

AI-Driven Energy Auditing for Solar Heat Exchanger Optimization in Hybrid Geothermal-Solar Thermal Systems: A Review

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Abstract. Hybrid geothermal-solar thermal systems have the potential to enhance renewable energy efficiency, but their performance may be hindered by variable solar input, temperature imbalances, and fouling. Maximizing efficiency requires optimizing critical components, particularly the solar heat exchanger, which ensures efficient thermal energy transfer between subsystems. Energy auditing plays a crucial role in identifying inefficiencies and optimizing solar heat exchanger performance by analyzing energy consumption patterns and providing valuable insights for efficiency improvements. This review explores energy auditing methodologies and the integration of artificial intelligence (AI)-driven optimization, with a focus on machine learning (ML) models for solar radiation and performance prediction, real-time fault detection, and adaptive system control. AI-driven approaches enhance efficiency and reduce operational costs by enabling data-driven adjustments in heat exchanger operation. However, challenges such as data quality issues, high computational demands, and model interpretability remain. Future research should focus on improving AI-based energy auditing techniques and addressing these challenges to further optimize system performance. Overall, AI-driven optimization integrated with energy auditing, presents a transformative approach to improving solar heat exchanger efficiency in hybrid renewable energy systems.

1 Introduction

The global shift toward sustainable energy has led to significant advancements in renewable technologies, reducing dependence on fossil fuels and mitigating environmental impacts. However, widespread implementation remains hindered by challenges such as reliability, intermittency, and discontinuity in energy supply. To address these limitations, hybrid renewable energy systems have emerged as a viable solution, integrating multiple energy sources to enhance efficiency and optimize resource utilization [1]. Among these hybrid systems, geothermal-solar thermal plants offer a promising approach by combining the stable baseload power of geothermal energy with the high-temperature heat input from solar thermal

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energy. This integration leverages the complementary characteristics of both sources, improving overall system performance [2]. However, their effectiveness is influenced by multiple factors, including how geothermal and solar thermal components are integrated, which depends on component placement, geothermal fluid properties, and overall plant performance [3]. Maximizing efficiency requires optimizing critical components, particularly the solar heat exchanger. Solar heat exchangers play a key role in hybrid geothermal-solar thermal plants by enabling efficient thermal energy transfer between geothermal and solar thermal subsystems [4]. Depending on the system design, they either raise the geothermal fluid temperature or superheat the organic Rankine cycle (ORC) working fluid using solar thermal energy from the solar field. Kariuki et al. [4] highlighted the challenges of integrating low-temperature geothermal resources with high-temperature solar-based technologies, noting that fouling and suboptimal thermal coupling can degrade performance. Additionally, the intermittent nature of solar energy complicates system management due to variations in weather conditions.

Energy auditing offers a solution to these performance challenges by identifying inefficiencies and improving system performance. By analyzing energy consumption patterns, energy audits provide valuable insights for enhancing efficiency [5], often leading to significant energy savings [6]. Gopinath et al. [7] emphasized the increasing importance of energy auditing in hybrid renewable systems, reporting efficiency improvements of approximately 25% and emissions reductions of up to 40% in hybrid solar-wind systems. Their study also underscored the role of data analytics and ML in modern energy auditing. Recent advancements in AI-driven optimization have significantly enhanced renewable energy systems, including solar, geothermal, and hybrid technologies [8]. In the context of energy auditing, AI improves data acquisition, refines predictive analysis, and enables operational optimization through various ML techniques [9]. This review investigates two main areas: Section 2 explores the role of energy auditing in solar heat exchangers within hybrid geothermal-solar thermal systems, while Section 3 examines recent trends in AI-driven optimization and their applications to solar heat exchangers. Additionally, key challenges and future research directions are discussed to support ongoing innovation in this field.

2 Energy auditing of solar heat exchangers

2.1 Purpose and objectives of energy auditing

An energy audit systematically identifies opportunities to reduce energy consumption and improve cost efficiency. It involves detecting areas of energy loss, recommending necessary modifications, and exploring alternative energy solutions. The audit process entails detailed analysis, measurement, and evaluation of both energy usage and waste. Energy auditors focus on identifying feasible, cost-effective strategies for energy savings while setting long-term goals for continuous improvement in energy performance [10]. For solar heat exchangers in hybrid geothermal-solar thermal plants, energy audits help assess thermal efficiency, identify sources of heat loss, and recommend improvements to enhance heat transfer performance. The auditing process evaluates key parameters such as temperature differentials, flow rates, and fouling accumulation, which affect the overall efficiency of the heat exchanger. By addressing these inefficiencies, energy audits contribute to optimizing system operations and reducing energy waste.

The objectives of energy auditing for solar heat exchangers include evaluating variations in heat exchanger efficiency, assessing the impact of scaling and fouling on thermal performance, determining optimal heat exchanger configurations, identifying energy conservation technologies, and implementing retrofit strategies to enhance heat transfer

effectiveness [11]. These targeted objectives ensure that solar heat exchangers operate at peak efficiency, ultimately improving the performance of hybrid geothermal-solar thermal systems.

2.2 Benefits of energy auditing

Energy auditing offers a range of benefits that significantly improve the performance, cost-effectiveness, and sustainability of energy systems. By systematically assessing energy flows and identifying inefficiencies, audits provide actionable insights that support strategic optimization across technical, economic, and environmental dimensions [12].

2.2.1 Energy savings

Optimization plays a crucial role in improving energy efficiency by identifying areas for improvement and implementing solutions that reduce waste and enhance system performance. Regular energy audits are key to this process, as they help pinpoint inefficiencies such as suboptimal flow rates or excessive heat loss in heat exchangers. A case study conducted by Bureau of Energy Efficiency (BEE)-certified energy auditors on a 1050 MW thermal power plant demonstrated the tangible impact of such audits, revealing a total energy saving of over 12 million kWh per year and a reduction of more than 25,000 metric tons of coal annually through measures such as air leakage arrest in air-preheaters, insulation upgrades, pump replacements, and compressor pressure optimization [13].

In addition to audit-driven strategies, component-level optimization also contributes significantly to energy savings. For example, the volume optimization of permanent magnets in electric vehicle motors has been shown to reduce power loss and enhance the overall efficiency of the motor system, highlighting the value of precision engineering in energy systems [14]. Likewise, advances in material optimization, such as the development of electrospun zeolite-filled acrylonitrile butadiene styrene (ABS) membranes, improve gas separation efficiency for biogas purification under low-pressure conditions, minimizing energy demand in small-scale applications [15]. These examples demonstrate how both system-wide audits and targeted component innovations can collectively improve energy efficiency across diverse energy technologies.

2.2.2 Cost savings

By enhancing heat exchanger efficiency, energy audits contribute to significant cost savings through improved heat transfer rates and reduced energy waste. Wu and Calderon [16, 17] demonstrated how infrastructure optimization in energy systems can reduce operational costs and improve financial viability. In their studies on electric vehicle charging stations along the Jiangsu Intercity Expressway (G15), they applied a road section power consumption model to assess charging demand and determine the optimal number of stations. By analyzing the cost recovery timeline and profit expectations, the studies emphasized the importance of strategic infrastructure planning to minimize operational losses and ensure financial sustainability. Similarly, in energy audits, financial assessments such as payback period calculations are crucial in determining the feasibility of upgrades, such as high-performance heat exchanger materials or advanced insulation techniques.

2.2.3 Emission reduction

Optimizing solar heat exchanger performance reduces reliance on backup fossil-fuel-based heating systems, thus lowering greenhouse gas (GHG) emissions. Energy audits play a crucial role in quantifying these reductions, ensuring compliance with environmental

regulations and supporting sustainability goals. In hybrid geothermal-solar thermal systems, ORC refrigerants are integral to improving energy efficiency. ORC systems enhance energy conversion by utilizing low-boiling-point refrigerants to transform low-grade heat into usable power. A parallel can be drawn from the National Cooling Action Plan (NCAP) of the Philippines, which demonstrated that transitioning to high-efficiency, climate-friendly refrigerants can significantly reduce emissions [18]. Developed under the United Nations Environment Programme (UNEP)-led Cool Coalition, the NCAP methodology showed that such transitions could lead to a net reduction of 10.68 million tons of CO₂ equivalent, representing nearly 12% of the country's unconditional target submitted to the United Nations Framework Convention on Climate Change (UNFCCC). Implementing ORC systems with low-global-warming-potential (GWP) refrigerants and optimized heat exchangers can maximize efficiency gains while advancing sustainability in renewable energy applications.

2.2.4 Process optimization

Audits help identify operational improvements such as better heat exchanger cleaning schedules and fluid selection strategies, which extend equipment lifespan and enhance system reliability. By preventing scaling and fouling, audits ensure consistent thermal performance and reduce maintenance costs. Trafczynski et al. [19] demonstrated how optimizing cleaning schedules in a heat exchanger network (HEN) based on historical fouling resistance data and a least-squares monitoring approach can significantly improve heat recovery, reducing fuel consumption and carbon dioxide (CO₂) emissions. The avoided costs for various cases ranged from 29,300 kPLN to 63,830 kPLN, while cleaning costs varied from 780 kPLN to 4,470 kPLN. These figures highlight that the energy savings from optimized cleaning far outweigh the maintenance costs, underscoring the value of audit-informed optimization in improving system performance and reducing operational expenses.

2.2.5 Multidimensional benefits

Energy audits also enhance energy security by optimizing the use of available resources. Satiada and Calderon [20] conducted a comparative analysis of existing waste-to-energy (WtE) reference plants, evaluating various thermal conversion technologies such as gasification and pyrolysis. Their study highlighted the importance of considering technological, economic, and environmental factors when selecting energy generation systems. Similar audit methodologies can be applied to hybrid renewable energy systems, identifying opportunities to invest in advanced heat exchanger technologies, such as phase-change materials or nanofluid-based enhancements. These innovations not only improve energy efficiency but also foster innovation and sustainability in renewable energy systems.

2.3 Types of energy audits

Energy audits for solar heat exchangers can be categorized into two main types based on the level of analysis and the potential for efficiency improvements [21]:

2.3.1 Preliminary audit

This type of audit involves a basic assessment of the heat exchanger's energy performance, relying on operational data such as inlet and outlet temperatures, flow rates, and historical maintenance records. It does not require extensive instrumentation, making it a cost-effective

and rapid evaluation method. Preliminary audits help identify common inefficiencies such as scaling, fouling, or improper flow distribution, that may be degrading heat transfer efficiency. The economic evaluation in this audit primarily focuses on estimating the simple payback period of corrective actions such as cleaning schedules or minor operational adjustments. A similar approach was used in the analysis of a subcritical ORC system for waste heat recovery. Wang et al. [22] showed that the payback period of the ORC system decreases with the increase in evaporation temperature, condensation temperature, and the pinch point temperature differences in the evaporator and condenser. However, it also increases with these parameters beyond a certain threshold. The results also highlighted that the minimum payback period of the ORC system decreases monotonically with the increase in the inlet temperature, mass flow rate of the flue gas, and electricity price. The study offers insights into how parameter optimization can influence the payback period, similar to how operational adjustments in heat exchangers can be optimized for cost savings during energy audits.

2.3.2 Detailed audit

A detailed audit involves in-depth data collection and real-time monitoring of key performance indicators, including heat exchanger effectiveness, pressure drops, and variations in solar radiation input. This audit may incorporate advanced diagnostic tools such as infrared thermography, Red, Green, Blue, (RGB) imaging, and thermal modeling to precisely quantify inefficiencies. Bajaro and Calderon [23] demonstrated the effectiveness of infrared thermal imaging in energy audits, identifying localized heat losses and structural inefficiencies in buildings. Applying similar imaging techniques such as drone-mounted thermal cameras and RGB imaging to solar heat exchanger audits can enable real-time thermal mapping, helping to detect heat distribution inconsistencies that may indicate fouling or insulation deficiencies.

Beyond identifying immediate performance issues, detailed audits also consider long-term strategies for optimization. This may include upgrading heat exchanger materials or integrating automated cleaning systems. Additionally, economic assessments such as internal rate of return (IRR), net present value (NPV), and life cycle cost (LCC) analysis, are crucial for determining the feasibility of recommended upgrades. Mateo et al. [24] demonstrated how life cycle assessments (LCA) can quantify both environmental impacts and cost-efficiency in energy evaluations. Their study on nipa-based bioethanol revealed that it had a lower carbon footprint and a 32.7% lower production cost compared to conventional fermented sugar ethanol. This highlights the value of LCA-based audits in guiding sustainable energy investments, offering insights into both environmental and economic benefits.

2.4 Key performance indicators for solar heat exchanger efficiency

The performance of a solar heat exchanger is evaluated based on several key parameters that influence its efficiency, heat transfer effectiveness, and operational reliability. These indicators provide critical insights into thermal performance and help identify potential areas for optimization.

2.4.1 Heat duty

Heat duty refers to the rate of heat transfer in a heat exchanger, typically measured in watts (W) or kilowatts (kW). Variations in solar radiation intensity can lead to fluctuating heat duty, requiring periodic assessment to ensure stable efficiency. Deviations from the design heat

duty may indicate thermal losses, scaling due to mineral deposits, or reduced flow rates caused by operational inefficiencies [25].

2.4.2 Effectiveness

Effectiveness represents the ratio of actual heat transfer to the maximum possible heat transfer in an ideal exchanger. Due to daily and seasonal solar fluctuations, effectiveness provides a means to assess how efficiently the exchanger utilizes the available thermal energy. Maintaining high effectiveness is crucial for ensuring consistent energy conversion and storage.

2.4.3 Logarithmic mean temperature difference (LMTD)

The average temperature difference between two fluids across a heat exchanger, considering variations along the exchanger. Fluctuations in inlet temperature due to changing solar irradiance affect LMTD, influencing the overall heat transfer efficiency. A well-optimized design ensures that LMTD remains adequate despite external temperature variations.

2.4.4 Overall heat transfer coefficient

Overall heat transfer coefficient quantifies the rate of heat transfer, accounting for convection, conduction, and fouling accumulation. Exposure to high-temperature cycles and potential particulate contamination from atmospheric dust can degrade this coefficient over time. Regular energy audits help monitor these changes and recommend cleaning or material improvements to sustain efficiency [26].

2.5 Factors affecting solar heat exchanger performance

In hybrid geothermal-solar thermal systems, the performance of solar heat exchangers is influenced by several key factors that determine efficiency, reliability, and overall system effectiveness [5]. Understanding these factors is essential for identifying areas for improvement and enhancing system performance.

2.5.1 Heat transfer efficiency

Efficiency is largely dictated by the temperature differential between the solar-heated fluid and the geothermal or working fluid. A higher temperature differential improves heat transfer rates, but fluctuations in solar radiation intensity introduce variability in performance. Additionally, heat exchangers often require materials with high thermal conductivity and corrosion resistance to withstand prolonged exposure to solar-heated fluids [26].

2.5.2 Heat exchanger type

The choice of heat exchanger type depends on the system's operational requirements. Flat-plate and shell-and-tube heat exchangers are widely used in solar thermal applications. Plate heat exchangers offer higher efficiency in low-to-medium-temperature solar applications due to their compact design and high heat transfer rates. In contrast, shell-and-tube heat exchangers provide greater durability and better performance under fluctuating thermal loads, making them suitable for high-temperature and industrial solar thermal systems [27].

2.5.3 Fluid flow distribution

Uniform fluid distribution is crucial, as uneven flow can lead to localized overheating and reduced system efficiency. Flow maldistribution is a particular challenge in hybrid geothermal-solar systems due to intermittent solar heating, which leads to temperature variations that may reduce heat transfer effectiveness. Optimizing flow patterns through design modifications and active flow control strategies can mitigate these effects. Similar approaches are employed in circulating fluidized bed (CFB) boilers, where optimizing the distribution of primary and secondary air is essential for achieving better fluidization and combustion performance. A computational fluid dynamics (CFD) simulation study by Gonzales et al. [28] demonstrated that air distribution adjustments significantly impact fluid dynamics, improving overall system efficiency by preventing issues like localized overheating, which could parallel flow issues in solar heat exchangers.

2.5.4 Fouling and scaling

Solar heat exchangers are particularly vulnerable to fouling and scaling due to the use of mineral-rich water or heat transfer fluids exposed to high temperatures. In solar-geothermal systems, such as the hybrid configuration proposed for the Cerro Prieto Geothermal Power Plant, silica scaling and salt deposition were identified as limiting factors for increasing steam generation [29]. The integration of a parabolic trough solar field aimed to boost steam flow by 10% during peak demand hours, but this enhancement was constrained by the risk of high salt concentrations leading to scaling. Lentz and Almanza [29] emphasized that the potential for Direct Steam Generation (DSG) in such systems hinges on effective scale control strategies. They proposed modifying the pH of the fluid as a viable method for controlling silica deposition. Furthermore, they recommended water treatment measures, routine inspections, and cleaning of pipes to maintain system efficiency and mitigate thermal resistance caused by scaling and fouling.

2.6 Performance assessment for solar heat exchangers

A key method for assessing solar heat exchanger performance involves determining and monitoring the overall heat transfer coefficient (U) over time [25]. Regular calculation of U -values, along with maintaining technical records of heat exchanger performance, helps systematically identify efficiency losses. By plotting historical datasets of heat transfer coefficient values, proactive maintenance actions, such as scheduling cleaning, can be planned to restore optimal heat transfer rates. The overall heat transfer coefficient is calculated using the equation:

$$U=Q/(A \times LMTD) \quad (1)$$

where Q is the heat duty, A is the heat transfer surface area, and $LMTD$ is the logarithmic mean temperature difference. The U -value in solar heat exchangers is influenced by factors such as solar input fluctuations, material properties, and seasonal variations.

2.6.1 Determination of overall heat transfer coefficient

The procedure for determining the overall heat transfer coefficient is described in the following sections.

2.6.2 Monitoring steady-state parameters

Flow rates, temperatures, and pressures of the solar-heated and working fluids are recorded under different solar conditions to establish baseline performance.

2.6.3 Evaluating physical properties

Density, viscosity, thermal conductivity, and specific heat capacity of heat transfer fluids are measured, as these properties may change due to prolonged solar exposure or thermal degradation.

2.6.4 Computing thermal performance parameters

Heat duty, pressure drops, temperature ranges, capacity ratio, effectiveness, LMTD, and overall heat transfer coefficient are calculated. These parameters help assess heat exchanger efficiency and identify performance deviations.

2.6.5 Instrumentation for performance monitoring

The evaluation process involves measuring key operating parameters of the exchanger to assess efficiency and heat transfer characteristics. To ensure accuracy, these measurements should be performed using calibrated and verified instruments. Regular calibration enhances data reliability, ensuring precise performance evaluation and optimization [25].

2.6.6 Flow measurement

Fluid flow in solar heat exchangers can be measured using orifice flow meters, vortex flow meters, Venturi meters, Coriolis flow meters, and magnetic flow meters, depending on the fluid type, temperature range, and operating conditions.

2.6.7 Temperature monitoring

Temperature is measured using thermocouples, resistance temperature detectors (RTDs), and thermo-gauges, selected based on the operating temperature range and fluid type.

2.6.8 Pressure monitoring

Pressure can be monitored using liquid manometers, draft gauges, Bourdon and diaphragm-type pressure gauges, and absolute pressure transmitters.

2.6.9 Fluid property evaluation

American Society for Testing and Materials (ASTM)-standard laboratory methods are used to determine density, viscosity, composition, thermal conductivity, and specific heat capacity of heat transfer fluids.

3 Optimization of solar heat exchangers through energy auditing

Energy audits play a crucial role in evaluating solar heat exchanger performance. They help identify inefficiencies, including temperature imbalances, fouling accumulation, and pressure

drops. These insights enable targeted optimizations to enhance heat transfer efficiency and maintain stable operation under variable conditions. A data-driven approach further strengthens these efforts, particularly in hybrid geothermal-solar thermal systems.

3.1 AI-driven optimization strategies

Integrating AI into solar heat exchanger optimization enhances system performance through accurate prediction, real-time monitoring, and automated control. Traditional optimization methods often struggle to adapt to the dynamic nature of solar energy systems, where variations in solar radiation and environmental conditions introduce complexities such as nonlinearity and uncertainty [30]. AI technology, however, is widely used in the prediction of renewable energy power generation, offering significant advantages by improving prediction accuracy and adaptability in real-time operation. AI-driven approaches leverage ML, deep learning, and hybrid computational techniques to systematically address these challenges.

The optimization strategies can be categorized into these key areas: solar radiation prediction improves forecasting accuracy, allowing dynamic system adjustments that enhance heat exchanger efficiency; hybrid plant performance prediction optimizes heat exchanger operation within integrated geothermal-solar thermal systems, ensuring stable performance and efficient energy utilization; fault detection and predictive maintenance increase system reliability by identifying operational anomalies and preventing performance degradation; performance monitoring and control use SCADA, IoT, and AI-driven controllers for real-time adjustments, maintaining optimal heat transfer under varying conditions. By integrating these AI-driven strategies, solar heat exchangers can achieve higher energy efficiency and reduced operational costs, paving the way for smarter renewable energy systems. The following subsections explore these AI-based methodologies and their role in optimizing solar heat exchanger performance.

3.1.1 Solar radiation prediction

Recent advancements in AI-based solar radiation prediction have demonstrated improvements in accuracy and reliability. Fig. 1 highlights the performance of several AI models by comparing their prediction error values. Dahmani et al. [31] compared the performance of single neural networks (SNN) and bootstrap aggregated neural networks (BANN) for predicting hourly global solar radiation using a dataset of 3606 data points from a radiometric station in Bouzareah, Algeria. The results showed that BANN outperformed SNN, achieving lower root mean square error (RMSE) values of 62.4856 Wh/m² compared to 68.3968 Wh/m² during testing. BANN's improved accuracy and robustness, even with limited training data, highlight its potential for enhancing solar radiation prediction in regions lacking direct measurement equipment. The effectiveness of ensemble-based neural networks in capturing complex solar radiation patterns makes them valuable for real-world applications in solar energy system design.

In addition to neural network-based approaches, Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have also been widely explored for solar radiation prediction. Dos Santos et al. [32] applied ANFIS models to estimate the direct beam transmittance (K_{tb}) based on atmospheric transmissivity (K_t) and the insolation ratio (n/N) using both hourly and daily datasets. Among the tested models, ANFIS4, which combined K_t and n/N as inputs, achieved the highest predictive accuracy with a relative RMSE (rRMSE) of 14.6%, significantly outperforming statistical models that had rRMSE values as high as 25.97%. These findings demonstrate the adaptability of ANFIS models across different datasets, making them useful for recovering historical solar radiation data and supporting solar power plant operation.

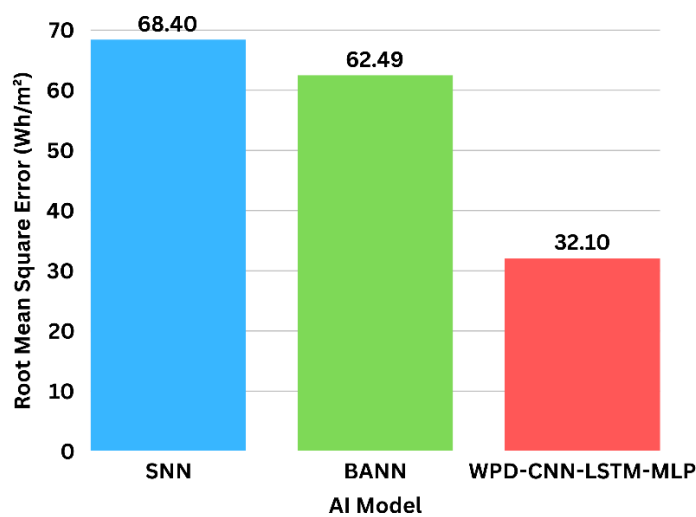


Fig. 1. Comparison of prediction error among selected AI models in solar radiation prediction studies [31, 33].

Comparative studies have further evaluated various AI models, including traditional approaches like backpropagation neural networks (BPNN), support vector machines, and recurrent neural networks. These studies highlight the advantages of more advanced methods such as long short-term memory (LSTM) networks and ensemble-based models. For instance, Huang et al. [33] proposed a WPD-CNN-LSTM-MLP model, which combines wavelet packet decomposition (WPD), convolutional neural networks (CNN), LSTM, and multi-layer perceptron (MLP) networks into a multi-branch architecture. This model processes multi-variable inputs, including hourly solar irradiance, temperature, relative humidity, and wind speed, effectively capturing the complex relationship between irradiance and meteorological parameters. The hybrid model demonstrated improved prediction accuracy, with a minimum RMSE of 32.1 W/m², highlighting its potential for practical applications in hour-ahead solar forecasting and energy system planning.

In the context of improving solar energy systems, AI-based forecasting models are critical for the optimization of concentrated solar power (CSP) systems, particularly those incorporating thermal energy storage (TES). The integration of AI models such as the Random Forest Regressor (RFR) has proven effective for optimizing system parameters, such as mirror angles and heat transfer fluid flow rates, in power tower CSP systems with TES. As shown in a study by Gul et al. [34], the proposed model demonstrated a high level of accuracy in forecasting output power with a mean squared error (MSE) of 0.0676 and an R² score of 0.9999. By incorporating economic evaluations such as NPV and levelized cost of energy (LCOE), and conducting sensitivity analysis under varying weather conditions, this AI-based approach enhanced the operational performance and reliability of CSP systems. Furthermore, the model proved to be resilient under changes in fuel prices and technology costs, further promoting sustainable energy solutions.

Accurate solar radiation forecasting enhances the performance of solar heat exchangers by enabling real-time adjustments to system parameters. Improved prediction accuracy allows for dynamic optimization of flow rates, inlet temperatures, and heat transfer rates, resulting in greater thermal efficiency and reduced energy losses. AI models such as BANN and ANFIS can help solar heat exchangers respond to sudden variations in weather conditions, ensuring stable operation and consistent heat transfer performance. By integrating reliable

forecasting models, solar energy systems can achieve higher efficiency and improved energy management, contributing to more sustainable energy utilization. As summarized in Table 1, several AI models have been evaluated and compared based on their performance in solar radiation prediction.

Table 1. Summary of AI-based solar radiation prediction studies.

Study	AI Model	Input Variables	Prediction Error	Key Findings
Dahmani et al. [31]	SNN, BANN	Temperature, relative humidity, pressure, wind speed and direction	RMSE = 62.49 Wh/m ² (BANN), 68.40 Wh/m ² (SNN)	BANN outperformed SNN with higher accuracy and robustness, even with limited training data
Dos Santos et al. [32]	ANFIS	Kt, n/N	rRMSE = 14.6%	ANFIS4 achieved superior accuracy compared to statistical models, useful for recovering historical data
Huang et al. [33]	WPD-CNN-LSTM-MLP1	Hourly solar irradiance, temperature, humidity, wind speed	RMSE = 32.1 Wh/m ²	Hybrid model improved prediction accuracy for solar radiation forecasting and energy system planning
Gul et al. [34]	RFR	Solar irradiance, ambient temperature, wind speed, humidity	MSE = 0.0676, R ² = 0.9999	AI-based RFR model optimized CSP system performance with economic evaluations, ensuring resilience under varying conditions

¹Although the unit is labeled as W/m² in the original study, the 1-hour-ahead forecasting objective suggests that the values represent hourly solar irradiation, i.e., Wh/m².

3.1.2 Hybrid plant performance prediction

AI-driven predictive modeling has emerged as a valuable tool for optimizing hybrid renewable energy systems, including improving the efficiency of solar heat exchangers. As shown in Table 2, various studies have employed different AI models to enhance the performance of systems that integrate solar and geothermal energy sources. Hu et al. [35] trained a BPNN to predict hourly performance metrics of an ORC-based hybrid system over a 30-year period, achieving prediction accuracy within 2% while significantly reducing computational time. By integrating BPNN with a multi-objective optimization framework, the study improved system-level outputs such as lifetime electricity generation (E_{tot}) and NPV by up to 17% and 14%, respectively. The optimization process also led to improved thermal performance of solar heat exchangers by enhancing heat transfer efficiency in varying solar and geothermal input conditions.

Khosravi et al. [36] applied ANFIS-particle swarm optimization (PSO) and MLP-PSO models to optimize the geothermal-based Organic Rankine Cycle (GORC) integrated with a solar thermal unit. These AI models were trained using key parameters such as solar radiation, well temperature, mass flow rate, turbine output pressure, and solar collector surface area. The performance metrics, including net power output, energy efficiency, exergy efficiency, and LCOE, were predicted with high accuracy. Specifically, the ANFIS-PSO model achieved an RMSE of 12.023 kW for power generation, 3.587×10^{-4} for energy efficiency, 3.278×10^{-4} for exergy efficiency, and 1.332×10^{-4} for LCOE. Compared to MLP-PSO, ANFIS-PSO demonstrated superior performance, providing more accurate results in predicting critical indicators and enabling real-time adjustments in the heat exchanger operation. These findings

highlight the effectiveness of AI models in modeling complex renewable energy systems, offering both operational and economic advantages.

Table 2. Summary of AI-based hybrid plant performance prediction studies.

Study	AI Model	Hybrid System	Performance Metrics	Key Findings
Hu et al. [35]	BPNN	ORC-based hybrid system (Solar & Geothermal)	Etot = 17%, NPV = 14%, accuracy within 2%	Enhanced efficiency and thermo-economic benefits for renewable systems
Khosravi et al. [36]	ANFIS-PSO, MLP-PSO	GORC with integrated solar thermal units	Net power RMSE = 12.02 kW, energy efficiency RMSE = 3.59×10^{-4} , exergy, LCOE	Superior adaptability to fluctuating conditions; ANFIS-PSO outperforms MLP-PSO for predicting critical performance metrics
Farajollahi et al. [37]	ANN & GA	Hybrid geothermal-solar plant (without TES)	Thermal efficiency = 30.47%, LCOE = 13.04 \$/GJ, $R^2 = 1$	High thermal efficiency with low cost
Wang et al. [38]	ANN & NSGA-II	Hybrid solar and waste heat incineration system with ORC	Exergy efficiency = 22.98%, hourly cost = \$43.08	Optimization improved thermal performance and provided cost insights
Liu et al. [39]	DNN	Solar-geothermal hybrid plant	$R^2 \geq 0.95$, error $\approx 0.55\%$, LCOE, electricity generation	Supercritical hybrid configuration increased generation and reduced LCOE

Farajollahi et al. [37] employed a coupled artificial neural network (ANN) and genetic algorithm (GA) framework to model and optimize a hybrid geothermal-solar plant without relying on solar TES. Using response surface methodology (RSM) for simulation-based data generation, the study identified optimal conditions for maximizing thermal efficiency and minimizing the levelized cost of product. The ANN-based model achieved exceptional prediction accuracy ($R^2 = 1$), and the GA optimization yielded a thermal efficiency of 30.47% and a levelized cost of 13.04 \$/GJ at specific parameter settings, including a desalination mass ratio of 2.43 and evaporator temperature of -11.51°C. This work highlights the algorithmic flexibility of AI techniques in mapping complex system interactions and guiding the design of economically and thermally efficient hybrid configurations.

Wang et al. [38] focused on multi-objective optimization in hybrid solar and waste heat systems, integrating solar energy with waste heat incineration and optimizing the system using a combination of ANNs and non-dominated sorting genetic algorithm II (NSGA-II). Their system utilized ORC for medium and low-temperature applications, and results showed an exergy efficiency of 22.98% and an hourly cost of USD 43.08. The economic analysis highlighted the significant cost contribution of the solar collector, demonstrating how optimization not only improves thermal performance but also provides insights into cost management in hybrid systems.

Liu et al. [39] proposed a deep learning-based optimization framework for a solar-geothermal hybrid power plant developed for the NEOM city project in Saudi Arabia. Their approach fully coupled geothermal reservoir modeling, a solar field, and power plant performance using decline curve analysis (DCA) and deep neural networks (DNN). The DNN predicted geothermal production parameters with high accuracy ($R^2 \geq 0.953$) and very low error ($\approx 0.55\%$), while offering fast processing (0.0026s per case). The validated model

was optimized through a multi-objective approach, identifying a supercritical configuration as optimal for both standalone and hybrid systems. The hybrid design resulted in greater electricity generation and lower levelized cost of electricity, demonstrating the effectiveness of AI integration in real-time performance optimization and long-term energy planning. The integration of AI-driven performance prediction models into hybrid solar-thermal systems improves solar heat exchanger efficiency and operational stability. These models allow for real-time optimization of key parameters, including inlet and outlet temperatures, heat transfer coefficients, and working fluid flow rates, ensuring stable performance under varying solar and geothermal contributions. By enhancing predictive capabilities, AI-based models facilitate better coordination between solar and geothermal heat sources, leading to more efficient thermal energy distribution, reduced fouling, and extended system longevity.

3.1.3 Fault detection and predictive maintenance

Effective fault detection and predictive maintenance are crucial for ensuring the long-term efficiency and reliability of solar heat exchangers. AI-driven approaches have increasingly been adopted to identify performance anomalies, detect fouling, and optimize maintenance schedules. The prediction accuracy of selected AI models is shown in Fig. 2. Feierl et al. [40] introduced Fault-Detective, a Random-Forest Regression model designed to identify operational anomalies in solar thermal systems by comparing predicted and actual sensor values. Tested on three large-scale installations, the model achieved R^2 values between 0.91 and 1.00 for thermal power monitoring and an average precision score of 91% for detecting performance faults. Notably, it identified all faults recognized by human experts and detected additional overlooked anomalies. However, its precision dropped to 30% when monitoring temperature sensors due to weather-related noise, highlighting a limitation in handling environmental variability.

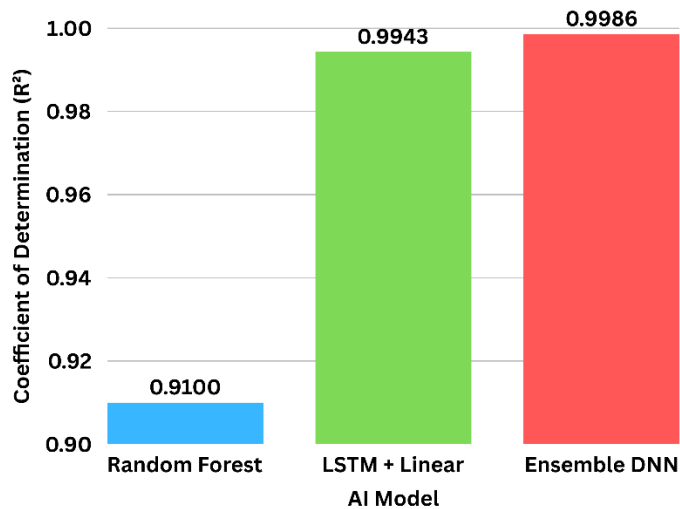


Fig. 2. Comparison of prediction accuracy among different AI models in fault and fouling detection studies [40–42].

Beyond Random-Forest Regression, ML-based approaches such as LSTM models have demonstrated strong potential for real-time health monitoring and fouling detection. Hou et al. [41] combined an LSTM model with a linear regression framework, achieving a prediction

accuracy of 0.9943 for fouling detection in plate heat exchangers, with a fouling thermal resistance threshold of 0.0003 m²K/W. This integrated method enabled accurate real-time monitoring of heat transfer efficiency and provided early warnings for fouling-related performance degradation. Sundar et al. [42] further enhanced predictive accuracy by implementing an ensemble DNN framework for fouling detection in cross-flow heat exchangers used in waste heat recovery. Their model achieved R² values of 99.86%, 99.14%, and 99.24% for overall, flue-gas side, and water-side fouling resistance, respectively. Even under sensor noise, it maintained predictive accuracy of 86.03%, 91.63%, and 73.95% for the corresponding metrics. The modular structure of the ensemble model allows adaptation to different heat exchanger configurations and operating conditions, making it suitable for large-scale applications. Furthermore, integrating this approach with LSTM frameworks can enhance predictive accuracy and optimize fouling maintenance schedules. For solar heat exchangers, these AI-driven techniques enable real-time monitoring, early fouling detection, and predictive maintenance, reducing energy losses and enhancing solar thermal system sustainability. Table 3 provides a comparative overview of these methods and their performance.

Table 3. Summary of AI-based fault detection and predictive maintenance studies.

Study	AI Model	Application	Prediction Accuracy	Key Findings
Feierl et al. [40]	Random Forest Regression (Fault-Detective)	Fault detection in solar thermal systems	R ² = 0.91–1.00 (thermal power); 91% avg. precision (fault detection); 30% (temp sensors)	High accuracy for thermal power; detected all human-identified faults and more; less accurate under weather noise
Hou et al. [41]	LSTM + Linear Regression	Fouling detection in plate heat exchangers	R ² = 0.9943; fouling threshold = 0.0003 m ² K/W	Enabled real-time fouling monitoring; early warning for performance degradation
Sundar et al. [42]	Ensemble DNN Framework	Fouling detection in cross-flow heat exchangers	R ² = 99.86%, 99.14%, 99.24%; noise-affected accuracy = 86.03%, 91.63%, 73.95%	High accuracy and adaptability; maintained strong performance under sensor noise

3.1.4 Performance monitoring and control

Traditional control systems such as Supervision, Control, and Data Acquisition (SCADA)-based automation, have been widely used for real-time monitoring and regulation. However, recent advancements in Internet of Things (IoT)-based monitoring and AI-driven control strategies have significantly improved system adaptability, efficiency, and remote accessibility. Díaz-Choque et al. [43] demonstrated the successful integration of a programmable logic controller (PLC) and Arduino Nano controller for automated regulation and real-time data acquisition of a concentric tube heat exchanger. The SCADA system was implemented using a temperature transducer composed of a MAX6675 converter module and an Arduino Nano controller. Temperature regulation was achieved through a Pulse Width Modulation (PWM) signal, which was amplified using a TL081CP operational amplifier and transmitted to the analog inputs of a Siemens 1214C PLC. Experimental tests confirmed that the flow rate of the automated system was directly proportional to the temperature drop in the hot fluid and inversely proportional to the increase in temperature in the cold fluid. The system's Human-Machine Interface (HMI) displayed real-time temperature values and tank filling levels, demonstrating the effectiveness of the automated control system in optimizing heat exchanger performance.

Building on traditional SCADA-based control, IoT-based monitoring and control systems have emerged as a more flexible and scalable solution for real-time heat exchanger performance optimization. Sridharan et al. [44] developed an IoT-based system for a double pipe heat exchanger (DPHE) using a Raspberry Pi (R-Pi) platform integrated with a cloud-centric server profile. The system monitored input and output parameters, including hot and cold water inlet and outlet temperatures, detecting deviations from normal operating conditions. The IoT system’s embedded framework used a Peripheral Interface Controller (PIC)-based microcontroller to communicate with the cloud, enabling remote access to real-time performance data and abnormality detection. The system offered several advantages, including simple and flexible operation, real-time remote monitoring and control, live streaming of process parameters, and the ability to maintain continuous and scheduled operations. It also enabled unmanned monitoring and control, improving the overall efficiency and responsiveness of the heat exchanger.

AI-based controllers have also demonstrated significant improvements in temperature regulation and system stability. Emara [45] explored the application of Proportional-Integral-Derivative (PID) controllers, ANFIS, ANN, and GA-tuned PID controllers for heat exchanger optimization. AI-based approaches outperformed conventional PID controllers in both responsiveness and accuracy. ANFIS reduced the settling time by 59.08% with no overshoot, demonstrating superior adaptability and precision in nonlinear systems. ANN-based controllers also showed strong performance, while GA-tuned PID controllers reduced settling time by 48.86% and optimized overshoot values. The study highlighted the capacity of AI techniques to dynamically adjust control parameters based on real-time system behavior, enhancing overall heat exchanger efficiency and energy consumption. Integrated control strategies are particularly valuable for solar heat exchangers, where varying solar radiation and environmental conditions can significantly impact performance. By combining SCADA, IoT-based monitoring, and AI-driven control, solar heat exchangers can dynamically adjust flow rates, inlet temperatures, and heat transfer parameters based on real-time data. This ensures stable operation, improving heat transfer efficiency and reducing energy losses. A summary of recent studies highlighting these advancements is presented in Table 4.

Table 4. Summary of performance monitoring and control studies.

Study	System	Application	Key Findings
Díaz-Choque et al. [43]	SCADA with PLC and Arduino Nano	Real-time temperature regulation in concentric tube heat exchanger	Effective PWM-based control with HMI; flow rate correlated with thermal behavior; enhanced visualization
Sridharan et al. [44]	IoT-based control with Raspberry Pi and PIC	Remote monitoring and control of DPHE	Enabled cloud-based data access, live parameter streaming, fault detection, and unmanned operation
Emara [45]	AI-based controllers (PID, ANFIS, ANN, GA)	Dynamic optimization of heat exchanger performance	ANFIS: 59.08% reduction in settling time, no overshoot; GA-PID: 48.86% improvement; high adaptability and precision

3.2 Challenges

AI-driven energy auditing for solar heat exchanger optimization offers significant potential, but several challenges must be addressed based on the reviewed literature. These challenges stem from data quality issues, computational demands, environmental variability, and the

complexity of AI models. Addressing these challenges is crucial for advancing AI-based optimization strategies.

3.2.1 Data quality and variability

High-quality input data is essential for ensuring the accuracy and reliability of AI-driven energy auditing models. Low-quality data and noise from environmental factors such as sensor errors and inconsistent weather conditions can distort model performance. AI models such as ANFIS, are particularly sensitive to the quality and range of input data, with variability in atmospheric and geographic conditions further constraining predictive capacity [8].

Sensor malfunctions in heat exchangers can also result in consecutive missing values, disrupting dataset integrity and reducing model accuracy [41]. Techniques like the sliding window approach help maintain time-series consistency and prevent information loss. However, determining the optimal window size remains challenging. Larger windows increase computational load, while smaller ones risk omitting critical information. Balancing training efficiency with data completeness is key to enhancing AI model robustness in handling missing data. Moreover, effective data preprocessing and improved data collection strategies are necessary to enhance model accuracy and broaden applicability.

3.2.2 Predictive accuracy and computational efficiency

AI-based solar radiation prediction models often involve trade-offs between short-term accuracy and long-term predictive capability, especially when applied to non-hourly data or extended prediction horizons [33]. Additionally, complex AI models require significant computational resources for both training and real-time inference, increasing hardware and energy costs [46]. Optimizing model architecture and resource utilization is critical to improving predictive accuracy while reducing computational load in solar heat exchanger optimization.

3.2.3 Design and operational uncertainty

Data-driven design and operational optimization are influenced by environmental and system-level uncertainties, including variations in ambient temperature, solar radiation, and geothermal degradation [35]. Improving model robustness under fluctuating conditions requires advanced ML algorithms and adaptive control strategies.

3.2.4 Fault detection accuracy and false alarms

AI-based fault detection systems struggle to improve fault coverage while reducing false alarm rates [40]. While high precision in fault identification is possible, distinguishing between actual faults and minor anomalies, particularly in sensor data, remains difficult. Minimizing false positives while maintaining fault detection accuracy is crucial for ensuring reliable AI-driven fault monitoring in solar heat exchangers.

3.2.5 Interpretability and complexity

AI-based models for predicting fouling resistance in heat exchangers often lack generalized mathematical frameworks to explain the relationship between input features and output targets [42]. This makes interpreting neural networks challenging. Local Interpretable

Model-Agnostic Explanations (LIME) approximates complex models with simpler linear models in the vicinity of a specific input sample. However, the accuracy of such approximations depends on how well the linear models reflect the local behavior of the complex prediction networks. Maintaining consistency in these local explanations remains challenging, especially for highly nonlinear and dynamic systems.

3.2.6 Verification and real-world implementation

AI-based control models require thorough testing and validation before real-world deployment to confirm their robustness and dependability under varying operational conditions [45]. Performance gaps between simulations and real-world conditions highlight the need for further verification to ensure the reliability of AI-based controllers in practical heat exchanger systems.

3.3 Future research directions

Advancing AI-driven energy auditing for solar heat exchanger optimization requires targeted research to enhance model accuracy, computational efficiency, and real-world applicability. Addressing existing challenges through innovative AI methodologies such as explainable AI, adaptive learning, and hybrid modeling can significantly improve the performance and reliability of hybrid renewable energy systems. The relationship between current challenges and proposed research directions is illustrated in Fig. 3. The following areas can drive further advancements in this field:

3.3.1 Improving data quality

Enhanced sensor technology, including more accurate and reliable sensors, along with regular calibration and maintenance, can reduce measurement errors. Additionally, data preprocessing techniques such as noise filtering and outlier removal, help refine input data for AI models. In cases where historical data is limited, data augmentation methods can generate synthetic data to improve model training and predictive performance [15].

3.3.2 Enhancing predictive accuracy and computational efficiency

Optimized AI algorithms such as model pruning and quantization can reduce processing requirements while maintaining predictive performance, thereby improving cost efficiency [15]. Additionally, edge computing enables real-time data analysis closer to the source, reducing reliance on centralized processing and improving system responsiveness. Hybrid AI models can further enhance prediction accuracy and reduce computational demand by determining the optimal parameters of individual models [47].

3.3.3 Strengthening model robustness under operational uncertainty

Adaptive ML algorithms, which adjust to fluctuations in solar radiation, ambient temperature, and geothermal degradation, are critical for improving operational reliability. Since solar heat exchanger conditions are inherently non-stationary, dynamic optimization techniques can support online learning by continuously updating model parameters as new data streams in. These techniques enable real-time adaptation, ensuring the system responds quickly to evolving conditions [48].

3.3.4 Improving fault detection and reducing false alarms

Requires more sophisticated anomaly detection techniques. Combining AI-based fault detection with expert systems may further enhance system efficiency by reducing false positives without compromising detection accuracy [49].

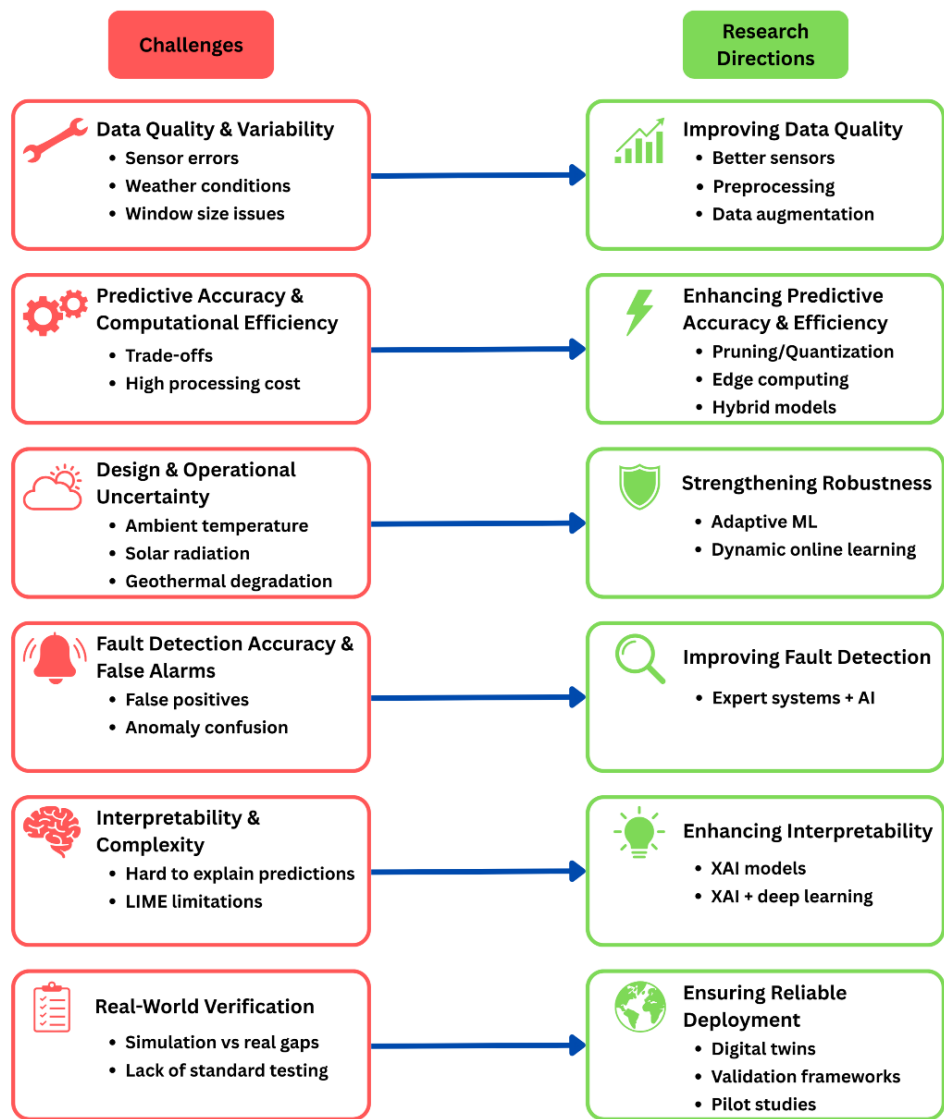


Fig. 3. Grouped flowchart illustrating the key challenges and corresponding future research directions identified in the reviewed literature.

3.3.5 Enhancing model interpretability

Explainable AI (XAI) methods can provide insights into energy consumption patterns in solar heat exchanger systems, helping identify inefficiencies and optimize performance. By

combining interpretable techniques with deep learning, hybrid XAI models could enhance both prediction accuracy and transparency, making AI-driven recommendations more actionable for operators and decision-makers [50].

3.3.6 Ensuring Reliable Real-World Deployment

Standardized testing protocols and validation frameworks are essential for ensuring reliability. Digital twin models can optimize AI-based controllers through simulated design and real-time testing before practical implementation [51]. Collaboration between industry and academia could accelerate large-scale pilot studies and facilitate the transition from research to commercial deployment. Establishing best practices for AI-driven optimization in solar heat exchangers will further ensure consistent performance and long-term success.

4 Conclusion

AI-driven energy auditing holds transformative potential for optimizing solar heat exchanger performance in hybrid geothermal-solar thermal systems. By integrating advanced ML techniques with real-time monitoring, predictive modeling, and intelligent control, energy audits can evolve beyond traditional static assessments into dynamic, data-informed optimization tools. This review has examined the current state of energy auditing frameworks, key performance indicators, and AI-based methods for fault detection, system prediction, and performance monitoring in energy systems. While substantial progress has been made, challenges such as data quality, computational demands, model interpretability, and operational uncertainties still hinder large-scale adoption and real-world implementation. However, emerging approaches such as adaptive learning, explainable AI, hybrid modeling, and digital twin integration offer promising solutions to these barriers.

Future research should prioritize advancements in sensor technology, improvements in algorithmic efficiency, and the development of robust, interpretable models capable of adapting to changing environmental and operational conditions. Collaboration between academia and industry will be essential to establish standardized protocols and accelerate deployment of AI-augmented energy auditing in renewable energy infrastructures. Ultimately, the convergence of AI and energy auditing presents a compelling pathway for enhancing the performance and sustainability of hybrid geothermal-solar thermal systems.

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