent optimization techniques have become increasingly important for improving the design and operation of complex renewable multigeneration systems [37]. Optimization is essential for improving cogeneration systems with complex nonlinear thermodynamic behavior [38–41]. However, conventional optimization methods are computationally expensive due to multi-objective formulations and repeated simulations [42,43]. To overcome this limitation, artificial neural networks (ANNs) are widely used as surrogate models to approximate system responses with high accuracy while significantly reducing computational cost [44,45]. When integrated with multi-objective optimization algorithms, ANN-based frameworks enable efficient exploration of the design space and identification of optimal trade-offs among exergy efficiency, cost, and environmental performance [46]. Recent studies confirm their effectiveness; Boujelbene et al. [47] achieved 32.6% exergy efficiency in a

Table 1
Comparison of representative renewable-driven multigeneration for hydrogen production and storage studies.

Ref.	Energy source	Hydrogen energy storage		Outputs	Analysis	Optimization method	
		Production	Storage			Using ANN	Optimization algorithm
[1]	Solar- geothermal	PEM electrolyzer	-	Power, cooling, hydrogen, fresh water	Energy, exergy, economic, environmental	Yes	NSGA-II
[25]	Solar	PEM electrolyzer	Hydrogen derived martials: ammonia & methane	Power, cooling, hydrogen, fresh water, ammonia, methane	Energy, exergy, economic, environmental	Yes	NSGA-II
[49]	Solar - wind	PEME	Compressed hydrogen gas	Power, hydrogen	Energy, exergy, economic	No	NSGA-II
[50]	Solar	PEME	Compressed hydrogen gas	Power, fresh water, hydrogen	Energy, exergy, economic	Yes	NSGA-II
[34]	Solar	Alkaline electrolyzer	Hydrogen derived martials: ammonia	Power, cooling, ammonia, fresh water	Energy, exergy	Yes	Moth-flame optimizer
[35]	Biogas	Solid oxide electrolyzer	Liquified hydrogen using Claude cycle	Power, heating, hydrogen, fresh water	Energy, exergy, economic, environmental	Yes	Grey wolf optimizer
[51]	Biomass	PEM electrolyzer	Liquified hydrogen using Claude cycle	Power, heating, hydrogen, fresh water	Energy, exergy, economic, environmental	Yes	Grey wolf optimizer
[52]	Biomass – geothermal	-	Liquified hydrogen using Claude cycle	Power, hydrogen	Energy, exergy, economic	-	Grey wolf optimizer
This study	Solar – Wind	PEM electrolyzer	Liquified hydrogen using Claude cycle	Power, heating, cooling, hydrogen, fresh water	Energy, exergy, economic, environmental	Yes	NSGA-II

biogas system using ANN-based optimization, while Mousaei et al. [48] increased exergy efficiency from 15.6% to 22.61% and reduced cost to 304.28 \$/h using an ANN-NSGA-II approach, both with substantially reduced computational time.

1.3. Research gaps, novelty, and contributions

Despite the significant progress achieved in renewable multi-generation systems, several important research gaps remain. First, most previous studies focus on gaseous hydrogen production or treat hydrogen liquefaction as an independent downstream process, whereas fully integrated systems capable of simultaneously producing liquefied hydrogen, electricity, cooling, and freshwater have received limited attention. Second, although HTCORCs offer superior power-generation efficiency through multi-level waste heat recovery and cascade utilization of thermal energy, their integration into renewable multigeneration systems remains underdeveloped. In particular, the thermodynamic interactions between HTCORCs and downstream subsystems, such as absorption refrigeration, desalination, hydrogen production, and hydrogen liquefaction, have not been comprehensively investigated. Third, most optimization studies rely on direct thermodynamic simulations under fixed operating conditions, while surrogate-assisted multi-objective optimization combined with realistic meteorological assessments remains relatively unexplored. Comparison of previous proposed renewable-driven multigeneration for hydrogen production and storage are shown in Table 1.

To bridge these research gaps, this study proposes a hybrid solar–wind multigeneration system integrating parabolic trough solar collectors (PTSCs), HTCORCs, a single-effect absorption refrigeration cycle (SEARC), a reverse osmosis desalination unit (RODU), a PEME, and a Claude hydrogen liquefaction cycle. The main contributions of this study are summarized as follows:

- A novel thermally integrated system is developed for the simultaneous production of grid-exportable electricity, liquefied hydrogen, cooling, and freshwater using complementary solar and wind resources.
- A thermally integrated three-stage high-temperature cascaded organic Rankine cycle is developed to maximize multi-level waste heat recovery, while the remaining low-grade thermal energy is effectively utilized by a single-effect absorption refrigeration cycle to enhance overall energy utilization.
- Surplus renewable electricity is strategically allocated to reverse-osmosis desalination, PEME, and hydrogen liquefaction, improving renewable-energy utilization, operational flexibility, and long-term energy storage capability.
- A comprehensive thermodynamic–economic–environmental assessment is performed using energy, exergy, economic, and operational CO₂-emission-mitigation analyses together with net present value (NPV) and payback-period evaluations to quantify both technical and economic feasibility.
- An ANN surrogate model is integrated with the NSGA-II algorithm to perform computationally efficient multi-objective optimization, enabling simultaneous maximization of overall exergy efficiency and minimization of the payback period while significantly reducing computational effort.
- The proposed system is validated under real meteorological conditions using hourly data for Dammam and Yanbu, Saudi Arabia, to demonstrate its practical applicability.

2. System description

The schematic configuration of the suggested hybrid renewable-based cogeneration system is shown in Fig. 1. The system is designed to simultaneously generate electricity, freshwater, hydrogen, and cooling energy by integrating solar and wind energy resources. It consists of

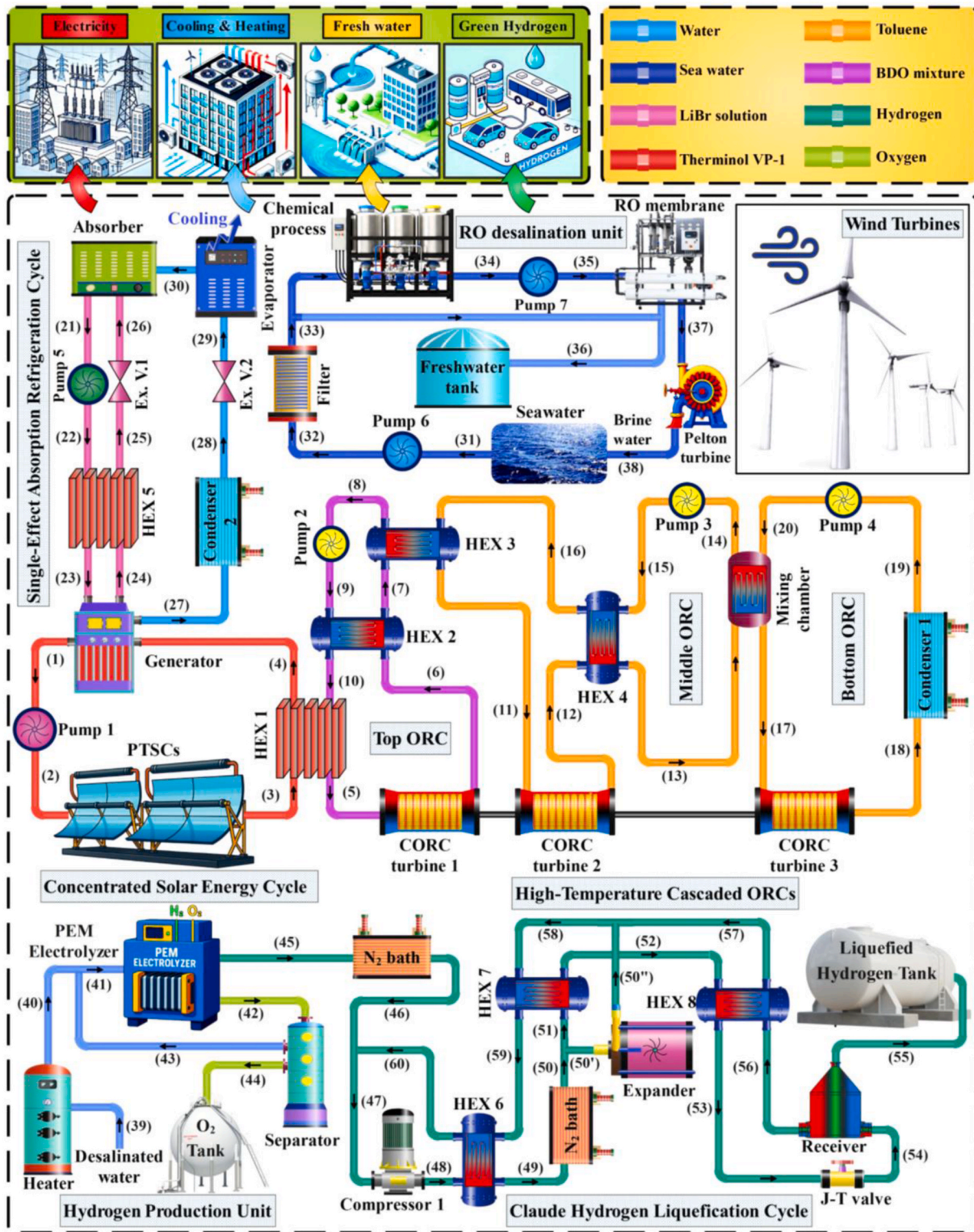


Fig. 1. Proposed hybrid renewable-based multi-generation system.

PTSCs, HTCORCs, an SEARC, an RODU, and a PEME. Wind turbines are incorporated to supply supplementary electricity, enhancing system reliability and enabling continuous operation under fluctuating environmental conditions.

2.1. Solar thermal subsystem and cascaded organic Rankine cycles

Solar energy is captured in the PTSC field using Therminol VP-1

(TVP1) as the heat transfer fluid. The fluid is pressurized (points 1–2), heated in the collectors (points 2–3), and then delivers thermal energy to the HTCORCs through HEX1 before entering the absorption cycle (points 4–1).

The HTCORC subsystem comprises a high-temperature top ORC thermally coupled with a dual-pressure bottom ORC consisting of high-pressure and low-pressure branches. In the top cycle, a butanediol (BDO) working fluid absorbs heat in HEX1, vaporizes, and expands through

Table 2

Key input parameters employed in the system modeling process [50,53,54].

Parameter	Value	Parameter	Value
P_0 , (bar)	1.013	RODU	
T_0 , (K)	298.15	Efficiency of pumps and turbine, (%)	85
Solar thermal cycle		Seawater salinity, (ppm)	35000
Length of single collector, (m)	12.27	Salinity of product water, (ppm)	450
Pressure drops in collector, (%)	5	Membrane recovery ratio,	0.55
Width of single collector, (m)	5.76	HTCORC	
Solar radiation, (W/m^2)	800	Efficiency of ORC turbines, (%)	85
PTSCs heat loss coefficient, ($W/m^2 \cdot ^\circ C$)	3.82	Efficiency of pumps (P1, P2, and P3), (%)	95
Solar collector area, (m^2)	20000	Regenerator efficiency, (%)	70
Wind turbines		Minimum temperature difference, ($^\circ C$)	85
Efficiency of the turbine, (–)	0.9	PEME	
Number of wind turbines	20	Operating temperature, (K)	353.15
Average wind speed, (m/s)	4	Operating pressure, (bar)	1.013
Power coefficient, (–)	0.55	Activation energy for anode, (kJ/mol)	76
Diameter of the turbine, (m)	44	Faraday constant, (–)	96,485
SEARC		Anode pre-exponential factor, (A/m^2)	1.7×10^5
Operating temperature of evaporator, ($^\circ C$)	5	Cathode water content, (–)	14
Effectiveness of HEX5, (–)	0.72	Anode water content, (–)	10
Operating temperature of condenser2, ($^\circ C$)	35	Cathode pre-exponential factor, (A/m^2)	4.6×10^3
Operating temperature of absorber, ($^\circ C$)	35	Membrane thickness, (μm)	100
Generator operating temperature, ($^\circ C$)	90	Activation energy for cathode (kJ/mol)	18

Turbine 1 (points 5–6), generating power. The exhaust stream transfers residual heat in HEX2 and is subsequently condensed in HEX3 (points 7–8), followed by pressurization and preheating (points 9–10).

The bottom cycle recovers heat rejected from the top cycle. Toluene is vaporized and expanded in Turbine 2 (points 11–12), producing additional power. The working fluid is then cooled, condensed, and partially expanded through a low-pressure turbine (points 17–18) to recover further energy before being recirculated. This cascading structure improves exergy efficiency by extracting useful work across multiple temperature levels and minimizing thermal losses.

2.2. Absorption refrigeration cycle

The remaining thermal energy of the HTF is utilized in the SEARC generator. A LiBr–water pair is employed, with water as the refrigerant. The strong solution is pressurized and heated (points 21–24), releasing refrigerant vapor, while the weak solution is throttled and returned to the absorber (points 25–26). The refrigerant vapor is condensed, expanded, and evaporated at low pressure (points 27–30), producing cooling. A solution heat exchanger enhances cycle efficiency by recovering internal heat. This configuration enables effective utilization of low-grade thermal energy without additional electrical input.

2.3. Wind energy subsystem

Wind turbines provide supplementary renewable electricity, supporting electricity-driven components such as the RODU and PEME. This integration mitigates solar intermittency and stabilizes overall system

performance.

2.4. Reverse osmosis desalination unit

The RODU is integrated into the proposed multigeneration system to produce freshwater using electricity generated by the renewable energy subsystem. Seawater is pressurized by a high-pressure pump and directed to the reverse osmosis membranes (points 31–32), where it is separated into two streams: a low-salinity freshwater (permeate) stream and a concentrated brine stream. The produced freshwater is collected in a storage tank for domestic and industrial use, constituting one of the useful outputs of the proposed multigeneration system. To improve the overall system efficiency, the high-pressure brine leaving the RO membranes (point 37) passes through a Pelton turbine for partial energy recovery before being discharged (point 38).

2.5. Hydrogen generation and liquefaction

Excess electricity generated by the hybrid solar–wind system is supplied to the proton exchange membrane electrolyzer (PEME), where water is electrochemically decomposed to produce hydrogen (points 39–45). The produced hydrogen is subsequently liquefied through a Claude-based cryogenic liquefaction cycle (points 45–60). The Claude process is selected due to its high efficiency and extensive application in hydrogen liquefaction. It utilizes multi-stage cooling, and expansion processes to achieve the cryogenic temperatures required for hydrogen liquefaction. The produced liquid hydrogen provides a high-density energy storage medium, improving renewable energy utilization and system flexibility.

3. Modeling and simulation

A comprehensive thermodynamic model of the proposed hybrid renewable-driven multi-generation system is developed to evaluate its energy, exergy, economic, and environmental performance. The simulation is implemented in MATLAB, where thermophysical properties of working fluids are obtained from the REFPROP database. The model ensures mass and energy balance in all components, and iterative calculations are performed until convergence is achieved for all state points and thermodynamic variables. The input values for system modeling under basic conditions are listed in Table 2.

3.1. Subsystem modeling

The proposed hybrid renewable multigeneration system integrates PTSCs, HTCORCs, a wind turbine, an SEARC, an RODU, a PEME, and a Claude hydrogen liquefaction cycle. The governing models for these subsystems are presented in the following sections. The analysis is based on the following assumptions:

- All components operate under steady-state and steady-flow conditions.
- Variations in kinetic and potential energies are negligible relative to enthalpy changes.
- The ambient conditions are adopted as the reference dead state for exergy calculations, with ($T_0 = 298.15\text{ K}$, $P_0 = 101.325\text{ kPa}$).

3.1.1. PTSCs

The PTSCs provide the main thermal input to the hybrid system by concentrating solar radiation onto a receiver tube carrying Therminol VP1. The collected heat supplies the HTCORCs and the absorption chiller. The useful heat gain is calculated as [50,55]:

$$\dot{Q}_u = F_R A_{ap} \left(G_{SCl} - \frac{A_{ap}}{A_r} U_L (T_n - T_0) \right) \quad (1)$$

Table 3

Properties of the BDO mixture [29].

Properties	Value
Maximum bulk temperature	400 °C
Normal boiling point	257 °C
Maximum film temperature	430 °C
Crystallizing point	12 °C
Pseudocritical pressure	33.1 bar
Pseudocritical temperature	499 °C

Table 4

Electrochemical reactions driving the PEME [60].

Parameter	Equation
Nernst equation	$V_0 = 1.229 - 8.5 \times 10^{-4}(T_{PEM} - 298)$
Cell overpotential	$V = V_0 + V_{ohm} + V_{activ,a} + V_{activ,c}$
Overactivation potential	$V_{activ,i} = \frac{RT}{F} \sin h^{-1} \left(\frac{J}{2J_{0,i}} \right) \quad i = a, c$
Ohmic overpotential	$V_{ohm} = JR_{PEM}$
Electrical energy input for electrolysis	$E_{elec} = Q_{elec} = JV$
Energy needed for the reaction	$\Delta H = \Delta G + T\Delta S$
Exchange current density for electrolysis	$J_{0,i} = J_i^{ef} \exp \left(-\frac{E_{activ,i}}{RT} \right) \quad i = a, c$
Total ohmic resistance	$R_{PEM} = \int_0^D \frac{dx}{\sigma[\lambda(x)]}$
Moisture level at a location in the membrane	$\lambda(x) = \frac{\lambda_a - \lambda_c}{D} x + \lambda_c$
Local ionic conductivity	$\sigma[\lambda(x)] = [0.5139\lambda(x) - 0.326] \exp \left[1268 \left(\frac{1}{303} - \frac{1}{T} \right) \right]$

where F_R is the heat removal factor, U_L is the overall heat loss coefficient, S_{CL} is the absorbed solar radiation, A_r and A_{ap} are the receiver and aperture areas, and T_{ri} and T_0 denote the inlet fluid and ambient temperatures, respectively. The receiver efficiency is given as [50,55]:

$$\eta_r = \beta \gamma \xi \alpha \kappa \quad (2)$$

and the absorbed solar energy:

$$S_{CL} = G\eta_r \quad (3)$$

where G is the solar irradiation. The heat removal factor is evaluated by Refs. [50,55]:

$$F_R = \frac{\dot{m}_r C_{p,CL}}{A_r U_L} \left[1 - \exp \left(\frac{-A_r U_L F_{CL}}{\dot{m}_r C_{p,CL}} \right) \right] \quad (4)$$

$$F_{CL} = \frac{\frac{1}{U_L}}{\frac{1}{U_L} + \frac{D_{ro}}{h_{ri}} + \left(\frac{D_{ro}}{2k} \ln \frac{D_{ro}}{D_{ri}} \right)} \quad (5)$$

A constant heat loss coefficient (U_L) is assumed under steady-state operation because the collector functions within a limited temperature range [56,57].

3.1.2. High-temperature cascaded organic Rankine cycles

The HTCORCs recover high-grade thermal energy and convert it into electrical power through a cascaded configuration comprising a top ORC and a dual-pressure bottom ORC. The top cycle operates with a BDO mixture, whereas the high- and low-pressure bottom cycles employ toluene and utilize the residual heat rejected from the upper cycle. This arrangement improves heat recovery across different temperature levels and enhances the overall power output and exergy utilization of the integrated system [29]. The main thermophysical properties of the BDO mixture are listed in Table 3. The detailed energy and exergy balance equations for each component of the HTCORCs are provided in Table 5.

3.1.3. Wind turbine

The wind turbine transforms the kinetic energy of the airflow into useable electrical power, serving as a key renewable power source in the hybrid multi-generation system. The aerodynamic power extracted from the wind is expressed as [58]:

$$\dot{W}_{wt} = \frac{1}{2} \eta_{wt} \rho_{air} A_{wt} C_{p,wt} (V_{wind})^3 \quad (6)$$

where η_{wt} represents the overall efficiency of the turbine, ρ_{air} is the air density, A_{wt} is the rotor swept area, $C_{p,wt}$ is the power coefficient, and V_{wind} is the wind velocity. The generated electricity supplies the PEME, RODU, Claude cycle, and other auxiliary equipment [58].

3.1.4. Single-effect LiBr absorption refrigeration cycle

The SEARC utilizes the waste heat from the solar cycle to produce cooling. The working pair is LiBr–water, with water serving as the refrigerant. It includes a generator, absorber, condenser, evaporator, solution heat exchanger, pump, and two expansion valves. Its principal performance relations are:

$$\dot{Q}_{evap} = \dot{m}_{ref} (h_{out,evap} - h_{in,evap}) \quad (7)$$

$$\dot{Q}_{gen} = \dot{m}_{sol} (h_{out,gen} - h_{in,gen}) \quad (8)$$

$$COP = \frac{\dot{Q}_{evap}}{\dot{Q}_{gen}} \quad (9)$$

Here $\dot{m}_{ref}$ is the refrigerant mass flow rate, and $\dot{m}_{sol}$ is the mass flow rate of the LiBr solution. Furthermore, $\dot{Q}_{gen}$ is thermal energy required in the generator, known as the generator heat input, $\dot{Q}_{evap}$ is the cooling load generated in the evaporator, and COP represents the cycle's efficiency, indicating how effectively the system converts input thermal energy into useful cooling. Detailed energy and exergy balances for the SEARC components are presented in Table 5.

3.1.5. Reverse osmosis desalination unit

The RODU converts seawater into freshwater using electrical energy supplied by the hybrid renewable energy system. The process is driven by a high-pressure pump that forces seawater via a selective membrane that permits the passage of water molecules while retaining dissolved salts and impurities. The permeate flow rate, pump power, and recovery ratio are expressed as [59,60]:

$$\dot{V}_p = A_m L_p (\Delta P - \Delta \pi) \quad (10)$$

$$\dot{W}_{pump} = \frac{\dot{V}_f \Delta P}{\eta_{pump}} \quad (11)$$

$$R_r = \frac{\dot{V}_p}{\dot{V}_f} \quad (12)$$

where A_m , L_p , ΔP , and $\Delta \pi$ are the membrane area, permeability coefficient, transmembrane pressure difference, and osmotic-pressure difference, respectively. Furthermore, $\dot{V}_f$ is the volumetric flow rate of the feed seawater, and $\dot{V}_p$ is the permeate volumetric flow rate. A Pelton turbine recovers part of the pressure energy from the discharged brine. The component-level balances of the membrane, pumps, and Pelton turbine are included in Table 5.

3.1.6. Hydrogen production unit

The PEME generates hydrogen and oxygen through the electrolysis of water, utilizing electricity supplied by the hybrid renewable-based system. In this unit, electrical energy is converted into chemical energy stored in hydrogen molecules. Governing equations for PEME modeling are listed in Table 4.

Table 5
Component-wise energy and exergy balance equations.

Component	Energy balance	Exergy balance
Concentrated solar energy cycle		
PTSCs	$\dot{m}_2 h_2 + \dot{Q}_u = \dot{m}_3 h_3$	$\dot{E}x_{D,PTSCs} = \dot{E}x_2 + \dot{E}x_{Sun} - \dot{E}x_3$
Pump 1	$\dot{m}_1 h_1 + \dot{W}_{P1} = \dot{m}_2 h_2$	$\dot{E}x_{D,P1} = \dot{E}x_1 - \dot{E}x_2 + \dot{W}_{P1}$
HTCORCs		
Mixing chamber	$\dot{m}_{13} h_{13} + \dot{m}_{20} h_{20} = \dot{m}_{14} h_{14} + \dot{m}_{17} h_{17}$	$\dot{E}x_{D,Mix} = \dot{E}x_{13} + \dot{E}x_{20} - \dot{E}x_{14} - \dot{E}x_{17}$
HEX 1	$\dot{m}_3 h_3 + \dot{m}_{10} h_{10} = \dot{m}_4 h_4 + \dot{m}_5 h_5$	$\dot{E}x_{D,HEX1} = \dot{E}x_3 + \dot{E}x_{10} - \dot{E}x_4 - \dot{E}x_5$
HEX 2	$\dot{m}_6 h_6 + \dot{m}_9 h_9 = \dot{m}_7 h_7 + \dot{m}_{10} h_{10}$	$\dot{E}x_{D,HEX2} = \dot{E}x_6 + \dot{E}x_9 - \dot{E}x_7 - \dot{E}x_{10}$
HEX 3	$\dot{m}_7 h_7 + \dot{m}_{16} h_{16} = \dot{m}_8 h_8 + \dot{m}_{11} h_{11}$	$\dot{E}x_{D,HEX3} = \dot{E}x_7 + \dot{E}x_{16} - \dot{E}x_8 - \dot{E}x_{11}$
HEX 4	$\dot{m}_{12} h_{12} + \dot{m}_{15} h_{15} = \dot{m}_{13} h_{13} + \dot{m}_{16} h_{16}$	$\dot{E}x_{D,HEX4} = \dot{E}x_{12} + \dot{E}x_{15} - \dot{E}x_{13} - \dot{E}x_{16}$
Condenser 1	$\dot{m}_{18} h_{18} = \dot{m}_{19} h_{19} + \dot{Q}_{Cond1}$	$\dot{E}x_{D,Cond1} = \dot{E}x_{18} - \dot{E}x_{19} - \dot{E}x_{Q,Cond1}$
Pump 2	$\dot{m}_8 h_8 + \dot{W}_{P2} = \dot{m}_9 h_9$	$\dot{E}x_{D,P2} = \dot{E}x_8 - \dot{E}x_9 + \dot{W}_{P2}$
Pump 3	$\dot{m}_{14} h_{14} + \dot{W}_{P3} = \dot{m}_{15} h_{15}$	$\dot{E}x_{D,P3} = \dot{E}x_{14} - \dot{E}x_{15} + \dot{W}_{P3}$
Pump 4	$\dot{m}_{19} h_{19} + \dot{W}_{P4} = \dot{m}_{20} h_{20}$	$\dot{E}x_{D,P4} = \dot{E}x_{19} - \dot{E}x_{20} + \dot{W}_{P4}$
CORC turbine 1	$\dot{m}_5 h_5 = \dot{m}_6 h_6 + \dot{W}_{T1}$	$\dot{E}x_{D,T1} = \dot{E}x_5 - \dot{E}x_6 - \dot{W}_{T1}$
CORC turbine 2	$\dot{m}_{11} h_{11} = \dot{m}_{12} h_{12} + \dot{W}_{T2}$	$\dot{E}x_{D,T2} = \dot{E}x_{11} - \dot{E}x_{12} - \dot{W}_{T2}$
CORC turbine 3	$\dot{m}_{17} h_{17} = \dot{m}_{18} h_{18} + \dot{W}_{T3}$	$\dot{E}x_{D,T3} = \dot{E}x_{17} - \dot{E}x_{18} - \dot{W}_{T3}$
SEARC		
HEX 5	$\dot{m}_{22} h_{22} + \dot{m}_{24} h_{24} = \dot{m}_{23} h_{23} + \dot{m}_{25} h_{25}$	$\dot{E}x_{D,HEX5} = \dot{E}x_{22} + \dot{E}x_{24} - \dot{E}x_{23} - \dot{E}x_{25}$
Generator	$\dot{m}_4 h_4 + \dot{m}_{23} h_{23} = \dot{m}_1 h_1 + \dot{m}_{24} h_{24} + \dot{m}_{27} h_{27}$	$\dot{E}x_{D,Gen} = \dot{E}x_4 + \dot{E}x_{23} - \dot{E}x_1 - \dot{E}x_{24} - \dot{E}x_{27}$
Absorber	$\dot{m}_{26} h_{26} + \dot{m}_{30} h_{30} = \dot{m}_{21} h_{21}$	$\dot{E}x_{D,Abs} = \dot{E}x_{26} + \dot{E}x_{30} - \dot{E}x_{21} - \dot{E}x_{Q,Abs}$
Evaporator	$\dot{m}_{29} h_{29} + \dot{Q}_{Eva} = \dot{m}_{30} h_{30}$	$\dot{E}x_{D,Eva} = \dot{E}x_{29} - \dot{E}x_{30} + \dot{E}x_{Q,Eva}$
Condenser 2	$\dot{m}_{27} h_{27} = \dot{m}_{28} h_{28} + \dot{Q}_{Cond2}$	$\dot{E}x_{D,Cond2} = \dot{E}x_{27} - \dot{E}x_{28} - \dot{E}x_{Q,Cond2}$
Pump 5	$\dot{m}_{21} h_{21} + \dot{W}_{P5} = \dot{m}_{22} h_{22}$	$\dot{E}x_{D,P5} = \dot{E}x_{21} - \dot{E}x_{22} + \dot{W}_{P5}$
Exp. Valve 1	$\dot{m}_{25} h_{25} = \dot{m}_{26} h_{26}$	$\dot{E}x_{D,Exp,V1} = \dot{E}x_{25} - \dot{E}x_{26}$
Exp. Valve 2	$\dot{m}_{28} h_{28} = \dot{m}_{29} h_{29}$	$\dot{E}x_{D,Exp,V2} = \dot{E}x_{28} - \dot{E}x_{29}$
PEME unit		
Heater	$\dot{m}_{39} h_{39} + \dot{Q}_{Heater} = \dot{m}_{40} h_{40}$	$\dot{E}x_{D,Heater} = \dot{E}x_{39} - \dot{E}x_{40} + \dot{E}x_{Q,Heater}$
Electrolyzer stack	$\dot{W}_{PEME} = JV$	$\dot{E}x_{D,PEME} = \dot{E}x_{41} - \dot{E}x_{42} - \dot{E}x_{45} + \dot{W}_{PEME}$
RODU		
RO membrane	$\dot{m}_{35} h_{35} = \dot{m}_{36} h_{36} + \dot{m}_{37} h_{37}$	$\dot{E}x_{D,RO} = \dot{E}x_{35} - \dot{E}x_{36} - \dot{E}x_{37}$
Pump 6	$\dot{m}_{31} h_{31} + \dot{W}_{P6} = \dot{m}_{32} h_{32}$	$\dot{E}x_{D,P6} = \dot{E}x_{31} - \dot{E}x_{32} + \dot{W}_{P6}$
Pump 7	$\dot{m}_{34} h_{34} + \dot{W}_{P7} = \dot{m}_{35} h_{35}$	$\dot{E}x_{D,P7} = \dot{E}x_{34} - \dot{E}x_{35} + \dot{W}_{P7}$
Pelton turbine	$\dot{m}_{37} h_{37} = \dot{m}_{38} h_{38} + \dot{W}_{Pelton}$	$\dot{E}x_{D,Pelton} = \dot{E}x_{37} - \dot{E}x_{38} - \dot{W}_{Pelton}$
Claude liquefaction cycle		
HEX 6	$\dot{m}_{48} h_{48} + \dot{m}_{59} h_{59} = \dot{m}_{49} h_{49} + \dot{m}_{60} h_{60}$	$\dot{E}x_{D,HEX6} = \dot{E}x_{48} + \dot{E}x_{59} - \dot{E}x_{49} - \dot{E}x_{60}$
HEX 7	$\dot{m}_{51} h_{51} + \dot{m}_{58} h_{58} = \dot{m}_{52} h_{52} + \dot{m}_{59} h_{59}$	$\dot{E}x_{D,HEX7} = \dot{E}x_{51} + \dot{E}x_{58} - \dot{E}x_{52} - \dot{E}x_{59}$
HEX 8	$\dot{m}_{52} h_{52} + \dot{m}_{56} h_{56} = \dot{m}_{53} h_{53} + \dot{m}_{57} h_{57}$	$\dot{E}x_{D,HEX8} = \dot{E}x_{52} + \dot{E}x_{56} - \dot{E}x_{53} - \dot{E}x_{57}$
Compressor 1	$\dot{m}_{47} h_{47} + \dot{W}_{Comp1} = \dot{m}_{48} h_{48}$	$\dot{E}x_{D,Comp1} = \dot{E}x_{47} - \dot{E}x_{48} + \dot{W}_{Comp1}$
Expander	$\dot{m}_{50} h_{50} = \dot{m}_{50'} h_{50'} + \dot{W}_{Expand}$	$\dot{E}x_{D,Pelton} = \dot{E}x_{50} - \dot{E}x_{50'} - \dot{W}_{Expand}$
J-T valve	$\dot{m}_{53} h_{53} = \dot{m}_{54} h_{54}$	$\dot{E}x_{D,J-T} = \dot{E}x_{53} - \dot{E}x_{54}$
Receiver	$\dot{m}_{54} h_{54} = \dot{m}_{55} h_{55} + \dot{m}_{56} h_{56}$	$\dot{E}x_{D,RO} = \dot{E}x_{54} - \dot{E}x_{55} - \dot{E}x_{56}$

3.1.7. Claude hydrogen liquefaction cycle

The hydrogen generated by the PEME is compressed, precooled, and expanded in the Claude cycle to produce liquid hydrogen. Part of the high-pressure stream expands through a cryogenic expander, while the remaining stream undergoes Joule–Thomson throttling. The resulting two-phase mixture is separated in a receiver, and the unliquefied vapor is recycled through the regenerative heat exchangers. The governing

relations for the compressor, expander, Joule–Thomson valve, heat exchangers, and separator are provided in Table 5. Their corresponding energy and exergy balances are presented in Table 5. Integration of this cycle enables compact hydrogen storage and facilitates long-term utilization of surplus renewable electricity.

3.2. Energy analysis

The thermodynamic analysis of the proposed hybrid renewable cogeneration system is conducted using the fundamental laws of mass, energy, and exergy conservation, assuming steady-state and steady-flow operation. Component-level performance is assessed through the formulation of energy and exergy balance equations. For a generic control volume, the mass balance is defined as:

$$\sum_{in} \dot{m}_{in} - \sum_{out} \dot{m}_{out} = 0 \quad (13)$$

where $\dot{m}$ represents the mass flow rate of the working fluid entering or leaving the control volume. Similarly, the energy balance, derived from the First Law of Thermodynamics, is given by:

$$\sum_{in} \dot{m}_{in} h_{in} + \dot{Q} = \sum_{out} \dot{m}_{out} h_{out} + \dot{W} \quad (14)$$

where $\dot{Q}$ is the heat transfer rate, $\dot{W}$ is the rate of work output (positive for work produced, negative for work consumed), and h is the specific enthalpy.

3.3. Exergy analysis

In order to better understand the quality and usefulness of energy transformations occurring within the hybrid system, an exergy-based evaluation is performed. Unlike the energy analysis, which only quantifies quantities of energy, exergy analysis reveals how effectively the system converts available energy into useful work and products by accounting for real losses caused by irreversibilities. The general exergy balance for a steady-state control volume is represented by:

$$\dot{E}x_Q + \sum_{in} \dot{m}_{in} ex_{in} = \dot{E}x_W + \sum_{out} \dot{m}_{out} ex_{out} + \dot{E}x_{dest} \quad (15)$$

$$\dot{E}x_Q = \left(1 - \frac{T_0}{T}\right) \dot{Q} \quad (16)$$

$$\dot{E}x_W = \dot{W} \quad (17)$$

Each stream of matter carries exergy that can be separated into several components including, physical, chemical, kinetic, and potential as expressed below:

$$ex = ex^{ph} + ex^{ch} + ex^{kn} + ex^{pt} \quad (18)$$

Because changes in elevation and velocity are insignificant compared to other effects in this system, the kinetic and potential contributions are neglected, resulting in:

$$ex \approx ex^{ph} + ex^{ch} \quad (19)$$

The physical part of exergy quantifies the departure of a stream from environmental conditions and is defined by:

$$ex^{ph} = h - h_0 - T_0(s - s_0) \quad (20)$$

Here, h and s represent the specific enthalpy and entropy of the working fluid, while h_0 and s_0 correspond to their values at the reference environment defined by temperature T_0 and pressure P_0 .

The overall exergy efficiency of the proposed hybrid renewable-based multi-generation configuration measures how effectively the available solar and wind exergy inputs are converted into useful energy

Table 6

Formulas employed to calculate the investment and operating costs associated with each component.

Subsystem	Cost functions	CEPCI	Ref.
Wind turbine	$Z_{WT} = 3465 \times (\dot{W}_{wt})^{0.5366}$	550.8	[61]
HEXs	$Z_{HX1} = 2143 \times (A_{HX1})^{0.514}$	567.5	[62]
Turbines	$Z_{tur} = 479.34 \times \left(\frac{\dot{m}}{0.92 - \eta_{tur}} \right) \times \log(R_{p,tur}) \times (1 + \exp(0.36 \times T_8 - 54.4))$	394	[63]
Pumps	$Z_{pump} = 200 \times (\dot{W}_{pump})^{0.65}$	394	[64]
Heater	$Z_{Pre} = 130 \times \left(\frac{A_{Pre}}{0.093} \right)^{0.78}$	468.2	[65]
PEME	$Z_{PEME} = 1000 \times \dot{W}_{elec}$	603.1	[66]
Absorber	$Z_{Abs} = 16000 \times (A_{Abs}/100)^{0.6}$	394.1	[67]
PTSCs	$Z_{PTSC} = 240 \times A_{ap,tot}$	550.8	[68]
RO membrane	$Z_{RO} = 10N A_m$	590.8	[69]
RO HPP	$\log_{10}(Z_{RO,P}) = 3.3892 + 0.0536 \log_{10}(\dot{W}_{RO,P}) + 0.1538 [\log_{10}(\dot{W}_{RO,P})]$	584.6	[69]
Pelton Turbine	$\log_{10}(Z_{PT}) = 2.2476 + 1.4965 \log_{10}(\dot{W}_{PT}) - 0.1618 [\log_{10}(\dot{W}_{PT})]^2$	584.6	[70]
Condenser	$Z_{Cond} = 516.62 (A_{Cond})^{0.6}$	584.6	[71]
Evaporator	$Z_{Evap} = 309.14 (A_{Evap})^{0.85}$	394.3	[71]
Claude compressor	$Z_{Comp} = 71.1 \times \left(\frac{\dot{m} \times R_{p,comp2}}{0.01} \right) \times \ln(R_{p,comp2})$	402	[72]
Claude HEXs	$Z_{Claude\ HEXs} = 2143 \times (A_{HEXs})^{0.514}$	394.3	[72]
Separator	$Z_{Sep} = 280.3 (\dot{m}_{in})^{0.67}$	567.5	[72]
J-T valve	$Z_{J-T} = 114.5 (\dot{m}_{in})$	541.7	[72]
Expander	$Z_{Exp} = 4750 \times (\dot{W}_{Exp})^{0.514}$	394.3	[72]

Table 7

Detailed cost breakdown, including both direct and indirect costs for the proposed system [73,74].

Parameter	Relations
Direct cost	Offsite costs + onsite costs
Onsite costs	
Purchased equipment cost (PEC)	$\sum Z_k$
Piping	$0.35 \times PEC$
Purchased-equipment installation (PEI)	$0.33 \times PEC$
Electrical equipment and materials	$0.13 \times PEC$
Offsite costs	
Civil, structural and architectural work	$0.21 \times PEC$
Land	$0.05 \times PEC$
Service facilities	$0.35 \times PEC$
Indirect costs	
Construction costs	$0.15 \times DC$
Engineering and supervision	$0.08 \times DC$
Contingencies	$0.15 \times (1.23 \times DC)$

products. It is formulated as:

$$\eta_{ex,overall} = \frac{\dot{W}_{grid} + \dot{E}x_{LH2} + \dot{E}x_{freshwater} + \dot{E}x_{cooling} + \dot{E}x_{heating}}{\dot{E}x_{solar} + \dot{E}x_{wind}} \quad (21)$$

$$\dot{W}_{net} = \dot{W}_{WT} + \dot{W}_{HTCORG} - \dot{W}_{aux} \quad (22)$$

$$\dot{W}_{grid} = \dot{W}_{net} - \dot{W}_{PEME} - \dot{W}_{RODU} - \dot{W}_{Claude} \quad (23)$$

The generated electrical power is distributed between the internal electricity-consuming units and the electrical grid. The net power is defined as the electricity generated by the wind turbines and the HTCORG after subtracting the auxiliary power consumption like pumps, whereas the grid power represents the remaining electricity available for export after supplying the PEME, RODU, and Claude liquefaction unit. Furthermore, energy and exergy balance formulations for the system's individual parts are detailed in Table 5.

3.4. Economic analysis

An economic analysis was conducted to assess the financial feasibility of the proposed hybrid wind-solar multigeneration system by considering capital investment, annualized costs, and long-term profit-

ability. The capital recovery factor (CRF) converts the initial investment into an equivalent annual cost while accounting for the time value of money:

$$CRF = \frac{i(1+i)^N}{(1+i)^N - 1} \quad (24)$$

Here, i is the annual interest rate and N is the project lifetime. A discount rate of 12% and a lifetime of 20 years were assumed. The component capital costs listed in Table 6 were updated to 2026 values using the chemical engineering plant cost index (CEPCI):

$$Z_{k,2026} = Z_k \frac{CEPCI_{2026}}{CEPCI_{reference}} \quad (25)$$

Here, $CEPCI_{reference}$, detailed in Table 6, refers to the cost index from the original reference year, while $CEPCI_{2026}$ specifically indicates the cost index for February 2026, with a value of 842.2. The total annualized system cost rate, including capital recovery and maintenance, was calculated as:

$$\dot{Z}_{tot} = \frac{CRF \times \varphi \times \sum Z_k}{t_{hour}} \quad (26)$$

where φ is the maintenance factor and t_{hour} is the annual operation time (8000 h). Long-term profitability was evaluated using the net present value (NPV):

$$NPV_t = (-FC \times IF_0 \times RDF_0) \times \sum_{i=1}^N (AS \times IF_i \times RDF_i) \quad (27)$$

In this framework, AS denotes the annual savings obtained from system operation, FC represents the fixed yearly expenses, IF_i and RDF_i correspond to the inflation and real discount factors, respectively, and N is the total system lifetime (20 years). The inflation and discount factors are determined by:

$$AS = AI - OC \quad (28)$$

$$IF_i = \left(1 + \frac{R}{100} \right)^{-i} \quad (29)$$

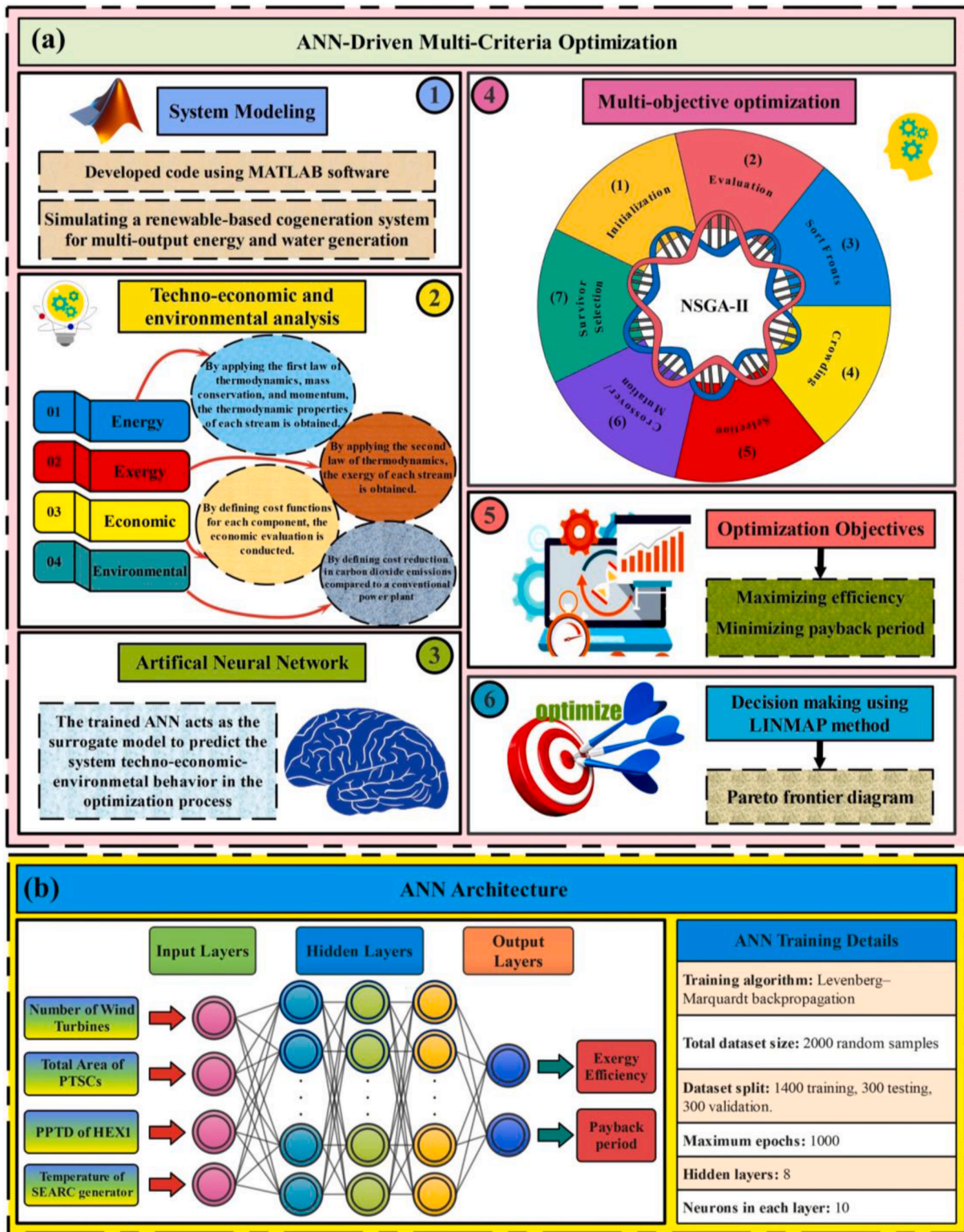


Fig. 2. (a) General methodology of the ANN-driven multi-criteria optimization and (b) ANN architecture utilized in this study.

$$RDF_i = \left(1 + \frac{RIR}{100}\right)^{-i} \quad (30)$$

$$RIR = DR - R \quad (31)$$

The payback period occurs when cumulative NPV reaches zero, while a positive NPV indicates economic profitability. Detailed direct and indirect cost equations for the proposed system are provided in

Table 7.

3.5. Operational CO₂-emission mitigation analysis

The operational environmental benefit of the proposed hybrid solar-wind multigeneration system is evaluated by quantifying the reduction in CO₂ emissions achieved through the displacement of

Table 8

Range of variation for the objective functions and decision variables.

Parameter	Lower bound	Upper bound
Decision variables		
Number of wind turbines (–)	1	20
Total area of PTSCs (m^2)	10000	30000
Pinch point temperature differences of HEX1 ($^{\circ}C$)	5	35
Operating temperature of SEARC generator ($^{\circ}C$)	70	100
Objective functions		
Exergy efficiency ($\eta_{ex,overall}$)	Should be maximized	
Payback period (PP)	Should be minimized	

Table 9

Configuration parameters applied in the NSGA-II.

Parameter	Method/Value
Maximum number of generations	100
Number of decision variables	4
Crossover rate	0.8
Population size	200
Convergence tolerance	1e-4
Selection strategy	Tournament

electricity generated by conventional natural gas-fired power plants. Since the proposed system operates using renewable energy sources without direct fuel combustion during normal operation, it does not produce direct operational CO₂ emissions. Therefore, this analysis focuses on operational CO₂-emission mitigation rather than a comprehensive environmental or life-cycle assessment. The avoided operational CO₂ emissions are determined by comparing the net electricity generated by the proposed system with an equivalent amount of electricity produced by a conventional natural gas-fired power plant. The operational CO₂-emission mitigation is calculated as:

$$\Delta \dot{m}_{CO_2} = \dot{W}_{net} \times e_{CO_2} \quad (32)$$

where $\dot{W}_{net}$ is the net electrical power generated by the proposed system and e_{CO_2} is the specific CO₂ emission factor of electricity generated by a natural gas-fired power plant, taken as 0.18 kg CO₂/kWh [56,57]. This parameter represents the amount of CO₂ emissions that would have been released if the same quantity of electricity had been generated using conventional natural gas-based power generation. Consequently, the calculated value represents the avoided operational CO₂ emissions attributable to the proposed renewable multigeneration system. The corresponding economic benefit associated with operational CO₂-emission mitigation is estimated through the emission reduction cost (ERC):

$$ERC_{CO_2} = \Delta \dot{m}_{CO_2} \times C_{CO_2} \quad (33)$$

where C_{CO_2} (USD/kg CO₂) is the unit cost associated with CO₂ emissions, assumed to be 0.024 USD/kg CO₂ [56,57]. This parameter represents the potential economic benefit obtained through avoided carbon taxes or participation in carbon-pricing and carbon-credit mechanisms. These indicators provide a quantitative measure of the environmental and economic benefits associated with replacing fossil-fuel-based electricity generation with renewable energy.

4. ANN-based optimization

Optimizing a hybrid renewable energy system that simultaneously targets high efficiency, low cost, and sustainable performance presents a complex multi-objective challenge. Conventional optimization methods that directly rely on thermodynamic simulations often require excessive computational resources due to the nonlinear and coupled nature of system components. To address this, an ANN is employed in this study as a high-fidelity surrogate model capable of emulating the system's

thermodynamic and economic behavior with remarkable precision and speed. The ANN learns from simulation-generated datasets, enabling rapid prediction of system responses during optimization while avoiding the need for repetitive, time-intensive numerical simulations. The general methodology of the ANN-based multi-objective optimization is illustrated in Fig. 2.

The developed neural model features a multi-layer architecture comprising an input layer, eight hidden layers, and an output layer. The selected input variables include the total aperture area of the PTSCs, the number of wind turbines, the pinch-point temperature difference in heat exchanger HEX1, and the generator operating temperature of the SEARC. The corresponding outputs are the overall exergy efficiency ($\eta_{ex,overall}$) and the payback period (PP), representing the system's thermodynamic and economic performance indicators, respectively. For network training, the Levenberg–Marquardt backpropagation algorithm is implemented due to its superior convergence rate and robustness in handling nonlinear regression problems. The dataset used for ANN development is divided into training, validation, and testing subsets to prevent overfitting and ensure generalization accuracy.

Table 8 outlines the selected decision variables along with their respective variation limits. These variables define the key design and operational characteristics of the proposed hybrid system. The optimization framework aims to maximize the exergy efficiency while minimizing the payback period, achieving a balanced trade-off among technical, economic, and environmental objectives.

The selected decision variables are chosen based on their significant impact on the thermodynamic performance and economic feasibility of the proposed system. The PTSC aperture area determines the available solar thermal input and affects both energy production and investment cost, while the number of wind turbines controls the renewable electricity contribution and hydrogen production potential. The pinch-point temperature difference of HEX1 influences heat recovery effectiveness and heat exchanger cost, and the SEARC generator temperature governs the utilization of low-grade thermal energy for cooling production. Therefore, optimizing these parameters enables the identification of the optimal system configuration that balances enhanced exergy performance and economic feasibility.

Once the ANN has been successfully trained and validated, it is integrated with the NSGA-II to perform multi-objective optimization. NSGA-II is an evolutionary algorithm renowned for its ability to handle complex, nonlinear, and conflicting objectives efficiently. It applies genetic operations such as crossover, mutation, and tournament-based selection to explore the design space and identify a set of Pareto-optimal solutions. The combination of ANN and NSGA-II offers a powerful hybrid optimization framework. The ANN model dramatically accelerates the optimization process by replacing computationally expensive thermodynamic simulations with fast, data-driven predictions. Meanwhile, NSGA-II systematically explores the trade-offs between competing objectives, generating a Pareto front that visually illustrates the balance between exergy efficiency and payback period. These Pareto-optimal points provide critical insights into how design and operational parameters influence overall system performance, supporting informed decision-making for real-world implementation. The primary control parameters used in the NSGA-II optimization are summarized in Table 9.

5. System validation

Owing to the novel integration of several subsystems within the proposed renewable-based cogeneration system, direct validation of the complete configuration against a single reference is not feasible. Therefore, a component-wise validation approach was adopted, in which each subsystem was evaluated against reliable experimental or numerical data available in the literature.

- PTSC, PEME, HTCORC, and Claude cycle validation

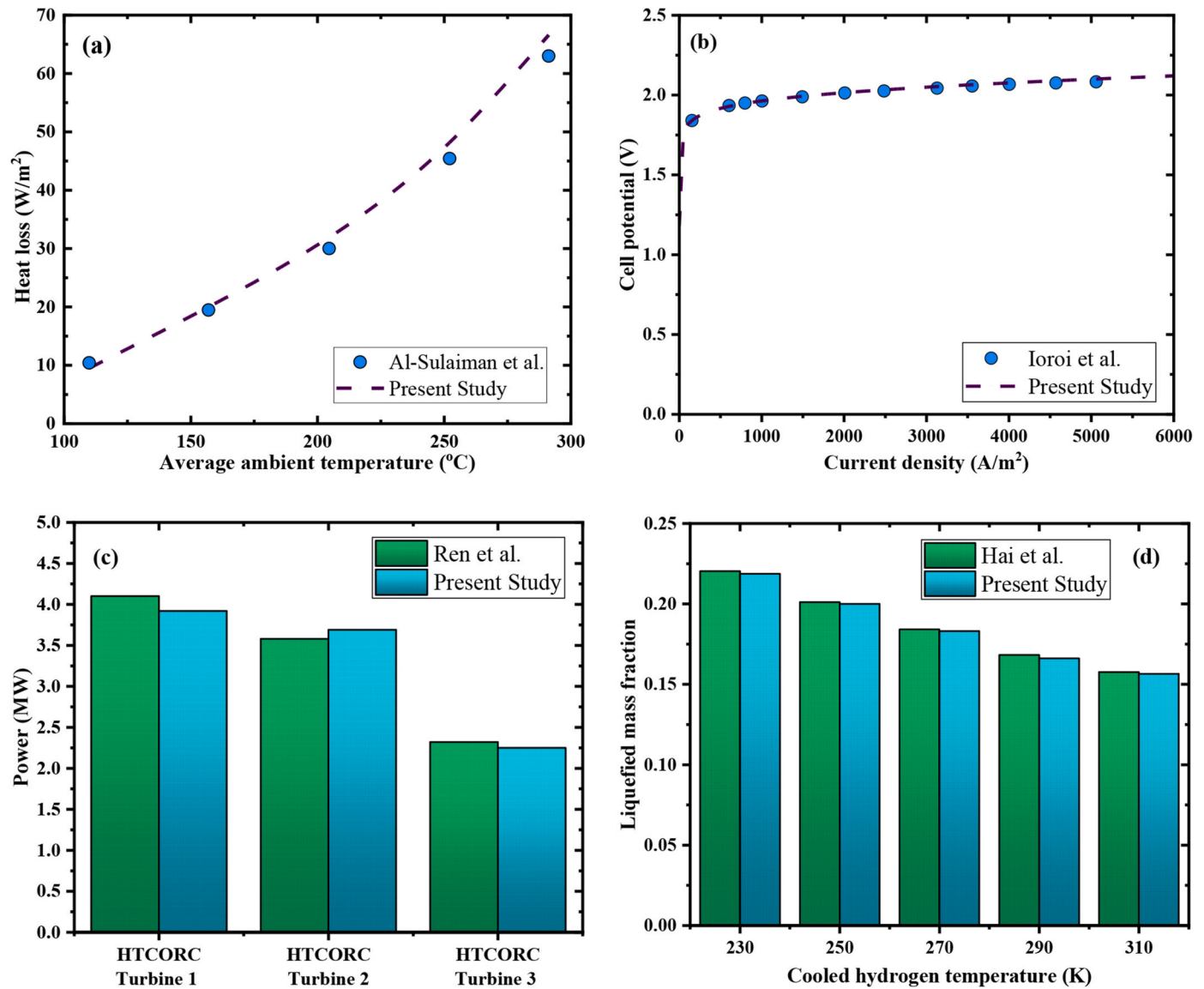


Fig. 3. (a) Validation of PTSCs against Al-Sulaiman et al. [75], (b) Validation of PEME against Ioroi et al. [76], (c) Validation of HTCORCs against Ren et al. [29], (d) Validation of Claude cycle against Hai et al. [77].

Table 10
Verification of the SEARC model against Maryami et al. [78].

Parameter	Present model	Maryami et al. [78]	Deviation (%)
Cooling generated (kW)	320.46	300	6.82
Absorber heat load (kW)	366.2	352.3	3.94
COP (–)	0.829	0.825	0.48
Solution-to-refrigerant mass flow ratio (–)	6.18	6.22	0.64

The PTSC model was validated against the experimental data reported by Al-Sulaiman et al. [75]. As illustrated in Fig. 3(a), the predicted heat loss per unit collector area follows the experimental trend over the investigated ambient-temperature range, with deviations remaining below 7%. The PEME model was evaluated using the polarization measurements of Ioroi et al. [76]. Fig. 3(b) shows close agreement between the predicted and measured cell voltages, with a maximum deviation of 1.6% across the considered current-density range. The HTCORC model was verified by comparing the predicted turbine power outputs with the results of Ren et al. [29]. As shown in

Table 11
Model validation of modeled RODU system.

Parameter	Present study	Sharqawy et al. [79]	Deviation (%)
Exergy destruction (kW)	128.66	128.7	0.031
Low-pressure pump power (kW)	31.84	31.84	0.000
High-pressure pump power (kW)	133.9	133.9	0.000
Exergy efficiency (%)	1.509	1.51	0.066

Fig. 3(c), the present results are consistent with the reference values, while the small discrepancies are mainly attributed to differences in operating assumptions and boundary conditions. Finally, the Claude liquefaction cycle was validated against the thermodynamic results of Hai et al. [77] under the same compressor discharge pressure and isentropic efficiencies of 80% and 85% for the compressor and expander, respectively. The maximum deviation was limited to 1.01%, confirming the accuracy of the cryogenic model [Fig. 3(d)].

Table 12
System results under base condition.

Parameter	Value
$\dot{W}_{wt} (kW)$	3310.8
$\dot{W}_{CORC1} (kW)$	1256.9
$\dot{W}_{CORC2} (kW)$	574.5
$\dot{W}_{CORC3} (kW)$	451.5
$\dot{W}_{Grid} (kW)$	4306.2
$\dot{Q}_{Cooling} (kW)$	2102.4
$\dot{m}_{Liquefied\ H_2} (kg/h)$	15.01
$\dot{m}_{freshwater} (kg/s)$	46.29
$\eta_{ex} (\%)$	29.02
PP (Year)	3.97
$\dot{Z}_{tot} (\$/h)$	544.6
$ERC_{CO_2} (\$/h)$	24.13
$\Delta m_{CO_2} (kg/h)$	1005.4

• SEARC model validation

The SEARC model was validated against the experimental results of Maryami et al. [78]. As listed in Table 10, the deviations in cooling capacity, absorber heat load, COP, and solution-to-refrigerant mass flow ratio were below 7%.

• RODU model validation

The RODU model was validated against the data of Sharqawy et al. [79]. Table 11 shows negligible deviations in exergy destruction, pump power consumption, and exergy efficiency, confirming the accuracy of the desalination model.

Overall, the close agreement with the reference data supports the reliability of the developed models for evaluating the integrated system.

6. Results and discussion

This section evaluates the proposed hybrid wind-solar multi-generation system from a 4E perspective. First, baseline performance is analyzed under reference conditions. Then, a parametric study examines the influence of key design variables. Multi-objective optimization is conducted to maximize exergy efficiency and minimize payback period. Economic feasibility is assessed using NPV and payback metrics, followed by a case study demonstrating system performance in meeting electricity, cooling, freshwater, and hydrogen demands.

6.1. Base system analysis

The baseline performance of the proposed hybrid cogeneration system is presented in Table 12. The system simultaneously produces

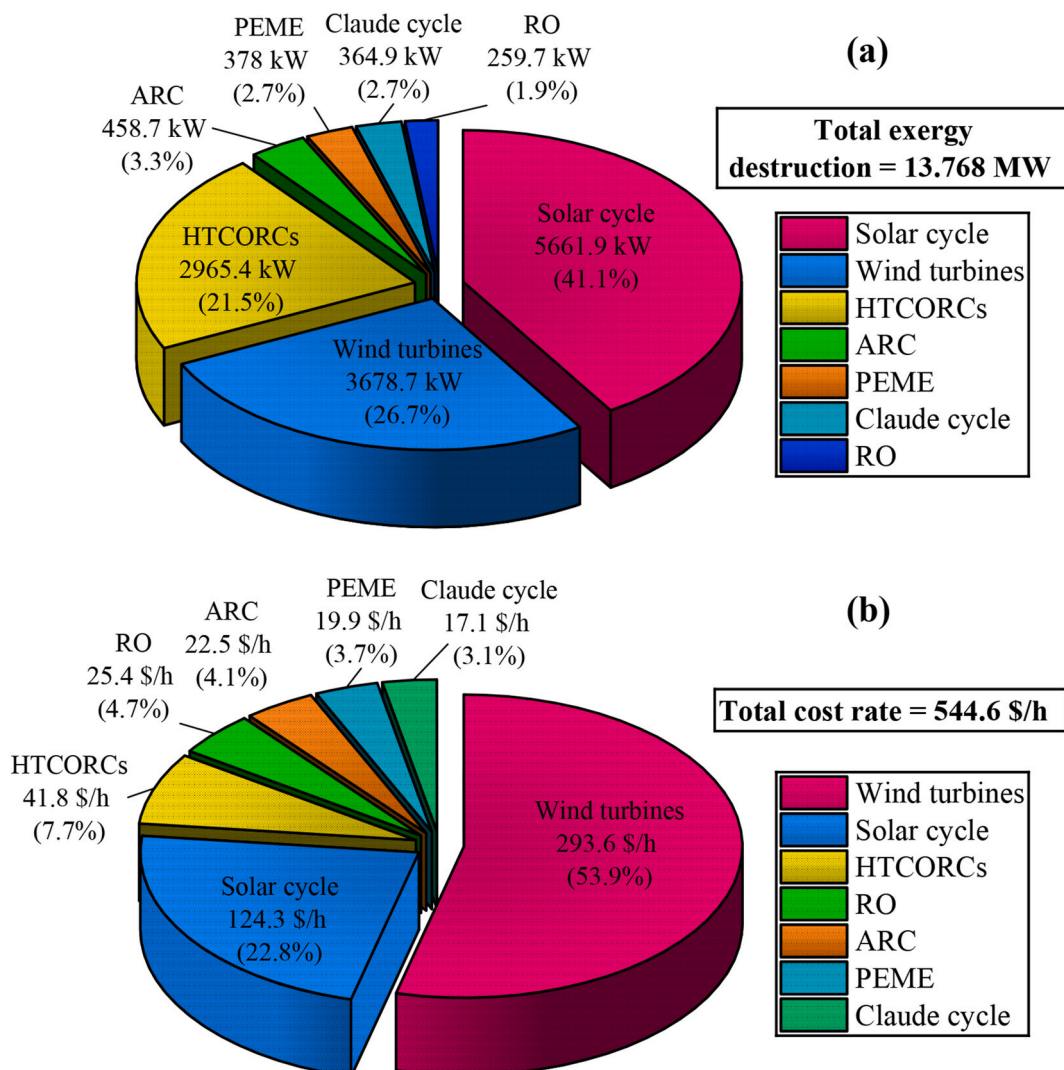


Fig. 4. Exergy destruction distribution (a), and cost rate distribution (b) across different subsystems.

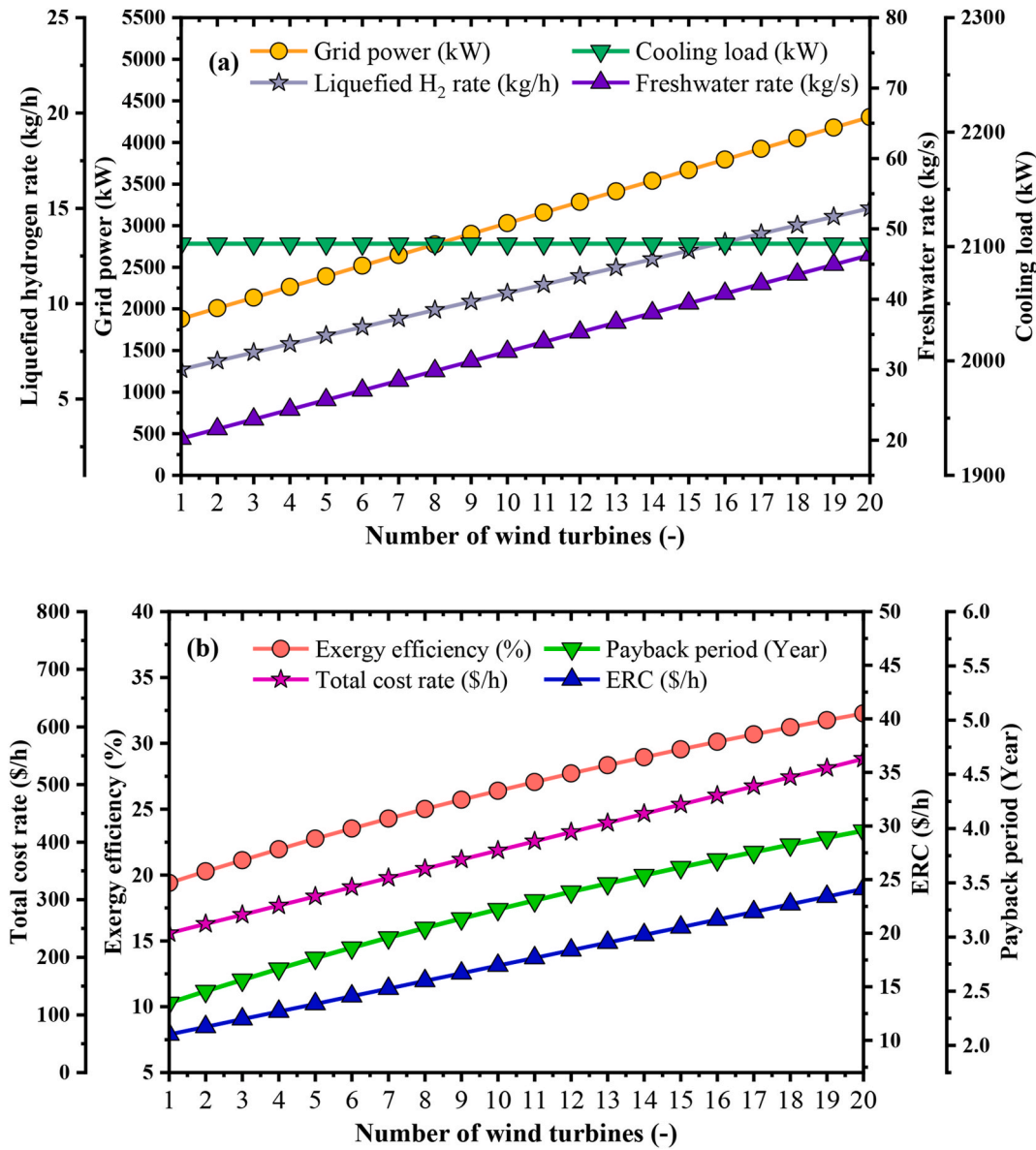


Fig. 5. System performance evaluation of the effect of changes in the number of wind turbines.

electricity, cooling, freshwater, and liquefied hydrogen with an overall exergy efficiency of 29.02%. Economically, it shows a total cost rate of 544.6 \$/h and a payback period of 3.97 years, while achieving an ERC of 24.13 \$/h. These results confirm the technical feasibility and integrated multi-generation capability of the system and provide a reference case for subsequent parametric and optimization analyses.

Fig. 4(a) presents the distribution of exergy destruction among the principal subsystems of the proposed hybrid wind and solar multi-generation system under baseline operating conditions. The total exergy destruction is determined to be 13.768 MW, representing the overall thermodynamic irreversibilities within the integrated configuration. Among the subsystems, the solar field exhibits the highest exergy destruction of 5661.9 kW, which can be attributed to radiative and convective heat losses from the PTSCs as well as heat transfer limitations in the receiver. The wind turbine array contributes 3678.7 kW of exergy destruction, mainly due to aerodynamic inefficiencies and mechanical frictional losses during power conversion. The HTCORCs subsystem accounts for 2965.4 kW, reflecting the influence of non-ideal expansion and condensation processes. In comparison, the absorption refrigeration cycle, the PEME, Claude cycle, and the reverse osmosis desalination unit

exhibit significantly lower exergy destruction rates of 458.7 kW, 378 kW, 364.9, and 259.7 kW, respectively.

Fig. 4(b) illustrates the corresponding distribution of cost rates among these subsystems, with the total economic cost estimated at 544.6 \$/h. The wind turbine system represents the largest share, amounting to 293.6 \$/h, primarily due to its substantial capital investment and ongoing maintenance expenses. The solar field ranks second at 124.3 \$/h, reflecting both the cost of solar collector installation and the operational costs associated with thermal oil circulation. The HTCORCs contributes 41.8 \$/h, while the reverse osmosis desalination and absorption refrigeration cycles account for 25.4 and 22.5 \$/h, respectively. The PEME and Claude cycle demonstrate the lowest costs rate of 19.9 and 17.1 \$/h, indicating its favorable cost-effectiveness in hydrogen production and storage. Overall, these findings reveal that renewable power generation units dominate both exergy destruction and cost allocation, suggesting that performance enhancements in the solar and wind subsystems would yield the greatest impact on the system's overall thermoeconomic efficiency.

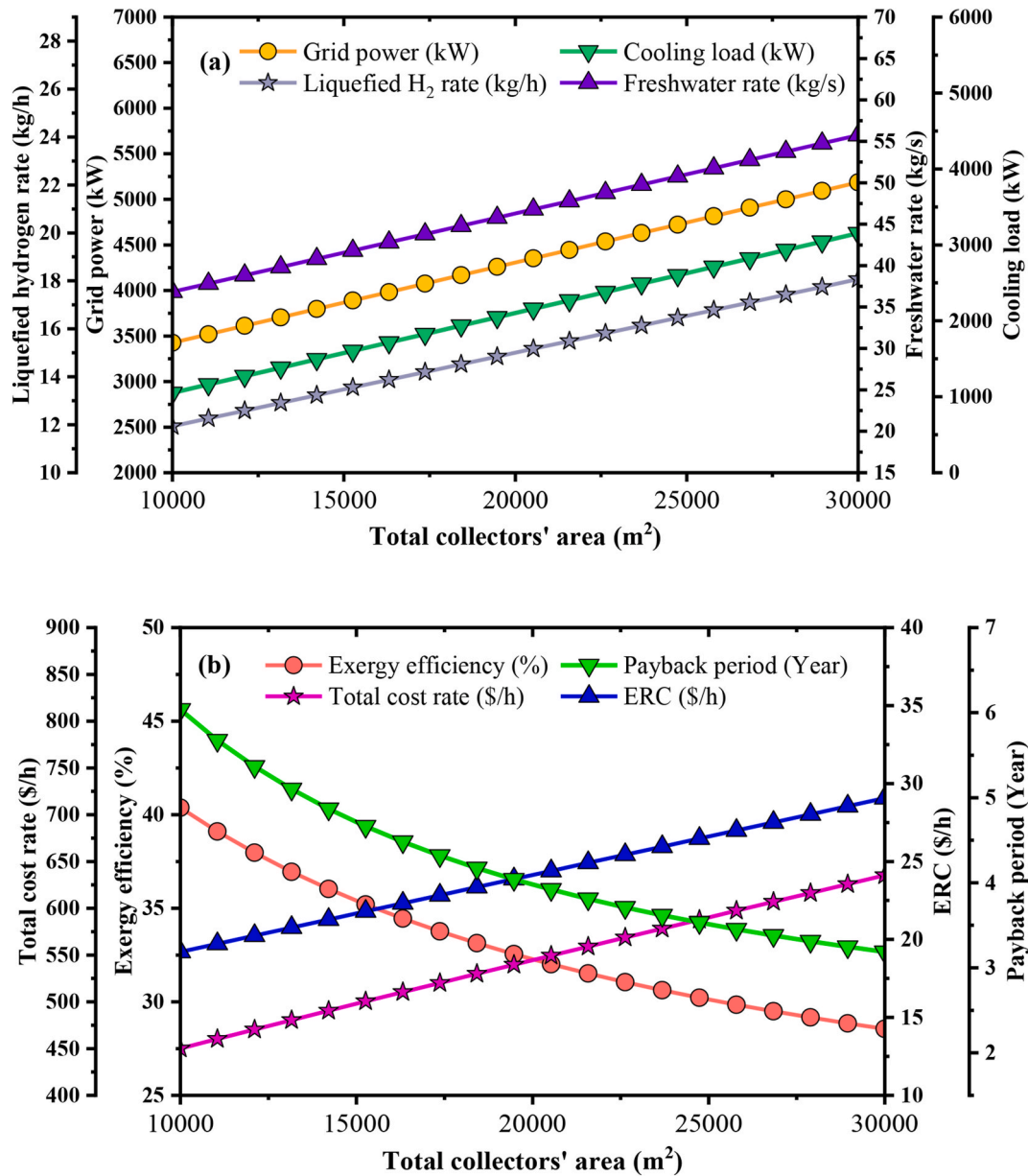


Fig. 6. System performance evaluation of the effect of changes in the total collectors' area.

6.2. Parametric analysis

This section presents a parametric investigation of the key factors influencing the performance of the proposed system. The parameters analyzed include the number of wind turbines, the total area of solar collectors, the pinch point temperature difference of HEX1, and the operating temperature of the SEARC generator.

6.2.1. Effect of number of wind turbines

The wind turbine subsystem strongly influences both the magnitude and reliability of electricity generation. As shown in Fig. 5(a), increasing the number of turbines from 1 to 20 raises the total power output from 1880.8 kW to 4306.2 kW. This improvement directly enhances the performance of electricity-driven subsystems, leading to higher freshwater production (20.22 to 46.29 kg/s) and hydrogen generation (6.55 to 15.01 kg/h). The increase is primarily due to greater electrical availability for the electrolyzer and desalination unit. In contrast, cooling capacity remains unchanged, as it is governed by thermal inputs rather than electrical supply.

Fig. 5(b) shows that exergy efficiency increases from 19.39% to 32.28%, reflecting more effective utilization of renewable exergy and reduced relative system irreversibilities. However, this improvement is accompanied by a significant rise in total cost ($\approx 134.6\%$) due to higher capital and maintenance requirements. Despite this, environmental performance improves, with ERC increasing from 10.54 to 24.13 \$/h, driven by greater displacement of fossil-based electricity. The payback period increases moderately (2.39 to 3.99 years), indicating a trade-off between enhanced performance and economic investment.

6.2.2. Effect of total collectors' area

The effect of the total PTSC area on system performance is shown in Fig. 6. Increasing the collector area from 10,000 to 30,000 m² enhances solar energy absorption, raising the temperature and thermal capacity of the heat transfer fluid. This improves heat transfer within the high-temperature ORC cascade, leading to a significant increase in net power output from 3426.7 to 5185.6 kW. The higher electricity availability directly boosts downstream processes, increasing hydrogen production (11.94 to 18.07 kg/h) and freshwater generation (36.84 to

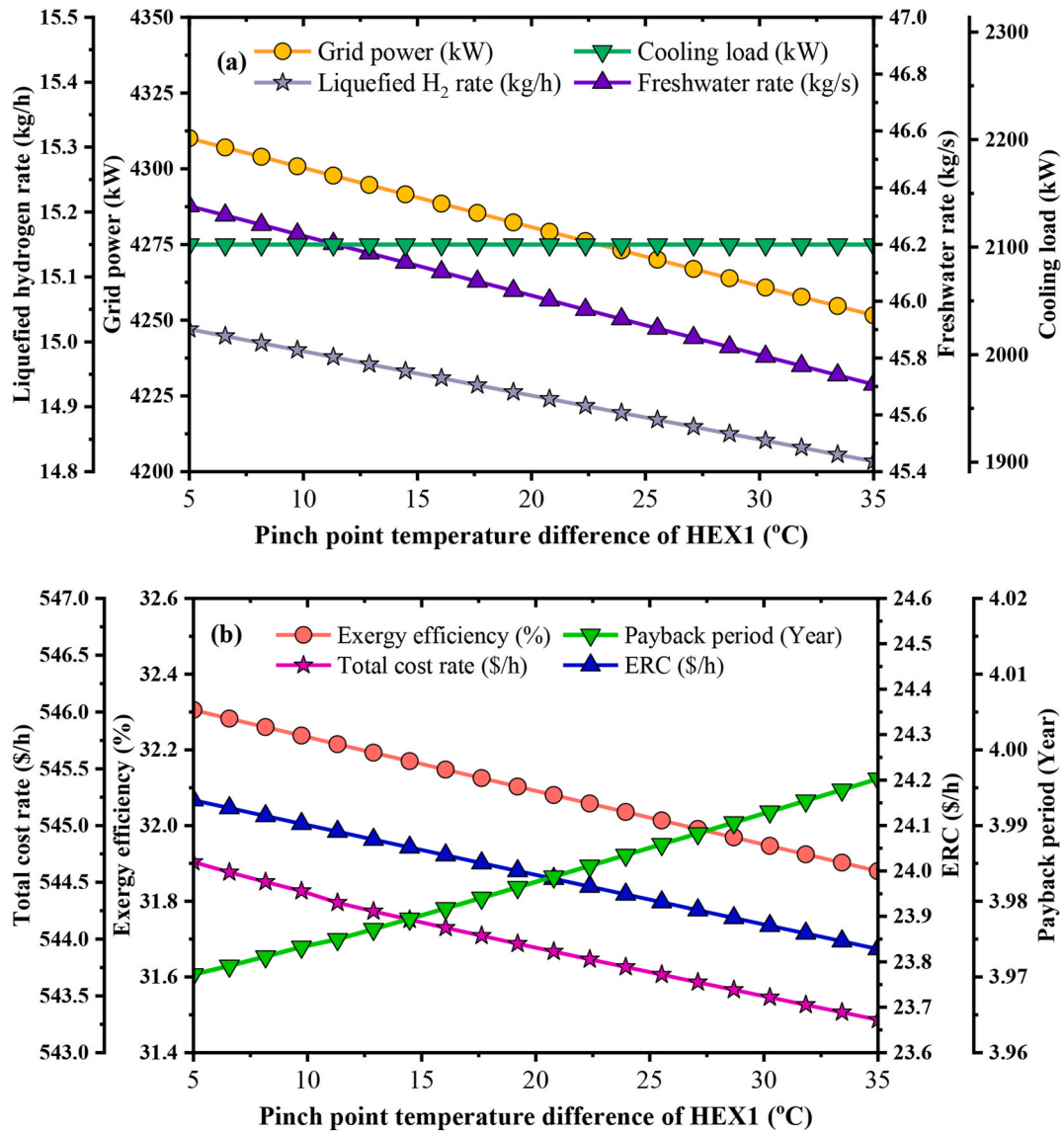


Fig. 7. System performance evaluation of the effect of changes in the pinch point temperature difference of HEX1.

55.75 kg/s). Additionally, greater low-grade heat availability strengthens the absorption refrigeration cycle, increasing cooling capacity from 1051.05 to 3153.84 kW. These trends confirm that system productivity is strongly dependent on solar field capacity.

However, increasing collector area also intensifies thermal gradients and heat transfer across components, leading to higher entropy generation and reduced exergy efficiency (40.38% to 28.56%). Economically, the larger solar field increases capital and operational costs, raising the total cost rate from 450.08 to 635.19 \$/h. Despite this, the payback period decreases from 6.04 to 3.18 years due to higher energy outputs and revenue generation. Furthermore, increased renewable utilization enhances environmental performance, with ERC rising from 19.21 to 29.06 \$/h. Overall, while larger collector areas improve system capacity and sustainability, they introduce efficiency penalties and cost increases, highlighting the need for optimal sizing.

6.2.3. Effect of pinch point temperature difference of HEX1

The effect of PPTD of HEX1 on system performance is shown in Fig. 7. Increasing PPTD from 5 °C to 35 °C reduces the effective temperature driving force for heat exchange between the solar field and the ORC cascade, thereby limiting heat recovery. As a result, turbine expansion work decreases, leading to a drop in net electricity output

from 4310.1 to 4251.6 kW. This reduction slightly constrains electricity-dependent subsystems, lowering hydrogen production (15.01 to 14.81 kg/h) and freshwater generation (46.33 to 45.70 kg/s). In contrast, cooling capacity remains nearly unchanged, as it primarily relies on low-grade thermal energy, which is less sensitive to PPTD variations.

Thermodynamically, higher PPTD increases irreversibilities in heat exchange, causing a slight decrease in exergy efficiency (32.31% to 31.88%). Economically, the total cost rate marginally decreases (544.67 to 543.29 \$/h) due to reduced heat exchanger size and cost, although the payback period slightly increases (3.97 to 3.996 years) because of lower system outputs. Environmentally, ERC declines from 24.15 to 23.82 \$/h, reflecting reduced renewable-based production. Overall, lower PPTD values improve heat recovery and system performance, highlighting the importance of optimal heat exchanger design.

6.2.4. Effect of generator operating temperature

The operating temperature of the SEARC generator strongly affects the cooling subsystem performance, as shown in Fig. 8. Increasing the generator temperature from 70 °C to 100 °C enhances the thermal driving force of the absorption cycle, which intensifies refrigerant desorption in the generator and increases the pressure difference across

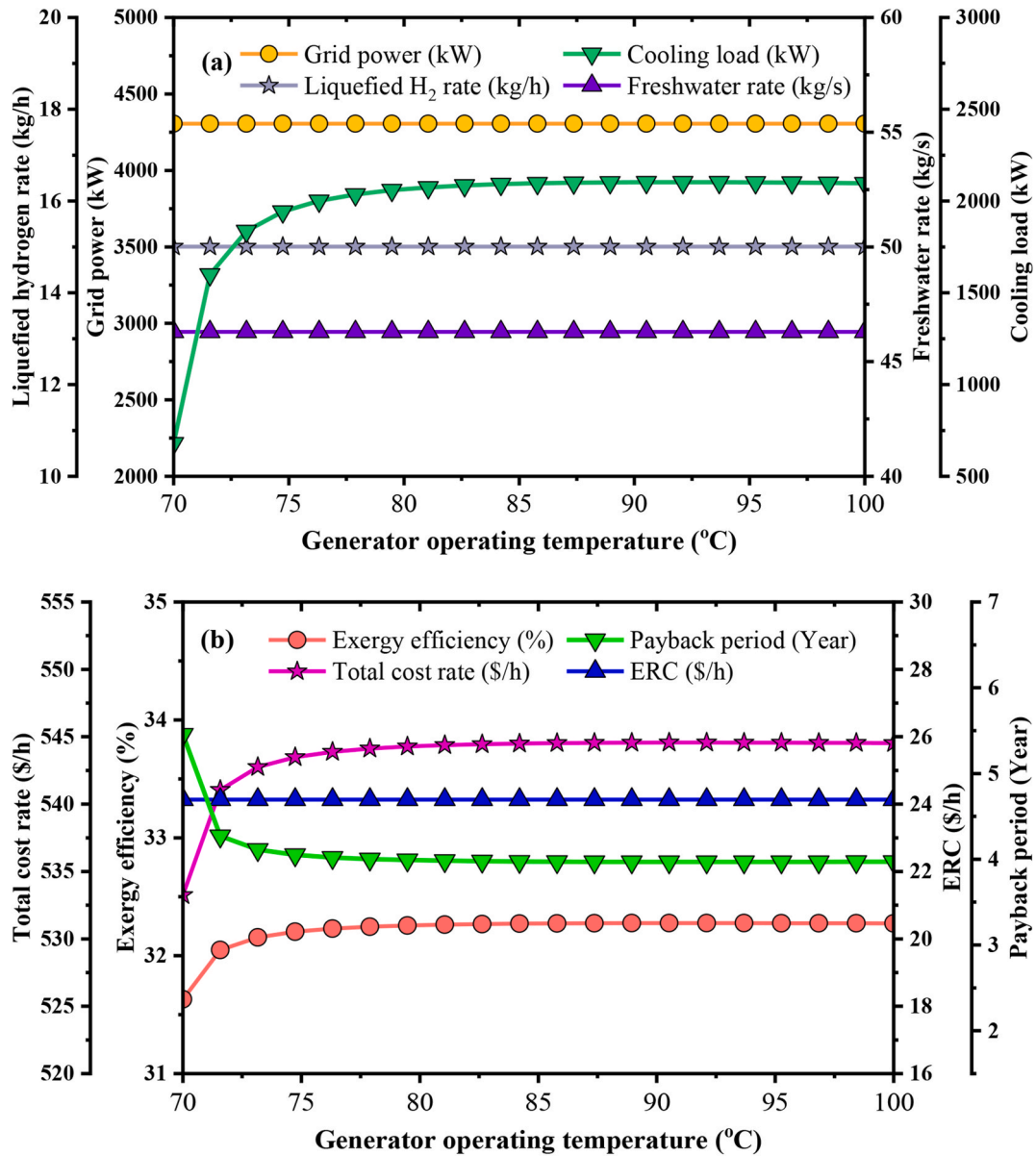


Fig. 8. System performance evaluation of the effect of changes in the generator operating temperature.

the cycle. As a result, the cooling capacity rises significantly from 680.12 kW to 2097.34 kW. In contrast, electricity, hydrogen, and freshwater outputs remain almost unchanged, since they are mainly governed by the solar field and HTCORC subsystem rather than the absorption cycle conditions.

Thermodynamically, higher generator temperatures slightly improve exergy efficiency from 31.63% to 32.27%, as the absorption system operates more effectively with better utilization of low-grade heat and reduced internal irreversibilities. However, the total cost rate increases from 533.24 to 544.53 \$/h due to the need for materials and components capable of operating at higher temperatures. Despite this, the payback period decreases from 5.45 to 3.97 years, driven by the substantial increase in cooling output and associated economic benefits. Overall, higher generator temperatures primarily enhance cooling performance while slightly improving system efficiency and economic feasibility.

6.3. ANN and NSGA-II integration optimization

The ANN was coupled with the NSGA-II algorithm to enable efficient

multi-objective optimization of the proposed hybrid renewable-based multi-generation system. A feedforward ANN trained on 2000 simulation samples was employed as a surrogate model to replace computationally expensive thermodynamic simulations during optimization. This approach substantially reduced computational time while preserving prediction accuracy for key performance indicators, namely exergy efficiency and payback period. The ANN demonstrated excellent predictive capability, with R^2 values of 0.99998 and 0.99997 for exergy efficiency and payback period, respectively, and low mean absolute errors (0.00144 and 0.00153). As shown in Fig. 9(a and b), the close agreement between predicted and simulated values confirms the robustness of the surrogate model and its suitability for integration with evolutionary optimization.

The NSGA-II optimization targeted simultaneous maximization of exergy efficiency and minimization of payback period, capturing the trade-off between thermodynamic performance and economic viability. The resulting Pareto front (Fig. 9(c)) illustrates that higher efficiencies are generally associated with increased payback periods, reflecting the cost-performance conflict inherent in system design. Overall, the ANN-NSGA-II framework provides a computationally efficient and

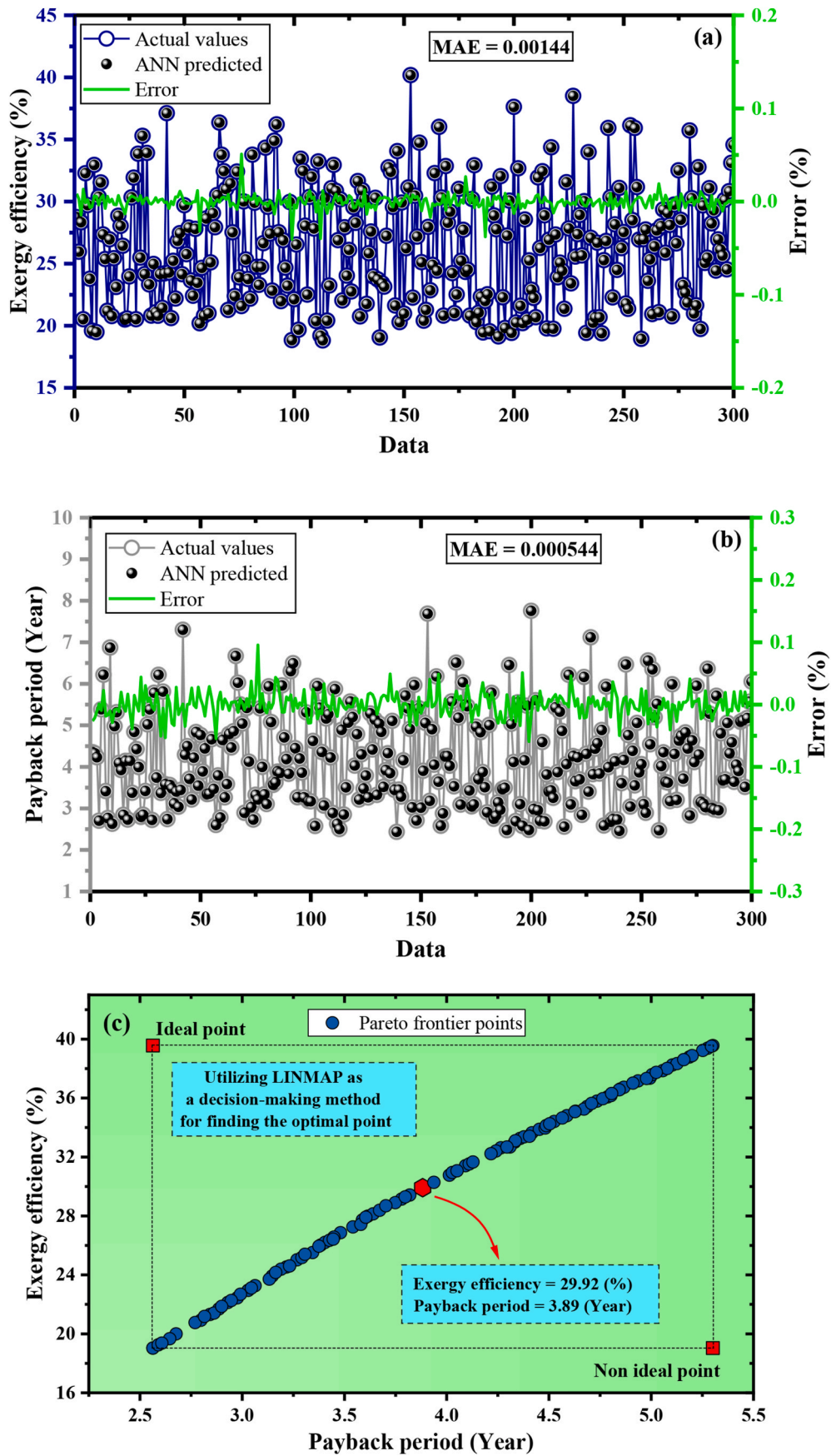


Fig. 9. ANN accuracy evaluation for a) exergy efficiency and b) payback period, and c) Pareto frontier diagram of conflicting objective functions.

Table 13
System results under optimum condition.

Parameter	Value
Decision variables	
Number of wind turbines (–)	19
Total area of PTSCs (m^2)	23834.91
Pinch point temperature differences of HEX1 ($^{\circ}C$)	11.46
Operating temperature of SEARC generator ($^{\circ}C$)	94.82
Outputs	
$\dot{W}_{we}$ (kW)	3108.9
$\dot{W}_{CORC1}$ (kW)	1480.9
$\dot{W}_{CORC2}$ (kW)	686.5
$\dot{W}_{CORC3}$ (kW)	539.5
$\dot{W}_{Grid}$ (kW)	4477.3
$\dot{Q}_{Cooling}$ (kW)	2504.8
$\dot{m}_{Liquefied\ H_2}$ (kg/h)	15.61
$\dot{m}_{freshwater}$ (kg/s)	48.13
η_{ex} (%)	29.92
PP (Year)	3.89
$\dot{Z}_{tot}$ (\$/h)	560
ERC_{CO_2} (\$/h)	25.09
$\Delta \dot{m}_{CO_2}$ (kg/h)	1045.42

accurate tool for identifying optimal configurations of complex renewable energy systems.

Under the optimized configuration (Table 13), the system demonstrates notable performance enhancements compared to the baseline results in Table 12. The grid-connected power output increases from 4306.2 kW to 4477.3 kW, driven by the reconfiguration of the parabolic trough collector area (23,834.91 m^2) and improved operating parameters across the HTCORCs units. Cooling production also rises from 2102.4 kW to 2504.8 kW, while liquefied hydrogen and freshwater generation rates improve to 15.61 kg/h and 48.13 kg/s, respectively. The total exergy efficiency increases from 29.02% to 29.92%, reflecting a more effective utilization of renewable inputs and reduced irreversibilities across subsystems. Economically, the payback period decreases from 3.97 to 3.89 years despite a modest increase in total cost rate from 544.6 \$/h to 560 \$/h, indicating improved investment viability through enhanced multi-product outputs. Furthermore, the equivalent CO_2 emission reduction cost rises slightly to 25.09 \$/h, reinforcing the system's environmental advantages.

6.4. Net present value and payback-period assessment

Fig. 10(a) compares the economic performance of the baseline and optimized configurations under an electricity price of 0.07 \$/kWh. Although both cases exhibit initial negative cash flow due to high capital investment, the optimized system achieves faster capital recovery, reaching the break-even point at 3.89 years compared to 3.97 years for the baseline. This improvement is mainly driven by higher multi-energy output (electricity, cooling, hydrogen, and freshwater), which increases annual revenue and accelerates cumulative cash flow growth. Over a 20-year period, the optimized configuration yields a net present value (NPV) of 58.23 million USD, exceeding the 50.64 million USD obtained from the baseline case, confirming improved long-term profitability.

Fig. 10(b) shows the sensitivity of the optimized system to electricity selling price. Increasing electricity price directly enhances revenue from grid export, thereby improving cash flow and reducing payback time. The payback period decreases from 4.23 years at 0.05 \$/kWh to 3.89 and 3.59 years at 0.07 and 0.09 \$/kWh, respectively. Similarly, the 20-year NPV increases from 52.31 to 58.23 and 64.15 million USD. Overall, the results demonstrate that both system optimization and electricity market conditions strongly influence economic feasibility and long-term profitability.

6.5. Case study

A case study is conducted to evaluate the real-world applicability of the proposed hybrid renewable multi-generation system using actual meteorological data from Dammam and Yanbu, Saudi Arabia. The selection of Saudi Arabia is motivated by its strong solar and wind potential as well as its strategic transition toward renewable energy under Vision 2030, which targets a substantial share of electricity from clean sources [80]. In this context, hybrid systems capable of producing electricity, cooling, freshwater, and hydrogen are particularly relevant for improving energy–water–environmental sustainability.

Dammam (26.43°N, 50.10°E) exhibits high solar irradiance and relatively stable coastal wind speeds, making it highly favorable for continuous renewable operation. Yanbu (24.09°N, 38.06°E) also benefits from strong solar availability with moderate but consistent wind resources, especially during daytime hours. Hourly direct normal irradiance and wind speed data for 2019, obtained from the National Solar Radiation Database [81], are used as inputs to evaluate system performance under realistic operating conditions and shown in Fig. 11.

Fig. 12 shows the monthly performance of the hybrid system in Dammam and Yanbu, highlighting the influence of DNI and wind variability on system outputs. In Dammam, performance follows a clear seasonal pattern, with peaks in June–July driven by higher DNI (417.82–483.6 W/m^2), which increases thermal input to the PTSC and enhances downstream conversion processes. During these months, grid power reaches 2.125 MW, freshwater 22.85 kg/s, and hydrogen 7.4 kg/h. In winter, reduced solar input lowers grid power to 1.159–1.848 MW and freshwater to 12.47–19.87 kg/s. Cooling demand also increases in summer due to higher ambient temperatures, directly affecting absorption chiller operation.

Yanbu shows higher and more stable performance due to consistently stronger solar resources, with DNI exceeding 540 W/m^2 in peak months (March and July). This results in grid power of 1.987 MW, freshwater production of 21.36 kg/s, and hydrogen output of 6.93 kg/h. The higher and steadier renewable input also sustains greater cooling loads, reaching 1.933 MW in July. Compared to Dammam, Yanbu exhibits more uniform annual performance, indicating better suitability for continuous operation. Overall, results confirm that system outputs are primarily governed by solar resource availability, with Yanbu offering more favorable conditions for stable year-round energy and water production.

Fig. 13 compares system performance on a summer day (June 18th, 2019) under different local solar–wind conditions. In Dammam, higher solar irradiance ($\sim 716\ W/m^2$) and stronger winds (8.5 m/s) increase renewable input to the system, improving exergy efficiency (42–50%) and raising peak grid power to 8.5 MW. This stronger energy supply also enhances downstream processes, resulting in higher hydrogen (29.6 kg/h) and freshwater production (91.3 kg/s) due to improved utilization of generated electricity and heat.

In Yanbu, slightly lower irradiance ($\sim 714\ W/m^2$) and moderate winds (6.5 m/s) reduce overall conversion intensity, limiting exergy efficiency to 24–43% and peak power to 5.7 MW. However, the steadier wind profile supports more stable operation, maintaining hydrogen production at 19.8 kg/h and cooling capacity around 2.2 MW. Overall, results show that higher combined solar–wind availability improves both efficiency and multi-output performance, while more stable but weaker resources lead to lower yet more uniform system output.

7. Conclusion

This study presented a novel hybrid renewable-based cogeneration system integrating wind turbines, PTSCs, HTCORCs, an SEARC, an RODU, a PEME, and a Claude cycle. The system was designed to simultaneously produce electricity, cooling, freshwater, and liquefied hydrogen while efficiently utilizing renewable energy and recovered waste heat. A comprehensive 4E (energy, exergy, economic, and

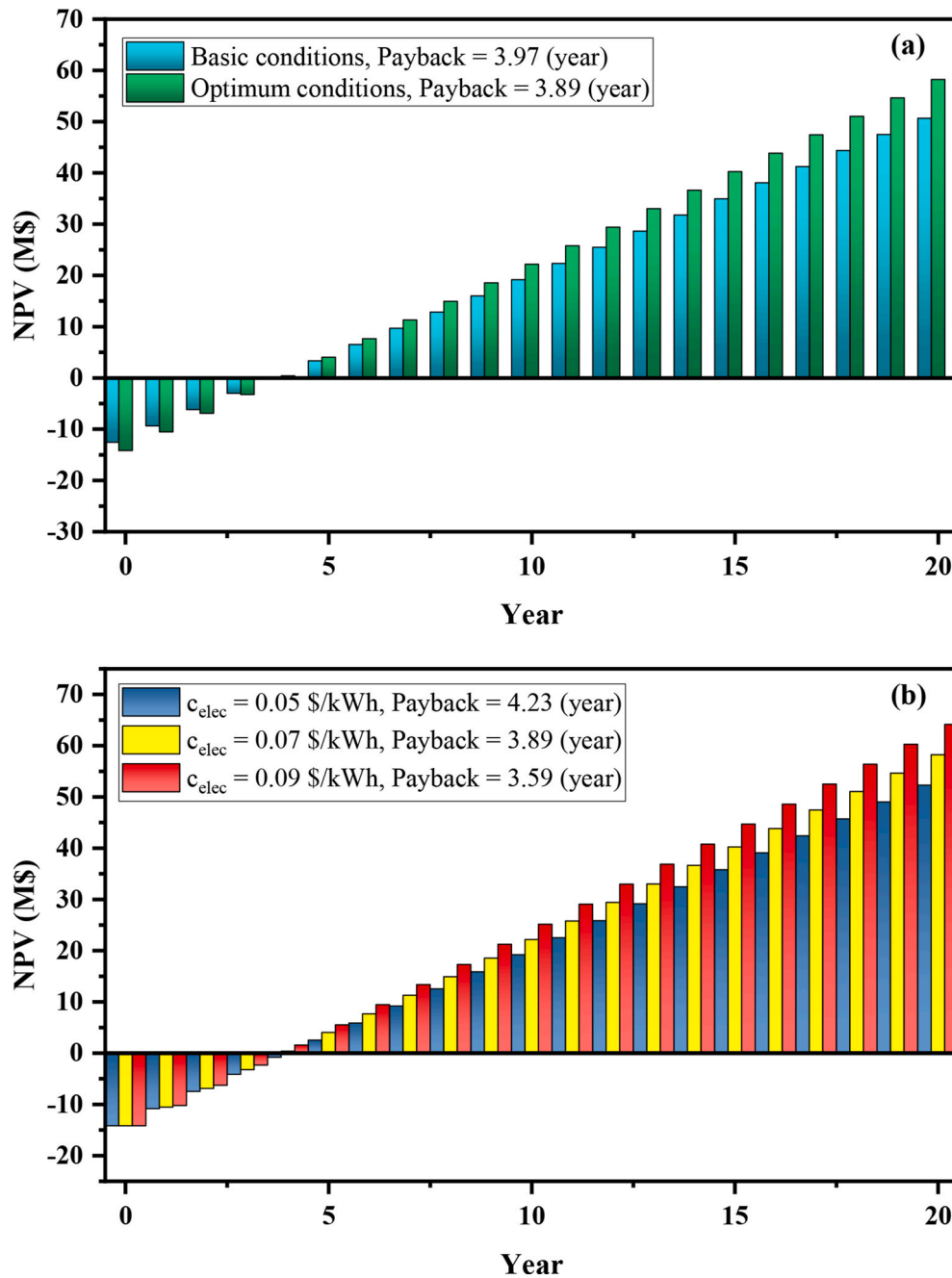


Fig. 10. Economic evaluation of the proposed system: (a) baseline vs. optimized NPV, and (b) effect of electricity price on NPV and payback period.

environmental) assessment, coupled with ANN-assisted NSGA-II multi-criteria optimization, demonstrated substantial improvements in both thermodynamic and economic performance. Case studies in Dammam and Yanbu, Saudi Arabia, confirmed the system's technical feasibility and its potential contribution to sustainable energy transitions in regions with abundant solar and wind resources. The principal outcomes of this study can be summarized as follows:

- The total exergy destruction of the system is 13.768 MW, with the solar field and wind turbine array accounting for the largest shares at 41.1% (5661.9 kW) and 26.7% (3678.7 kW), respectively.
- The system's total cost rate is 544.6 \$/h, dominated by wind turbines (53.9%, 293.6 \$/h) and the solar field (22.8%, 124.3 \$/h), with HTCORCs contributing 7.7% (41.8 \$/h), indicating that

improvements in these subsystems offer the greatest potential for enhancing overall thermoeconomic performance.

- The ANN-NSGA-II framework significantly reduced computational time for multi-objective optimization while maintaining high predictive accuracy. The trained ANN achieved mean absolute errors of 0.00144 for exergy efficiency and 0.00153 for payback period.
- Under optimal conditions, the system delivers 15.61 kg/h of liquefied hydrogen, exports 4477.3 kW of electricity, provides 2504.8 kW of cooling, and produces 48.13 kg/s of freshwater, achieving an exergy efficiency of 29.92% with a payback period of 3.89 years.
- Economic analysis demonstrated that the optimized system achieves faster payback (3.89 years vs. 3.97 years) and higher long-term profitability, with a twentieth-year NPV of 58.23 million USD compared to 50.64 million USD for the baseline configuration.

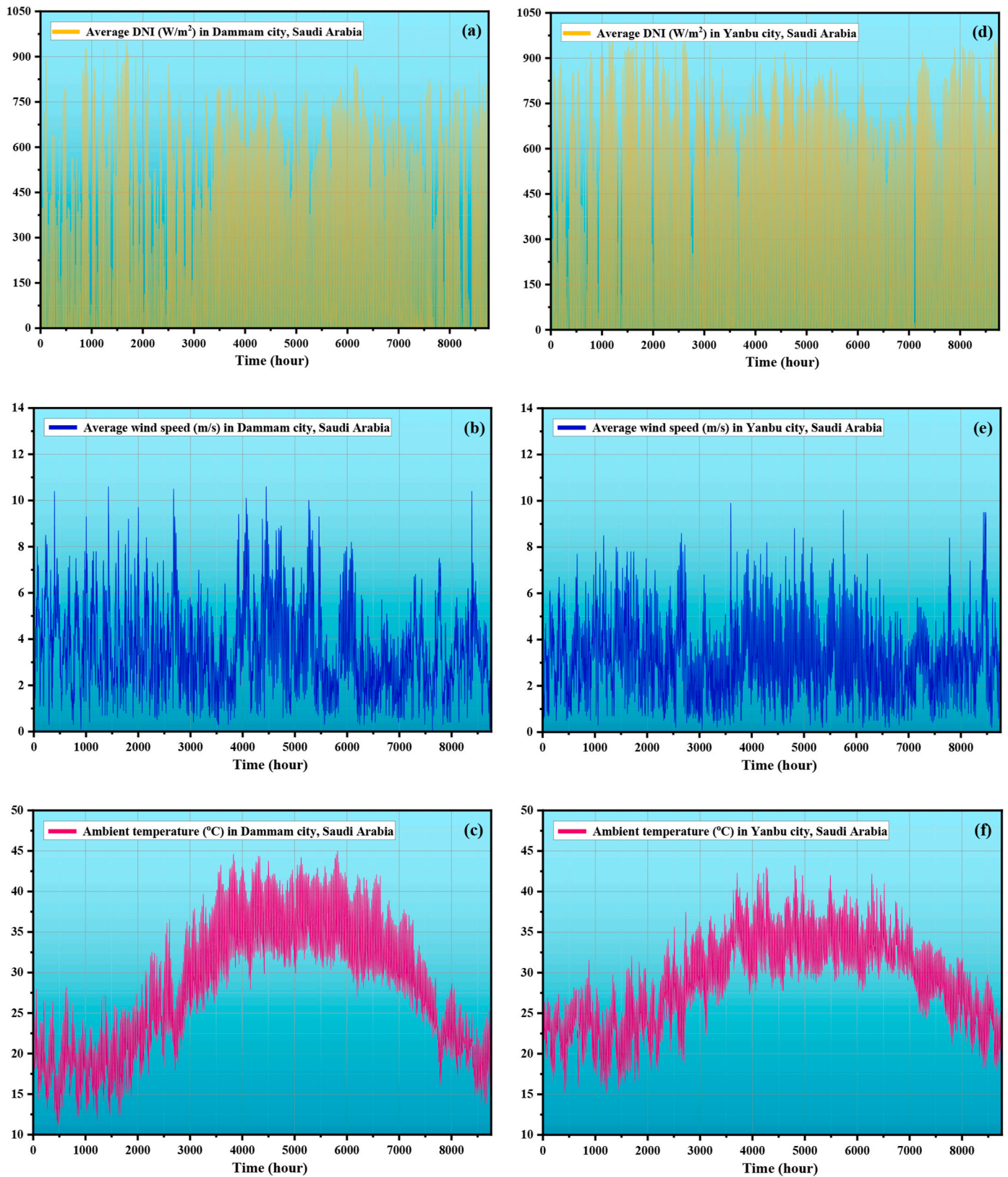


Fig. 11. Hourly variations of DNI, wind speed, and ambient temperature for Dammam (a, b, and c) and Yanbu (d, e, and f).

- The comparative monthly analysis reveals that the hybrid system performs more efficiently in Yanbu, achieving higher monthly averages of grid power (1.70 MW vs. 1.56 MW), cooling load (1.57 MW vs. 1.25 MW), and freshwater output (17.7 kg/s vs. 16.3 kg/s) than in

Dammam. This indicates that optimal site selection significantly enhances renewable energy utilization, waste heat recovery, and overall multi-output performance of the proposed hybrid solar–wind energy system.

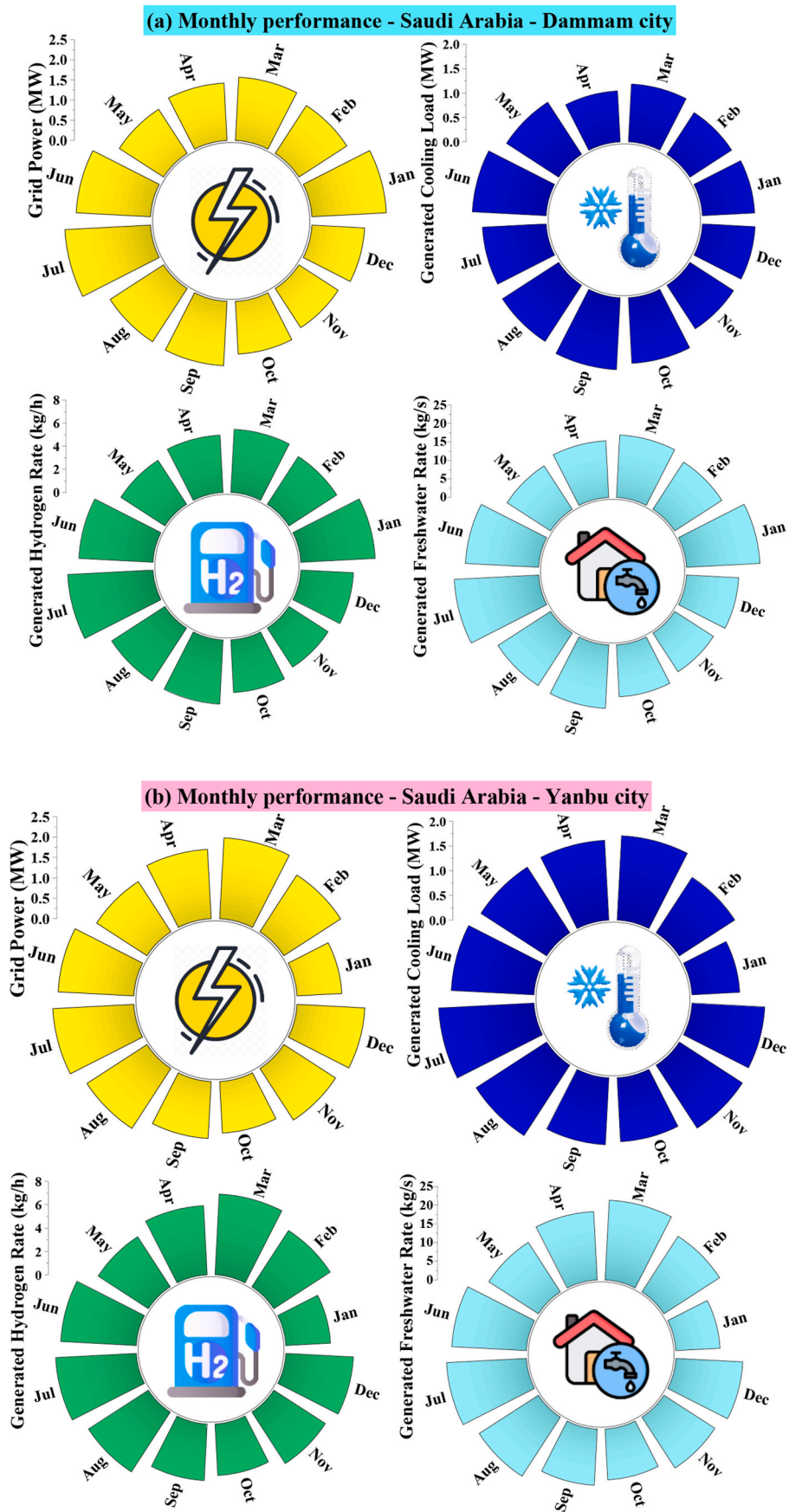


Fig. 12. Monthly performance analysis of the proposed hybrid system in a) Dammam and b) Yanbu cities in Saudi Arabia.

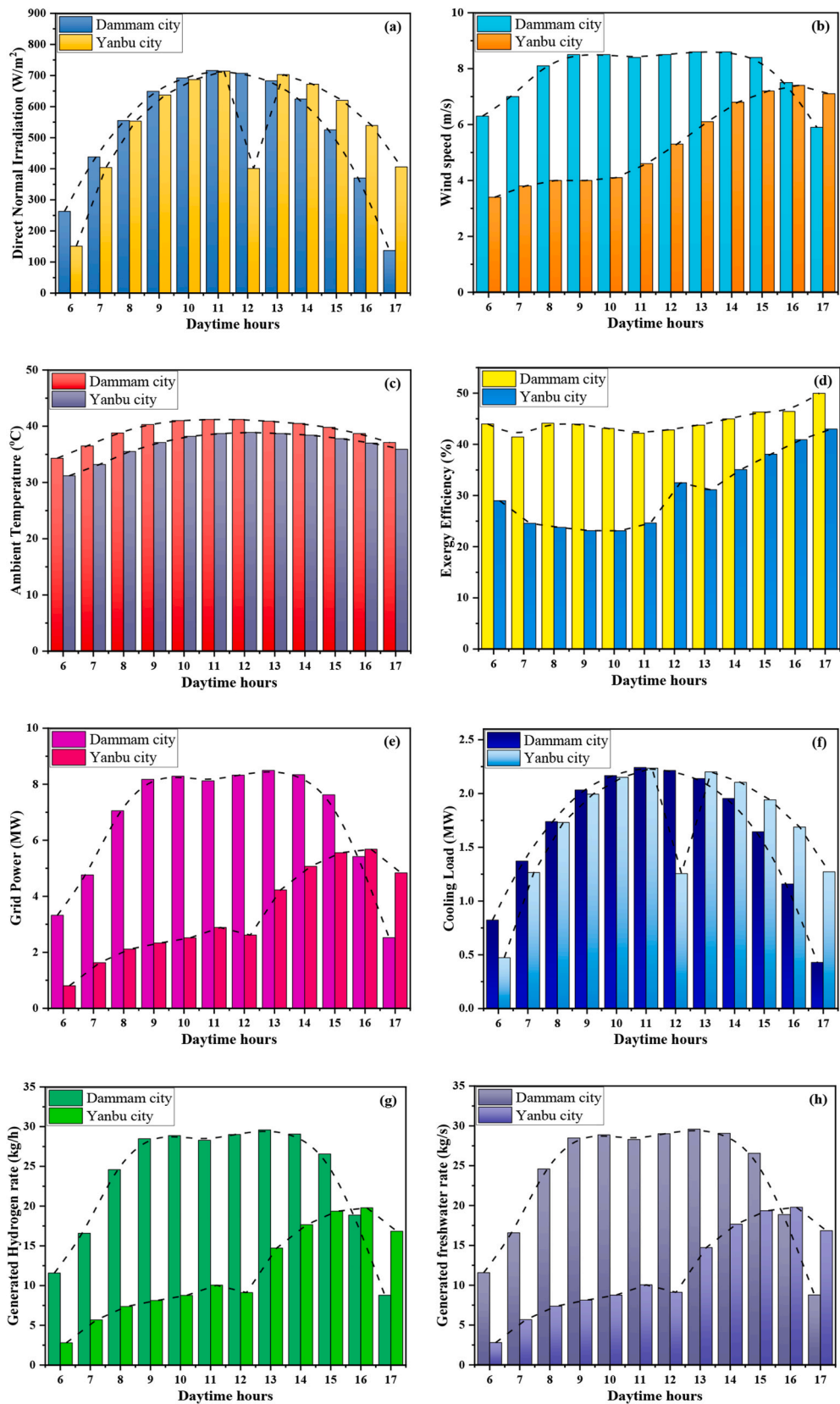


Fig. 13. Hourly performance analysis of the proposed hybrid system in both Dammam and Yanbu cities in Saudi Arabia, on June 18th, 2019.

CRediT authorship contribution statement

Yonghui Li: Conceptualization, Investigation. **Tirumala Uday Kumar Nutakki:** Formal analysis, Methodology. **Haibo Zhang:** Investigation, Supervision. **Mohamed Arbi Khelifi:** Formal analysis, Investigation. **Mohana Alanazi:** Data curation, Formal analysis. **Norah Alsairy:** Data curation, Validation. **Ashraf althbiti:** Data curation, Investigation. **Rakhmonjon Akhmadjonov:** Writing – original draft, Writing – review & editing. **Ibrahim Mahariq:** Investigation, Resources, Validation. **Yasser Fouad:** Conceptualization, Methodology, Project administration, Supervision.

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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