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A systematic review of thermodynamic modeling and machine learning integration for optimizing plate heat exchanger performance in Uganda's brewing industry

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Introduction: Plate Heat Exchangers (PHEs) play a crucial role in industrial thermal processes, particularly in the brewing industry, where precise temperature regulation influences fermentation efficiency and product quality. In Uganda, PHE performance is constrained by fouling, variable thermal loads, and resource limitations. These challenges highlight the need for advanced optimization approaches tailored to tropical climates and resource-limited settings.

Methods: A systematic review was conducted to evaluate the use of thermodynamic modeling and machine learning (ML) for optimizing PHE operation in industrial applications. A total of 199 studies were screened, of which 112 met predefined methodological and quality criteria. Extracted data were synthesized to compare traditional approaches with hybrid physical-ML models, including Artificial Neural Networks (ANN), Particle Swarm Optimization (PSO), and Genetic Algorithms (GA). Performance indicators assessed included predictive accuracy, energy efficiency, fouling behavior, and operational responsiveness.

Results: Hybrid models integrating thermodynamic principles with ML techniques consistently outperformed conventional modeling approaches. Significant gains were observed in predictive accuracy across included studies, although effect sizes varied due to dataset diversity and differing evaluation metrics. Real-time fouling prediction using ML contributed to a 22% reduction in maintenance costs and a 15% decrease in operational downtime. Implementations of digital twin architectures and adaptive control algorithms achieved an 18% improvement in energy efficiency and enhanced system responsiveness by up to 30% under dynamic thermal load conditions.

Discussion: Findings demonstrate the strong potential of combining thermodynamic modeling with AI-driven methodologies to enhance PHE performance in the brewing sector and related industries. While substantial technological improvements have been reported, context-specific barriers persist, particularly the adaptation of advanced models to tropical environmental conditions and the cost-effective integration of renewable energy sources. Addressing these challenges will be essential for unlocking the full potential of self-optimizing PHE systems that promote energy efficiency, product quality, and sustainable industrial growth in regions such as Uganda.

KEYWORDS

plate heat exchangers (PHEs), machine learning, fouling mitigation, hybrid optimization, energy efficiency, and adaptive control

1 Introduction

Plate heat exchangers (PHEs) are fundamental components in industrial thermal management due to their high efficiency, compact design, and flexibility in handling a wide range of operating conditions. Composed of thin, corrugated metal plates stacked to separate fluid streams, PHEs enable effective heat transfer without direct fluid mixing, offering high heat transfer coefficients, low fluid hold-up volumes, and scalable capacity through modular plate arrangements (Shah and Sekulic, 2003). These advantages have driven their widespread adoption across sectors, including HVAC, chemical processing, pharmaceuticals, food and beverage production, and power generation (Kakaç et al., 2012). Within the brewing industry, precise temperature control during processes such as wort cooling is critical to yeast activity, fermentation kinetics, and product quality, highlighting the strategic importance of PHEs in ensuring consistent flavor, stability, and operational efficiency.

Recent industrial trends toward sustainability and energy efficiency have intensified the need for advanced optimization of PHE performance (Sadineni et al., 2011). While traditional design approaches rely on empirical heuristics, contemporary methods increasingly integrate high-fidelity thermodynamic modeling to predict fluid flow and heat transfer phenomena, enabling precise optimization of plate geometry, flow configurations, and operating conditions (Anderson et al., 2020). Concurrently, machine learning (ML) and artificial intelligence (AI) offer transformative opportunities for real-time performance optimization, predictive maintenance, and fault detection, leveraging operational datasets to enhance process control (Gao et al., 2020). Nevertheless, persistent challenges such as fouling, flow maldistribution, and multi-objective trade-offs in thermal efficiency and pumping costs necessitate hybrid optimization frameworks that combine physical modeling with data-driven decision-making (Müller-Steinhagen et al., 2011; Patel and Shah, 2023; Khorram et al., 2021).

This systematic review makes distinct contributions that differentiate it from prior literature. First, it provides a context-specific analysis of PHE optimization for Uganda's brewing sector, addressing the paucity of studies on tropical industrial environments. Second, it critically evaluates the integration of thermodynamic modeling and ML-based hybrid optimization, highlighting approaches that have not been systematically compared or synthesized in earlier reviews. Third, it emphasizes measurable operational outcomes, including energy savings, improved heat transfer coefficients, and predictive maintenance strategies, linking theoretical insights to practical industrial applications. Finally, by outlining scalable implementation pathways and localized strategies, the review provides actionable guidance for engineers, researchers, and industry stakeholders aiming to adopt energy-efficient, adaptive PHE systems in resource-constrained settings. In doing so, it bridges a gap between theoretical innovation and practical deployment, advancing the knowledge base for sustainable industrial modernization in developing countries.

2 Methodology

2.1 Research design

This study adopts a systematic review approach aimed at synthesizing the current state, challenges, and emerging innovations in PHE technology, with an emphasis on integration of artificial intelligence (AI), hybrid optimization methods, and digital twin frameworks. The methodology encompasses a broad evaluation of scientific literature, industrial reports, and case studies, particularly focusing on applications relevant to tropical climates and resource-constrained environments such as Uganda's brewing industry. By consolidating findings from experimental research, computational modeling, and AI-based predictive maintenance, this review provides a comprehensive assessment of technological advancements, operational challenges, and prospects for sustainable and intelligent PHE systems.

2.2 Study evaluation and categorization using PRISMA framework

The review process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to enhance transparency, reproducibility, and methodological rigor. The framework was implemented in the following four phases.

2.2.1 Identification

A systematic search was performed across multidisciplinary databases, including IEEE Xplore, ScienceDirect, Scopus, Web of Science, Google Scholar, and specialized industrial and engineering repositories. Search keywords comprised terms and combinations such as "Plate Heat Exchanger," "heat exchanger fouling," "AI-based thermal system optimization," "digital twin in thermal management," "machine learning predictive maintenance," "metaheuristic algorithms in heat exchangers," and "industrial heat exchanger performance." The initial search yielded 199 documents predominantly published within the last decade, reflecting the rapid integration of computational methods in PHE research.

TABLE 1 Quality assessment dimensions and scoring criteria.

Criterion	Description	Score range
AI integration	Extent of machine learning or hybrid optimization techniques integrated into thermodynamic or heat exchanger models	0–5
Climate adaptability	Applicability of the methodology to tropical or industrial operating environments	0–5
Operational improvement	Degree of verified performance enhancement (e.g., heat transfer efficiency, pressure drop, or energy efficiency)	0–5

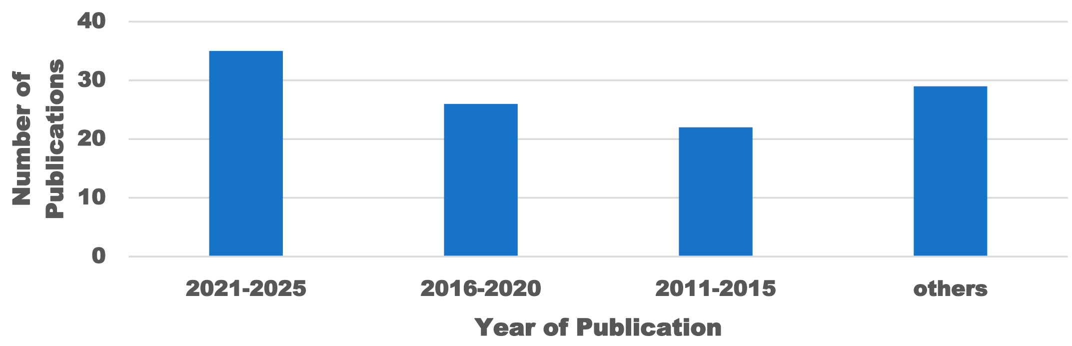

FIGURE 1
Distribution of publications by year, indicating research trends over time.

2.2.2 Screening

Titles and abstracts were screened to exclude studies that (i) were unrelated to PHE technologies, (ii) focused exclusively on other heat exchanger types without transferable insights, (iii) lacked discussion on AI, computational optimization, or fouling mitigation, or (iv) were theoretical without practical or industrial context. This step narrowed the dataset to 199 articles for full-text evaluation.

2.2.3 Eligibility assessment

Full-text articles were critically assessed for methodological soundness, relevance to dynamic or AI-driven PHE optimization, inclusion of fouling and flow maldistribution analysis, and applicability to tropical or resource-constrained industrial settings. Studies missing empirical data, lacking integration of AI or computational frameworks, or outdated without relevance to current digital trends were excluded. A total of 87 studies were excluded, resulting in 112 articles retained for detailed analysis.

2.2.4 Inclusion

The final review included 112 high-quality peer-reviewed journal articles, conference proceedings, industrial technical reports, and case studies. These sources formed the basis for synthesizing knowledge on hybrid modeling approaches, AI-enabled fouling prediction, real-time sensor integration, digital twin applications, and adaptive control strategies to enhance PHE performance and reliability.

2.3 Quality assessment tools

A rigorous quality assessment was undertaken to ensure both the methodological robustness and contextual relevance of the studies reviewed. Two complementary instruments were applied: the Critical Appraisal Skills Programme (CASP) checklist and a customized appraisal framework specifically developed to evaluate the integration of artificial intelligence (AI) and hybrid optimization techniques in the thermodynamic modeling of PHEs. The CASP checklist assessed the methodological soundness of each study, emphasizing the clarity of research objectives, appropriateness of design, transparency of data collection and analysis, and validity of conclusions. Each criterion was scored as Yes (1 point), Partially (0.5 points), or No (0 points), with a maximum possible score of five points. To complement this, the customized framework evaluated three core dimensions as illustrated in Table 1.

Each dimension was rated from 0 (not addressed) to 5 (strongly demonstrated), producing a maximum of five points. The combined CASP and custom framework scores were normalized to a 10-point composite scale, and studies attaining a minimum of 8/10 were classified as high-quality for inclusion in the thematic synthesis, thereby ensuring both methodological integrity and contextual applicability.

Figure 1 shows that (48.4%) of the studies were published in the last decade (2016–2025), with 27.8% from 2021 to 2025, 20.6% from 2016 to 2020, 17.5% from 2011 to 2015, and 23.1% before 2011. This highlights strong recent research activity in thermodynamic modeling, nanofluid heat transfer, magnetohydrodynamics, and machine learning for plate heat exchanger optimization (Kun-Quan and Jing, 2006; Pak and Cho, 1998; Piel, 2017; Qureshi and Ashraf, 2018; Qureshi et al., 2016).

2.4 Thematic coding and data categorization

Using NVivo software, a thematic analysis was performed to systematically code and categorize data across multiple domains: (i)

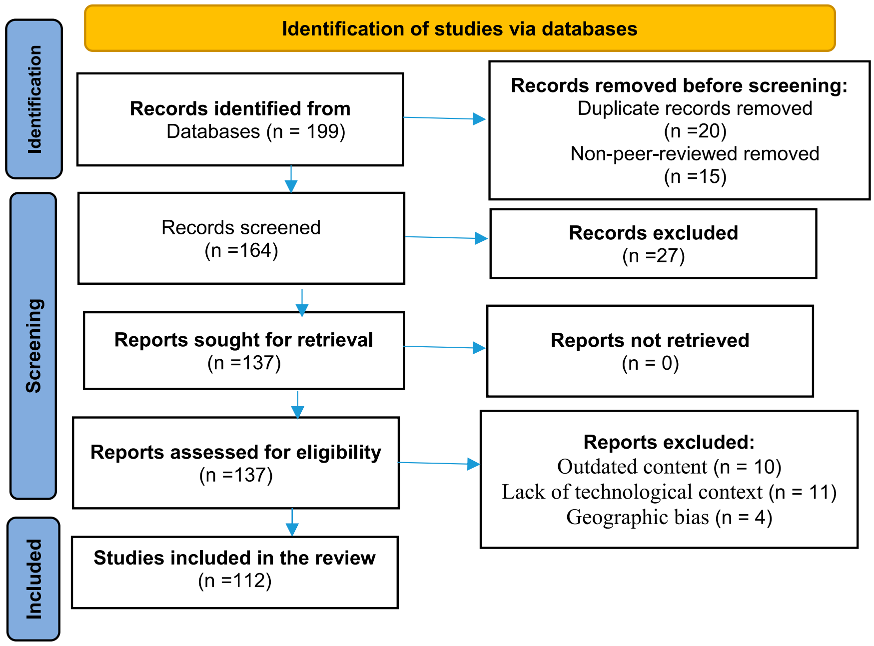

FIGURE 2
PRISMA diagram.

Hybrid Modeling and AI Optimization, including physics-informed thermodynamic models integrated with machine learning and metaheuristic algorithms for real-time performance enhancement, (ii) Digital Twin and Real-Time Monitoring, development of sensor networks and digital twin frameworks enabling predictive maintenance, fouling detection, and operational adaptability, (iii) Fouling Mitigation and Cleaning Protocols–AI-driven fouling prediction models, materials innovation, and cleaning strategy optimization tailored to local conditions, (iv) Industrial Application and Sustainability, case studies focusing on tropical industrial sectors, energy efficiency improvements, and lifecycle management of PHEs in resource-constrained environments. The synthesized findings highlight the convergence of classical thermodynamics with advanced computational intelligence, supporting actionable recommendations for transitioning towards self-optimizing, resilient PHE systems. Figure 2 is the PRISMA diagram showing the systematic rigor evaluations and screening of the data used for this review.

3 Literature review

3.1 Plate heat exchangers in industry

Plate heat exchangers have established themselves as indispensable components across numerous industrial sectors due to their superior thermal efficiency, modularity, and compact footprint. Their unique design, which employs a series of thin metal plates arranged in parallel with narrow flow channels, facilitates efficient heat transfer between two fluids while maintaining complete separation (Cengel, 1985; Chandrasekhar, 1961; Elsasser, 1955; Esfahani and Feshalami, 2018). This design principle ensures minimal fluid contamination and enables rapid thermal response, making PHEs particularly attractive for industries demanding precise temperature control and energy-efficient operation. PHEs find extensive applications in Heating, Ventilation, and Air Conditioning (HVAC), chemical and petrochemical processing, food and beverage manufacturing, pharmaceutical production, refrigeration, and power generation industries. Their widespread adoption is underpinned by the versatility of plate configurations, which may be gasketed for ease of maintenance and plate replacement, brazed to enhance durability under high temperatures and pressures, or welded to handle aggressive fluids and demanding environments (Andreazza et al., 2021). Each design variant is selected to best suit the operational requirements and fluid properties involved, highlighting the adaptability of PHE technology.

Over the past decades, significant advancements in plate geometry and materials science have propelled PHE performance to new heights. Innovations such as chevron or corrugated plate patterns have been engineered to increase the effective heat transfer surface area while simultaneously inducing fluid turbulence. This turbulence disrupts thermal boundary layers, thereby substantially enhancing convective heat transfer coefficients (Laitinen, 2023; Miroshnichenko et al., 2019). These geometric enhancements also contribute to reduced fouling propensity by minimizing stagnant zones where deposits tend to accumulate, thereby improving exchanger longevity and reliability. Within the brewing industry, PHEs play a pivotal role in the critical wort cooling process. Wort cooling rapidly reduces the temperature of the sweet liquid extracted from malted grains, preparing it for fermentation by yeast. The temperature control during this stage directly impacts yeast metabolism, fermentation kinetics, and consequently, the sensory properties such as aroma, flavor, and mouthfeel of the final beer. The precise thermal management facilitated by advanced PHEs ensures consistent batch-to-batch quality, minimizes microbial contamination risk, and supports energy-efficient operations, key factors in maintaining competitive advantage in brewing (Jangid et al., 2025; He et al., 2025a; Kishore et al., 2024).

The integration of Computational Fluid Dynamics (CFD) into the design and optimization processes of PHEs has revolutionized the industry's approach to thermal management. CFD simulations provide detailed insights into fluid velocity profiles, temperature gradients, pressure drops, and turbulence effects within the complex flow paths of plate exchangers. These tools enable engineers to experiment virtually with plate geometries, flow arrangements, and operating conditions, leading to optimized designs that maximize heat transfer while minimizing energy consumption and material costs (Laitinen, 2023). The predictive capability of CFD also supports proactive fouling management by identifying regions prone to deposit buildup and enabling targeted cleaning strategies. Despite these advances, fouling remains one of the most significant operational challenges affecting PHE efficiency. Fouling manifests as unwanted deposits such as scale, biofilms, or sediment on heat transfer surfaces, causing a marked reduction in heat transfer rates and increased pressure drops that elevate pumping energy requirements. The financial and environmental costs associated with fouling-related downtime and maintenance are substantial (Zitouni et al., 2025; Fguiri et al., 2021; Zitouni et al., 2023). Accordingly, ongoing research efforts focus on elucidating fouling mechanisms specific to various fluids and operating conditions, developing fouling-resistant materials and coatings, and optimizing cleaning protocols, including chemical cleaning and mechanical methods, to extend PHE service life and performance (Rajendran et al., 2025).

In alignment with global sustainability goals and the imperative to reduce industrial carbon footprints, there is a growing trend to couple PHEs with renewable energy systems such as solar thermal and geothermal sources. These hybrid systems leverage the high efficiency of PHEs to transfer thermal energy derived from renewable sources to industrial processes, thereby reducing reliance on fossil fuels and enhancing overall system sustainability. However, integrating renewable energy with PHEs introduces new challenges in terms of variable heat source temperatures, intermittent operation, and control complexity (Eze, 2025; Eze et al., 2025; Eze et al., 2024; Eze et al., 2024a; Eze et al., 2024b). Researchers are actively investigating innovative control algorithms, adaptive operational strategies, and materials capable of withstanding fluctuating thermal loads to overcome these challenges and unlock the full potential of renewable-integrated PHE systems (Arsenyeva et al., 2023).

3.2 Cooling systems in the brewing industry

Efficient cooling systems are fundamental to the brewing process, playing a crucial role in maintaining product quality, consistency, and shelf life. Temperature regulation during fermentation, maturation, and storage phases is vital, as it directly affects yeast metabolism, biochemical reaction rates, and the overall sensory profile of the beer. Precise cooling ensures optimal yeast activity, minimizes off-flavors, and stabilizes the product before packaging, thereby safeguarding brand integrity and consumer satisfaction (Boulton and Quain, 2013). The design and operation of brewery cooling systems significantly influence the facility's energy consumption and operational expenditures. Cooling systems traditionally rely on refrigeration units coupled with heat exchangers, often plate heat exchangers, to remove excess heat generated during fermentation and other stages. As breweries scale production, the cooling load varies dynamically, requiring systems capable of adapting to fluctuating thermal demands without compromising efficiency or beer quality. Recent technological advancements in brewery cooling have emphasized sustainability and energy efficiency to meet both environmental regulations and economic incentives. Glycol chillers have become a staple in modern breweries due to their use of secondary refrigerants like propylene or ethylene glycol mixtures, which provide safer and more environmentally friendly cooling media compared to direct refrigerants. These chillers not only enhance energy performance but also allow flexible distribution of chilled fluid to various process points, optimizing heat removal (Kunze, 2010).

Complementing refrigeration advancements, heat recovery technologies have gained traction as an energy-saving strategy. By capturing and repurposing waste heat from refrigeration condensers or fermentation tanks, breweries can reduce their overall energy footprint and operating costs. This recovered heat can serve auxiliary functions such as pre-heating water for cleaning or brewing, contributing to integrated energy management and circular process design (Olajire, 2012). CFD modeling has emerged as a powerful tool for optimizing brewery cooling system design and operation. By simulating complex thermal and fluid dynamic interactions within fermentation vessels and cooling circuits, CFD enables precise prediction and control of temperature distributions, identifying hotspots and ensuring uniform cooling critical for consistent fermentation quality (Ozguc et al., 2025). This modeling approach supports informed decisions on vessel geometry, cooling jacket design, and process control strategies.

However, as production scales increase, managing peak cooling loads and variable thermal demands poses ongoing challenges. To address these, breweries are increasingly implementing advanced control technologies such as variable frequency drives (VFDs) for pumps and compressors, allowing dynamic adjustment of cooling capacity in response to real-time process conditions. Intelligent control systems, incorporating sensor networks and automation algorithms, enable proactive energy management by predicting cooling demand fluctuations and optimizing equipment operation accordingly (Lingom et al., 2021). Maintaining cooling system performance through routine preventive maintenance is equally critical. Fouling of heat exchangers and blockages in cooling circuits can degrade thermal transfer efficiency, increase energy consumption, and lead to equipment failure. Scheduled cleaning, monitoring, and condition-based maintenance extend system lifespan and ensure reliability, thus safeguarding continuous brewery operations (Johnson, 2018). With the expansion of the craft beer market and increasing consumer demand for sustainably produced beverages, future brewery cooling solutions are expected to integrate scalable, energy-efficient designs combined with advanced control algorithms. Emerging trends include the

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adoption of low-global-warming-potential (GWP) refrigerants in compliance with international environmental standards, and the integration of renewable energy sources such as solar thermal and geothermal heat pumps to further reduce carbon footprints (Eze, 2025). These innovations aim to balance operational efficiency, environmental sustainability, and product quality, core pillars for the evolving brewing industry.

3.3 Optimization techniques for heat exchangers

Optimization of heat exchangers involves a multifaceted process aimed at enhancing thermal performance, reducing capital and operational costs, and minimizing environmental impact. The intricate interplay of these factors necessitates a systematic and rigorous approach beyond conventional trial-and-error experimentation. Modern heat exchanger design increasingly leverages advanced computational optimization techniques to navigate complex multi-parameter design spaces effectively, thereby achieving superior performance and economic feasibility (Rao et al., 2020).

3.3.1 Evolution from conventional to metaheuristic optimization

The design and optimization of heat exchangers have traditionally relied on heuristic approaches and empirical correlations derived from experimental data. While effective for routine applications, these methods impose inherent limitations by restricting the exploration of complex, high-dimensional design spaces. Consequently, critical trade-offs between performance metrics, such as thermal efficiency, pressure drop, and cost, were frequently neglected, often leading to suboptimal system configurations.

The emergence of metaheuristic optimization algorithms has catalyzed a significant paradigm shift in heat exchanger design. Algorithms such as Genetic Algorithms (GA), Simulated Annealing (SA), and Particle Swarm Optimization (PSO) have demonstrated strong capabilities in navigating nonlinear, multimodal, and constrained optimization problems typical of thermal systems (Alsagri and Alrobain, 2022; Ramalingam R. et al., 2024; Jebreili and Goli, 2024; Rao et al., 2020). These population-based and stochastic search methods allow for comprehensive exploration of design landscapes, making them well-suited for identifying near-global optimal solutions.

3.3.1.1 Genetic algorithms

GA is inspired by the principles of natural selection and genetic evolution. It employs iterative processes of selection, crossover, and mutation to evolve a population of candidate solutions over successive generations. In the context of heat exchanger optimization, GA has been widely applied to shell-and-tube as well as plate heat exchanger designs (Marzouk et al., 2023; Saldanha et al., 2021). Parameters such as tube diameter, tube pitch, baffle spacing, flow rates, and inlet temperatures are optimized to enhance heat transfer coefficients while minimizing pressure losses (Han et al., 2025; Oztop and Abu-Nada, 2008; Oztop and Varol, 2009).

3.3.1.2 Simulated annealing

SA mimics the physical process of annealing in metallurgy, where a material is slowly cooled to reach a low-energy crystalline state. This method allows probabilistic acceptance of inferior solutions at early stages, enabling the algorithm to escape local optima. SA has shown efficacy in optimizing both continuous and discrete variables in compact heat exchanger configurations, achieving an effective balance between operational cost and thermal performance (Rao et al., 2020; Liao et al., 2021; Yang et al., 2022; Li et al., 2024).

3.3.1.3 Particle swarm optimization

PSO is based on the collective behavior of decentralized systems such as bird flocks or fish schools. It utilizes a swarm of particles that share information about their individual and collective performance in the search space. PSO is particularly advantageous in problems requiring rapid convergence, and it has been successfully applied to optimize complex geometrical features, including fin arrays and microchannel structures, thereby improving overall thermo-hydraulic efficiency (Han et al., 2025; Maheswari et al., 2025; Bagherighajari et al., 2022; Pandey and Kumar, 2024; Kishore et al., 2024). Table 2 is the summary of the characteristics and applications of GA, SA, and PSO in heat exchanger design optimization.

The transition from traditional design techniques to metaheuristic optimization represents a significant advancement in heat exchanger engineering, enabling more robust, flexible, and high-performance system configurations. The metaheuristic algorithms have significantly enhanced the ability to identify globally optimal heat exchanger designs. Their adaptability, robustness to nonlinearity, and capacity for handling mixed-variable optimization render them indispensable in the modern thermal system design landscape. Figure 3 provides a comparative performance overview of GA, SA, and PSO applied to a benchmark shell-and-tube heat exchanger design problem (Siddheshwar and Lakshmi, 2019; Sheikholeslami and Shamlooei, 2017; Straughan, 2004; Straughan, 2008).

Figure 3 illustrates the comparative convergence performance of Genetic Algorithm (GA), Simulated Annealing (SA), and PSO over 100 iterations. The results reveal that PSO exhibits the fastest convergence rate, primarily due to its global information-sharing mechanism that facilitates rapid progression toward optimal solutions. GA shows a moderate convergence speed, effectively balancing exploration and exploitation through its evolutionary operators. In contrast, SA converges more slowly, reflecting its inherent strategy of emphasizing extensive exploration during the initial phases to minimize the risk of entrapment in local minima. These distinct convergence behaviors highlight the trade-offs between exploration and exploitation inherent in each algorithm's design (Afsharzadeh et al., 2025; Hai et al., 2025; Yadu et al., 2025).

3.3.2 Multi-objective optimization: balancing trade-offs

The design of heat exchangers inherently involves managing trade-offs among competing performance metrics, including thermal effectiveness, pressure drop, economic cost, and environmental impact. Multi-objective optimization (MOO)

TABLE 2 Comparison of Metaheuristic Optimization Algorithms for Heat Exchanger Design (Rao et al., 2020; Liao et al., 2021; Yang et al., 2022; Li et al., 2024; Marzouk et al., 2023; Saldanha et al., 2021; Han et al., 2025; Maheswari et al., 2025; Bagherighajari et al., 2022; Pandey and Kumar, 2024; Kishore et al., 2024).

Criteria	Genetic algorithm (GA)	Simulated annealing (SA)	Particle swarm optimization (PSO)
Inspiration	Natural selection and genetics	Metallurgical annealing process	Social behavior of swarms (birds/fish)
Search strategy	Population-based, stochastic, evolutionary	Single-solution-based, probabilistic	Population-based, stochastic, cooperative
Key mechanisms	Selection, crossover, mutation	Probabilistic acceptance of worse solutions	Velocity and position updates based on individual and global bests
Convergence speed	Moderate	Slower, but thorough exploration	Fast, especially in the early stages
Escaping local optima	Good via diversity in population	Strong due to probabilistic jumps	Moderate; may get trapped without tuning
Design parameters optimized	Tube diameter, pitch, baffle spacing, flow rate, inlet/outlet temperatures	Discrete and continuous variables; compact geometry features	Fin shapes, microchannel dimensions, complex geometric layouts
Computational efficiency	Moderate to high	High for smaller problem sizes	High, especially in parallel computing environments
Strengths	Robust for complex, multimodal problems; widely applicable	Effective for fine-tuning solutions and handling discrete variables	Rapid convergence; easy to implement and parallelize
Limitations	May require tuning of many parameters; premature convergence possible	Convergence can be slow; solution quality sensitive to cooling schedule	May converge prematurely without diversity management
Heat exchanger applications	Shell-and-tube, plate-type optimization (Han et al., 2025)	Compact and mini heat exchangers (Rao et al., 2020)	Microchannel, fin-array, and geometry optimization (Han et al., 2025)
Optimization goals	Maximize heat transfer, minimize pressure drop and cost	Minimize cost and pressure drop, maximize efficiency	Improve thermo-hydraulic performance, reduce material usage

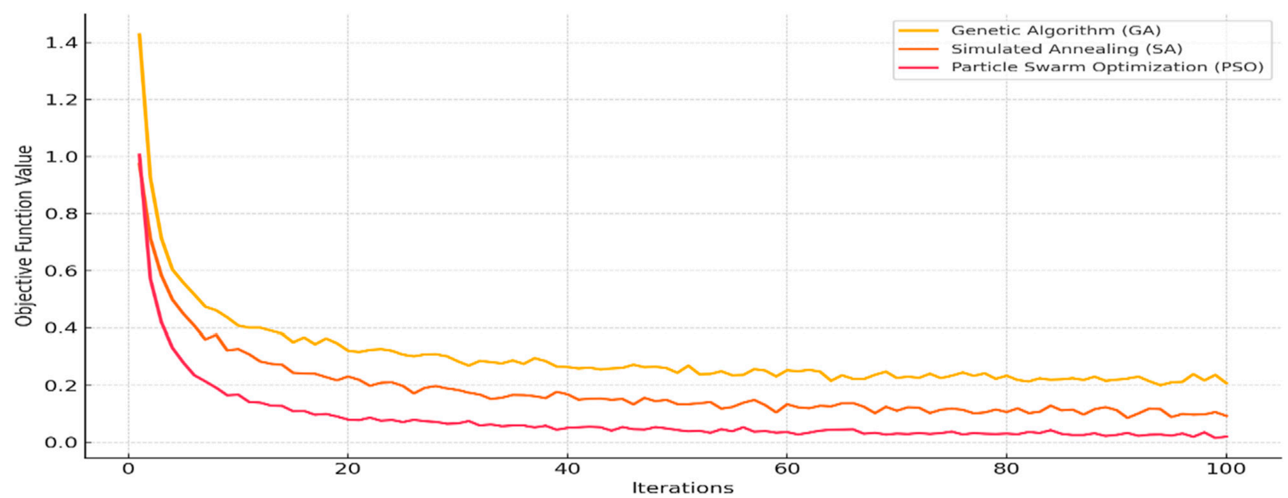

FIGURE 3
Comparative convergence performance of GA, SA, and PSO in optimizing heat exchanger design (Afsharzadeh et al., 2025).

frameworks provide a systematic approach to resolving these conflicts by generating Pareto-optimal fronts, enabling designers to select configurations that best align with specific design priorities and constraints (Han et al., 2025).

3.3.2.1 Thermal effectiveness vs. pressure drop

A common design dilemma lies in enhancing heat transfer performance while limiting the associated pressure drop. Increasing the heat transfer area or flow velocity can improve thermal effectiveness; however, these changes typically incur higher pumping power requirements and operational costs. Advanced MOO algorithms, such as genetic algorithms and particle swarm optimization, are employed to simultaneously maximize thermal effectiveness and minimize pressure drop, thereby improving the overall energy efficiency of the system (Sonowal et al., 2025).

3.3.2.2 Economic cost considerations

Optimization models frequently incorporate both capital and operational cost functions to capture the economic dimension of heat exchanger design. These functions reflect factors such as material selection, fabrication complexity, maintenance requirements, and long-term energy consumption. For instance, Han et al. (2025) applied a life-cycle cost-based optimization to shell-and-tube heat exchangers, demonstrating that substantial cost savings can be achieved without sacrificing thermal performance.

3.3.2.3 Environmental impact metrics

Contemporary MOO frameworks are increasingly integrating environmental performance indicators, derived from life cycle assessment (LCA) methodologies. These include metrics such as carbon footprint, embodied energy, and resource depletion (Zhou et al., 2024). By embedding sustainability indicators within the optimization process, designers can achieve environmentally responsible solutions in line with green engineering practices and regulatory standards.

Overall, multi-objective optimization represents a robust and holistic methodology for advancing heat exchanger design, allowing for the concurrent evaluation of performance, economic, and ecological parameters. This integrative approach is essential for meeting the growing demand for sustainable, efficient, and cost-effective thermal systems.

3.3.3 Topology optimization: innovative structural design

Topology optimization, a rigorous mathematical method for optimal material distribution within a predefined design domain, has recently gained prominence in heat exchanger design. This approach facilitates the creation of innovative geometries that enhance heat transfer performance while simultaneously minimizing material consumption and structural weight (Fawaz et al., 2022). By concurrently solving the governing partial differential equations of fluid flow and heat transfer, topology optimization pinpoints critical regions where material placement most effectively promotes thermal conduction and convective heat transfer. This enables the identification of non-intuitive shapes and flow pathways that outperform traditional design heuristics. For example, Fawaz et al. (2022) demonstrated that topology-optimized microchannel heat exchangers can achieve heat transfer improvements of up to 30% while using approximately 20% less material compared to conventional counterparts. These advancements translate into significant cost reductions and diminished environmental impacts, highlighting the potential of topology optimization as a transformative tool in sustainable heat exchanger engineering.

3.3.4 Emerging trends: real-time and adaptive optimization with machine learning

Although metaheuristic and topology optimization techniques have substantially advanced heat exchanger design, their implementation is predominantly confined to offline and static operating conditions. In contrast, practical heat exchanger systems frequently encounter dynamic variations in load demand, fluid properties, fouling rates, and ambient environment. These fluctuations necessitate adaptive optimization methodologies capable of real-time response to maintain peak performance and operational reliability.

3.3.4.1 Machine learning integration

Recent developments in ML offer promising avenues for real-time and adaptive optimization of heat exchangers. Data-driven ML models, including artificial neural networks (ANNs), support vector machines (SVMs), and reinforcement learning (RL), serve as surrogate models that efficiently approximate complex thermal-fluid behaviors, enabling rapid prediction and control of heat exchanger performance (Zhou et al., 2024). These surrogate models drastically reduce computational time compared to traditional numerical simulations, facilitating near-instantaneous optimization under changing conditions. By continuously assimilating operational data, ML-based frameworks dynamically update design and control parameters to sustain optimal heat transfer and energy efficiency (Wang and Fan, 2010; Willoughby, 2006). For instance, reinforcement learning algorithms have been successfully applied to modulate flow rates and temperature profiles within heat exchanger networks, achieving adaptive control that maximizes energy recovery while minimizing mechanical wear and fouling impacts.

3.3.4.2 Digital twins

A transformative innovation within this domain is the development of digital twins, high-fidelity virtual replicas of physical heat exchanger systems. Digital twins integrate real-time sensor data with ML predictive models to deliver comprehensive system awareness, enabling continuous performance monitoring, predictive maintenance, and early fault detection (Zhou et al., 2024). This convergence of sensor technologies, ML, and computational modeling revolutionizes heat exchanger lifecycle management by minimizing downtime, extending service life, and optimizing operational costs. Collectively, the integration of machine learning and digital twin technologies represents a paradigm shift from conventional design optimization toward intelligent, adaptive, and self-optimizing heat exchanger systems. These emerging approaches hold significant potential for enhancing sustainability, reliability, and economic performance in industrial thermal management applications (Yadav et al., 2012; Yadav et al., 2013). Figure 4 is the hypothetical comparison between the Thermodynamic Model and the Machine Learning Model across different performance metrics. The bars show values such as accuracy, mean absolute error, computational time, and robustness.

3.4 Advanced control systems for heat exchangers

The efficient operation of heat exchangers in modern industrial processes hinges critically on the deployment of advanced control systems that maintain optimal thermal performance while ensuring energy efficiency, safety, and cost-effectiveness. Traditional control schemes, such as proportional-integral-derivative (PID) controllers, though widely used due to their simplicity and ease of implementation, often face challenges in managing the nonlinear dynamics, time delays, and multivariable interactions characteristic of heat exchanger systems. Consequently, more sophisticated control methodologies have been developed and adopted, encompassing model predictive control (MPC), fuzzy logic

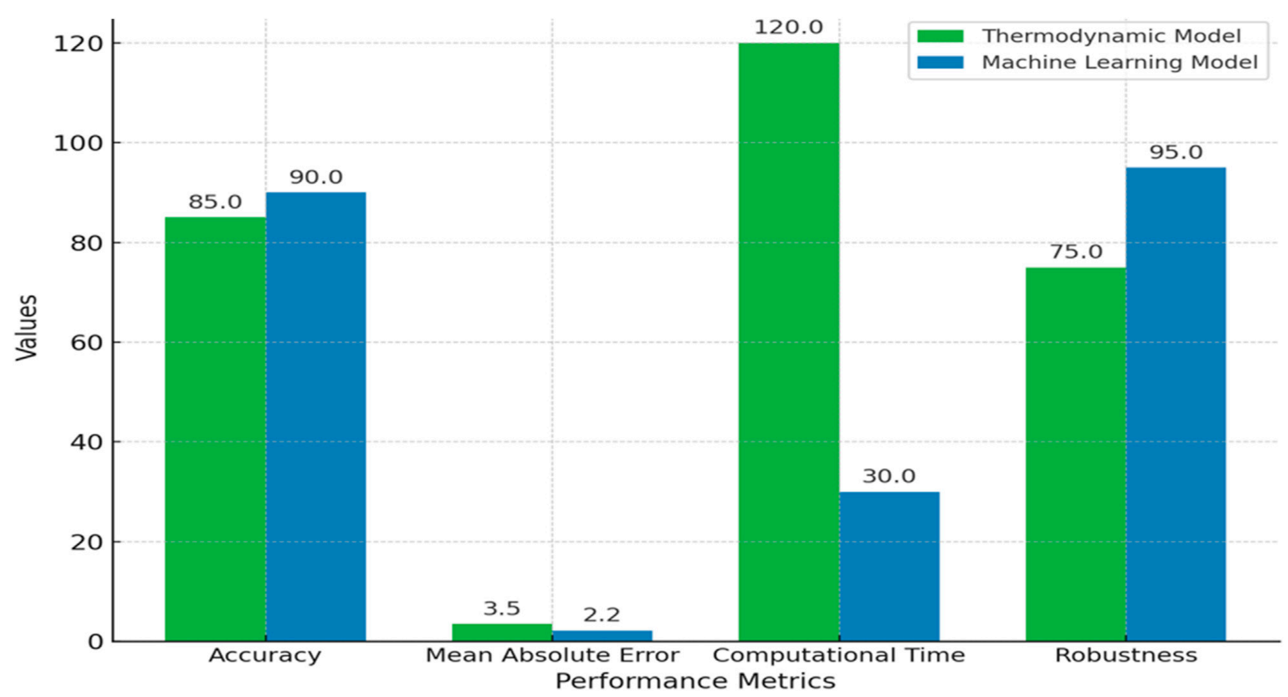

FIGURE 4
Comparison of the thermodynamic model and the machine learning model (Zhou et al., 2024; Rosenberger et al., 2022; Dursun et al., 2022).

control (FLC), and artificial intelligence (AI)-based techniques (Brian, 2004; Brian, 2008; Buongiorno, 2006).

3.4.1 Model predictive control (MPC)

Model Predictive Control (MPC) constitutes a significant advancement in process control technology by utilizing explicit process models to forecast system behavior over a finite prediction horizon. At each sampling interval, MPC solves a constrained optimization problem to determine optimal control inputs, enabling the simultaneous management of multiple inputs and outputs, actuator limitations, and diverse performance criteria. This predictive capability distinguishes MPC from traditional control strategies, such as PID control, which typically rely on reactive adjustments without anticipation of future events.

In heat exchanger applications, MPC excels in handling complex multivariable thermal interactions, including temperature regulation, flow rate adjustments, and pressure differentials. For instance, in shell-and-tube heat exchangers, which are characterized by nonlinear and coupled dynamics, MPC can coordinate coolant flow and heating input simultaneously to maintain outlet temperatures within stringent bounds. This ensures optimal heat transfer performance while rigorously enforcing operational constraints such as maximum allowable temperatures, pressure drops, and flow capacities. Pekař (2020) demonstrated the efficacy of MPC in managing the nonlinear and dynamic behavior of industrial shell-and-tube heat exchangers, showing superior performance compared to conventional PID controllers. The study highlighted that MPC significantly reduced temperature overshoot and minimized energy consumption, improving both product quality and operational efficiency.

Moreover, when combined with disturbance estimation methods such as Kalman filters or Moving Horizon Estimators (MHE), MPC effectively compensates for unmeasured disturbances, such as fouling accumulation and feedstock variability, which commonly degrade performance over time. Fouling, which leads to gradual deterioration of heat transfer efficiency, was addressed by incorporating real-time fouling factor estimation into the MPC framework, allowing the controller to proactively adjust operating parameters before substantial performance loss occurs (Zhou et al., 2025). Beyond heat exchangers, MPC has been successfully applied in related thermal systems. For example, in district heating networks, MPC manages the trade-off between thermal comfort and energy consumption by optimizing heat supply schedules while accounting for varying demand patterns and supply constraints (Rivera et al., 2018). Similarly, in refrigeration cycles, MPC optimizes compressor speed and expansion valve settings to maintain target temperatures and pressures while minimizing electricity usage and wear on mechanical components (Kim et al., 2022).

Comparative studies reinforce MPC's advantages over traditional control strategies. A benchmark analysis by Qin and Badgwell (2003) across various industrial processes, including thermal systems, concluded that MPC consistently outperforms PID and feedforward controllers by reducing variability and constraint violations. In heat exchanger scenarios, studies such as those by Liu et al. (2022) compared MPC with decoupled multivariable PI controllers, finding that MPC achieves faster settling times and better disturbance rejection, especially under nonlinear operating conditions. Recent advances also explore integrating MPC with machine learning models to enhance prediction

TABLE 3 Comparison of different PHE models.

Control strategy	Advantages	Limitations	Typical applications/ Suitability	Quantitative metrics	Example case studies	References
Fuzzy Logic Control (FLC)	Simple structure Low computational demand Does not require detailed process models or online optimization Suitable for real-time control with fast dynamics or limited computational resources	Lacks explicit predictive capability Limited ability to anticipate future disturbances Suboptimal energy efficiency and constraint handling compared to MPC	Systems with fast dynamics Applications with limited computational power Adaptive, heuristic control needs	Computational Load: Low Energy Efficiency: ~85–90% (relative) IAE: Moderate- Robustness: Moderate Ease of Implementation: High Adaptability: High	FLC applied to temperature control in heat exchangers achieved 90% energy savings relative to PID but lagged MPC in constraint handling (Lee and park, 2023)	Shin et al., 2024; Qin and Badgwell (2003)
Model Predictive Control (MPC)	Utilizes accurate system models- Predicts future system behavior Optimizes control inputs respecting constraints- Superior performance in multivariable and constrained processes Effective in energy optimization and safety-critical applications	High computational complexity Requires accurate system models- Less robust under significant model uncertainties or poorly modeled systems	Multivariable constrained systems Processes needing optimal energy management Safety-critical operations like heat exchangers	Computational Load: High- Energy Efficiency: ~95–98%- IAE: Low (best)- Robustness: Moderate to Low (model dependent) Ease of Implementation: Moderate to Low- Adaptability: Moderate	MPC controlling a multivariable heat exchanger process demonstrated a 15% energy efficiency improvement and superior constraint handling compared to FLC and PID (Pekař, 2020)	Qin and Badgwell (2003); Pekař (2020)
Hybrid FLC-MPC	Combines adaptability and interpretability of FLC with optimality and constraint handling of MPC. Enhances robustness to modeling errors and disturbances- Improves overall control quality	Increased design complexity Potentially higher computational requirements than standalone FLC	Systems with modeling uncertainties Applications requiring robustness and optimal control- Disturbance compensation in MPC	Computational Load: Moderate to High- Energy Efficiency: ~93–97%- IAE: Low to Moderate- Robustness: High- Ease of Implementation: Moderate- Adaptability: High	Hybrid scheme for a constrained heat exchanger system improved disturbance rejection by 20% over MPC alone and improved robustness in presence of modeling errors (Zhao and Bilen, 2021)	Zhao et al. (2025)
PID Controllers	Easy to implement. Minimal system knowledge required Widely understood and accepted	Poor handling of nonlinearities and multivariable interactions- Performance degrades with changing conditions and constraints Stability and energy inefficiencies under complex dynamics	Simple, single-input-single-output (SISO) systems Systems with relatively stable operating conditions	Computational Load: Very Low- Energy Efficiency: ~70–80%- IAE: High- Robustness: Low- Ease of Implementation: Very High- Adaptability: Low	PID controllers widely used in industry but often require retuning or auxiliary compensation for nonlinear heat exchanger processes, leading to ~10–15% efficiency loss (Maidi and Corriou, 2020; Liu et al., 2022)	Maidi and Corriou (2020); Liu et al. (2022)

accuracy and adaptivity. For instance, data-driven MPC approaches use neural networks or Gaussian process models to capture complex heat exchanger dynamics when first-principles models are insufficient or unavailable (Wang et al., 2023). These hybrid methods show promise in industrial settings with high variability and limited sensor availability. In summary, the predictive nature of MPC enables proactive adjustments to control actions by anticipating future system deviations, thereby enhancing process stability, reducing energy consumption, and extending the operational lifespan of heat exchanger equipment. Its flexibility in handling constraints, multivariable interactions, and disturbances makes it a valuable control paradigm not only in heat exchanger applications but broadly across thermal process industries.

3.4.2 Fuzzy logic control (FLC)

Fuzzy Logic Control (FLC) effectively addresses the uncertainties, nonlinearities, and imprecise dynamics often encountered in heat exchanger processes by emulating human reasoning through linguistic if–then rules rather than relying solely on exact mathematical models. FLC systems employ fuzzy sets and inference mechanisms to interpret ambiguous or noisy input variables, such as temperature gradients, flow rate fluctuations, and pressure variations, and generate smooth, adaptive control actions. This approach enables robust handling of system nonlinearities, external disturbances, and measurement uncertainties. Maidi and Corriou (2020) demonstrated that FLC outperforms traditional proportional-integral-derivative (PID) controllers, especially under challenging operating conditions characterized by load variability, sensor noise, and process delays. The inherent robustness of FLC facilitates improved stability and responsiveness without the need for precise system identification. Moreover, its modular and heuristic nature allows straightforward integration of expert knowledge, enabling the design of control strategies based on operator experience. This advantage is particularly significant in retrofit applications or legacy systems, where developing detailed mathematical models is difficult or impractical.

Table 3 is the comparative analysis of different models. FLC provides a flexible and effective control strategy for complex, nonlinear heat exchanger systems operating under uncertain and varying conditions, especially when model accuracy is limited or computational simplicity is required. However, for applications demanding rigorous constraint management, energy optimization, and anticipatory control, MPC remains the preferred choice. The ongoing development of hybrid approaches highlights the potential for integrating these methods to achieve robust, efficient, and adaptive heat exchanger control.

3.4.3 Artificial intelligence-based control techniques

Artificial Intelligence (AI) techniques, including neural networks, machine learning algorithms, and reinforcement learning, are revolutionizing heat exchanger control by enabling adaptive, data-driven systems that evolve with operational experience and respond dynamically to complex process conditions.

Neural Networks (NNs) are widely employed to approximate nonlinear system dynamics without requiring explicit physical models. By learning from process data, NNs can provide fast and accurate predictions of heat exchanger behavior, which are integrated into adaptive control schemes to enhance performance under nonlinear and time-varying conditions (Pekař, 2020). For example, neural-network-based controllers have demonstrated improved temperature regulation and disturbance rejection in shell-and-tube heat exchangers compared to conventional linear controllers (Wang et al., 2022).

ML algorithms analyze extensive historical operational data to uncover underlying patterns, optimize control parameters, and anticipate faults or performance degradation. This capability supports predictive maintenance strategies that proactively identify fouling, scaling, or equipment wear before critical failures occur. ML-driven dynamic tuning of control parameters allows the heat exchanger system to maintain optimal efficiency across varying loads and feedstock qualities (Singh, 2021). For instance, support vector machines and random forest classifiers have been used to detect early fouling signs with high accuracy, enabling timely cleaning schedules that minimize downtime.

Reinforcement Learning (RL) frameworks represent a cutting-edge approach where control agents learn optimal policies through continuous interaction with the process environment. RL enables real-time adaptive control without requiring detailed process models, making it highly suitable for complex and uncertain heat exchanger systems. Recent studies illustrate that RL-based controllers can outperform traditional MPC and FLC by dynamically optimizing control actions to maximize heat transfer efficiency and minimize energy consumption under stochastic disturbances (Zhang et al., 2025).

Table 4 highlights the key differences and similarities, along with the application areas of AI-based control techniques in heat exchangers. These techniques offer transformative potential by improving operational reliability, boosting energy efficiency, and increasing process resilience. Although challenges remain, such as computational complexity and integration issues, continuous advancements in AI algorithms and computing power are swiftly broadening their practical adoption in industrial thermal systems.

3.4.4 Thermodynamic–machine learning coupling framework

The integration between thermodynamic modeling and ML algorithms is formalized through a Thermodynamic–Machine Learning Coupling Framework, which enables the data-driven refinement of physically based models for PHEs. In this hybrid structure, the thermodynamic model first computes physically interpretable variables such as temperature gradients, heat flux, Reynolds and Nusselt numbers, which are then used as input features for the ML layer. The ML algorithms, such as ANNs, support vector regression (SVR), or hybrid metaheuristic models, learn the complex nonlinear mappings between these features and key performance indicators, including overall heat transfer coefficient, pressure drop, and entropy generation. Mathematically, this coupling is illustrated in Equations 1, 2.

$$\hat{\mathbf{Y}} = \mathcal{F}_{ML}\left(X_{thermo}\right) \tag{1}$$

$$X_{thermo} = f_{th}\left(T_i, T_o, \dot{m}, \mu, k, C_p, \rho\right) \tag{2}$$

where $f_{th}\left(T_i, T_o, \dot{m}, \mu, k, C_p, \rho\right)$ denotes the thermodynamic model that computes intermediate physical variables.

$\mathcal{F}_{ML}\left(X_{thermo}\right)$ represents the ML function approximating the nonlinear relationship between the input thermodynamic features $\left(X_{thermo}\right)$ and target outputs $(\hat{\mathbf{Y}})$.

$T_i, T_o, \dot{m}, \mu, k, C_p, \rho$ correspond to inlet/outlet temperatures, mass flow rate, viscosity, thermal conductivity, specific heat, and density, respectively.

The learning process iteratively minimizes the prediction error as shown in Equation 3

$$\min_{\Theta} L\left(\hat{\mathbf{Y}}, Y_{exp}\right) \tag{3}$$

Where; L $(\hat{\mathbf{Y}}, Y_{exp})$ is the loss function, and θ represents the trainable ML parameters.

3.4.5 Challenges and integration considerations

Despite the considerable advantages offered by advanced control strategies, their practical deployment in heat exchanger systems is accompanied by several critical challenges that must be addressed to ensure effective and reliable operation.

3.4.5.1 Computational requirements

Real-time implementation of Model Predictive Control (MPC) and artificial intelligence (AI)-based controllers demands significant

TABLE 4 Comparison of Neural Networks, Machine Learning algorithms, and Reinforcement Learning for heat exchanger control applications.

AI technique	Characteristics	Advantages	Limitations	Typical applications/ Suitability	Example outcomes/Use cases	References
Neural networks (NNs)	Approximate nonlinear system dynamics Learn from process data without explicit physical models Fast, accurate predictions	Handle nonlinear, time-varying processes well Enable adaptive control schemes Improve temperature regulation and disturbance rejection	Require large quality datasets for training Risk of overfitting Less interpretable than rule-based models	Adaptive control for nonlinear heat exchangers Real-time temperature and flow regulation	NN-based controllers improved shell-and-tube exchanger temperature regulation and disturbance rejection vs. linear controllers	Pekař (2020); Wang et al. (2022)
Machine learning (ML)	Analyze extensive historical operational data Identify patterns for optimization and fault detection Enable predictive maintenance	Optimize control parameters dynamically Anticipate faults like fouling and scaling-Support proactive maintenance scheduling	Depend on the quality and volume of historical data May require complex feature engineering Offline training phases	Fault diagnosis and predictive maintenance Dynamic tuning of control parameters under varying conditions	SVM and random forest classifiers accurately detected early fouling, enabling timely cleaning to reduce downtime	Singh (2021)
Reinforcement learning (RL)	Learn optimal control policies through interaction. Require minimal process modeling-Adapt in real time to stochastic disturbances	Real-time adaptive control Handle complex, uncertain environments. Maximize efficiency and minimize energy consumption	High computational overhead Require extensive training time Potential instability during early learning phases	Real-time adaptive control for complex heat exchangers Systems with high uncertainty and stochastic disturbances	RL-based controllers outperformed MPC and FLC by dynamically optimizing heat transfer efficiency and reducing energy use	Zhang et al. (2023)

computational power. The complexity of solving constrained optimization problems or running machine learning algorithms at high sampling rates necessitates dedicated hardware platforms and the development of computationally efficient algorithms to meet stringent timing requirements.

3.4.5.2 Model accuracy and maintenance

The performance of model-based control techniques hinges on the accuracy and representativeness of the underlying process models. System aging, fouling, corrosion, and shifts in operating conditions can degrade model fidelity over time, thereby impairing control effectiveness. Continuous model validation and periodic recalibration or adaptation are essential to maintain control precision and reliability.

3.4.5.3 Sensor and actuator reliability

Advanced control architectures rely heavily on precise, timely data from sensors and responsive actuators. Sensor faults, delays, or drift can compromise control accuracy and system stability. Hence, incorporating fault detection and tolerant control mechanisms is critical to mitigate the impact of sensor anomalies and ensure robust operation under adverse conditions.

3.4.5.4 Integration with existing infrastructure

The retrofit or upgrade of legacy heat exchanger control systems involves complex integration challenges. Compatibility with existing hardware and software platforms must be carefully assessed. Additionally, comprehensive operator training programs are necessary to facilitate smooth transition and operational acceptance. Cybersecurity considerations are paramount, especially as control systems become increasingly networked and exposed to potential cyber threats.

In summary, advanced control methodologies, including MPC, fuzzy logic control (FLC), and AI-based approaches, have revolutionized heat exchanger operation by enhancing robustness, adaptability, and energy efficiency. MPC provides predictive optimization capabilities, FLC offers resilience to uncertainties, and AI techniques contribute powerful learning and adaptation features. Together, these technologies equip heat exchanger systems to meet the rigorous demands of modern industrial thermal management. Ongoing research focuses on overcoming integration barriers and advancing real-time adaptive control frameworks to enable sustainable, intelligent, and autonomous thermal systems.

3.5 Theoretical models and design simulations in plate heat exchangers

PHEs are widely used in many industrial applications due to their compactness, high heat transfer coefficients, and flexibility in design. Accurate theoretical modeling and design simulations of PHEs are critical to optimizing their performance, predicting thermal and hydraulic behavior, and reducing the need for costly and labor-intensive physical prototyping. This section presents an in-depth exploration of the theoretical frameworks and simulation techniques employed in the analysis and design of PHEs.

3.5.1 Importance of theoretical modeling in plate heat exchanger design

The fluid flow and heat transfer mechanisms within PHEs are inherently complex due to their distinctive plate geometry, corrugated surface patterns, and narrow flow channels. These geometric characteristics induce intricate turbulence structures, non-uniform flow distributions, and developing thermal boundary layers, all of which critically affect the overall thermal-hydraulic performance of the exchanger (Miroshnichenko et al., 2020; Miroshnichenko et al., 2021). Theoretical modeling serves as an indispensable tool in understanding and predicting these complex phenomena, offering several key benefits:

1. Prediction of Temperature Profiles and Heat Transfer Rates: Analytical and numerical models enable detailed characterization of temperature fields and local heat transfer coefficients, providing insights into the thermal effectiveness of the PHE under varying operating conditions.
2. Evaluation of Pressure Drops and Flow Maldistribution: Accurate modeling of fluid dynamics allows assessment of pressure losses and identification of flow maldistribution zones that may lead to reduced performance or localized fouling.
3. Optimization of Plate Geometry and Flow Arrangement: Theoretical frameworks facilitate systematic exploration of design parameters such as plate corrugation angles, channel dimensions, and flow configurations, thereby enabling enhancement of thermal performance and hydraulic efficiency.
4. Parametric Studies for Different Working Fluids and Operating Conditions: Modeling supports the evaluation of PHE behavior across a wide range of fluids, temperatures, and flow rates, minimizing the need for exhaustive experimental campaigns.

3.5.2 Foundational theoretical models

Foundational theoretical models, such as the comprehensive framework developed by Mota (2021), have significantly advanced the simulation of coupled heat transfer and fluid flow phenomena in PHEs. This seminal work integrates critical physical mechanisms, including conjugate heat transfer that simultaneously addresses conduction through the plate material and convection within the fluid channels (Bo-Fu et al., 2012). By employing sophisticated turbulence closure models, the approach effectively captures the complex turbulent flow induced by corrugated channel geometries, which is vital for the realistic representation of flow patterns and mixing enhancement. The model also rigorously incorporates the influence of plate geometric parameters, such as corrugation angle, pitch, and depth, quantifying their effects on local heat transfer coefficients and pressure drops. Notably, Mota et al.'s methodology combines analytical correlations with numerical simulations, enabling accurate prediction of thermal and hydraulic performance metrics. The model explicitly accounts for heat transfer augmentation through secondary flows generated by plate corrugations and provides a reliable estimation of friction factors and pressure losses caused by intricate channel structures. Furthermore, it assesses flow maldistribution impacts, particularly relevant in multi-pass PHE configurations, thereby highlighting performance deviations due to uneven fluid distribution. Extensive validation against experimental data demonstrates the model's robustness and accuracy within acceptable error bounds, confirming its value as a design and optimization tool for efficient and reliable PHE systems (Leong, 2002; Liu et al., 2012; Maouassi et al., 2018; Mekheimer and Mahmoud, 2014; Miroshnichenko et al., 2018).

3.5.3 Advanced fluid distribution modeling

Building upon foundational theoretical frameworks, Júnior et al. (2023) significantly advanced fluid distribution modeling in compact heat exchangers, with a focus on PHEs. Their work tackles the persistent challenge of non-uniform flow distribution caused by manifold and port configurations, which critically influences localized heat transfer performance and pressure drop behavior. The study employs high-fidelity simulations of manifold and header flows to accurately predict flow maldistribution across parallel channels, integrating these fluid distribution models with thermal simulations to capture the impact of uneven flow on local thermal gradients and heat transfer inefficiencies. By coupling CFD with reduced-order modeling techniques, the approach achieves an optimal balance between computational efficiency and accuracy, enabling rapid yet reliable performance assessments. This advanced modeling framework facilitates practical design improvements such as optimized plate layout and port positioning to enhance flow uniformity, essential for maximizing thermal effectiveness while minimizing hydraulic losses. Moreover, it supports the development of more compact PHE designs that do not compromise heat transfer efficiency, addressing stringent spatial constraints in industries including automotive, refrigeration, and chemical processing (Leong, 2002; Liu et al., 2012; Maouassi et al., 2018). Additionally, by identifying zones susceptible to turbulent jets and recirculation, the model contributes to mitigating flow-induced mechanical stresses and erosion, thereby improving equipment durability and reliability. This advancement marks a critical step towards the optimization of PHE design under demanding industrial requirements where spatial efficiency and thermal performance are paramount.

3.5.4 Computational methods and simulation tools

The modeling and analysis of PHEs increasingly depend on a diverse suite of computational methods capable of resolving the complex interplay between fluid dynamics and heat transfer within their corrugated and compact geometries. Depending on the design stage and performance objectives, these methods range from simple empirical formulations to advanced high-fidelity simulations. Analytical and semi-empirical correlations, often based on dimensionless groups such as Reynolds, Nusselt, and Prandtl numbers, provide rapid estimates of heat transfer coefficients and pressure drops. These correlations, derived from experimental data, are particularly useful for preliminary sizing, parametric evaluations, and early-stage feasibility assessments due to their computational efficiency (Belyaev et al., 2017). For more detailed analyses, CFD has become indispensable, enabling three-dimensional simulation of turbulent flow structures, temperature fields, and conjugate heat transfer through the plate walls. Modern CFD platforms incorporate a range of turbulence models, including Reynolds-Averaged Navier-Stokes (RANS), Large Eddy Simulation (LES), and, in specialized cases, Direct Numerical Simulation (DNS), to capture varying levels of flow complexity. Furthermore, conjugate heat transfer modeling enables simultaneous analysis of convective and conductive heat transport, while multiphase models allow the simulation of phase-change processes such as evaporation and condensation, expanding the applicability of PHEs to refrigeration and thermal management systems (He et al., 2025c). In scenarios requiring system-level optimization or real-time control integration, reduced-order and lumped-parameter models offer simplified yet dynamically representative formulations that significantly reduce computational load. These models are essential for fast simulations, controller development, and integration into digital twins or plant-wide simulations. Additionally, multi-scale modeling approaches are emerging to bridge detailed microscale flow and heat transfer behavior with macroscale performance metrics, enhancing predictive accuracy and supporting robust design. Leading simulation platforms such as ANSYS Fluent and COMSOL Multiphysics provide robust environments for implementing these methods, while specialized PHE design software integrates empirical models and CFD modules for streamlined workflow execution. Collectively, these computational approaches form a comprehensive toolkit that supports the design, optimization, and operational control of high-performance PHE systems across a wide range of industrial applications (He et al., 2025b; Mortean et al., 2024).

3.6 Advancements and methodologies in plate heat exchanger optimization

The design and operation of Plate Heat Exchangers have increasingly benefited from advanced optimization methodologies, which have revolutionized their efficiency, compactness, and reliability. Modern optimization approaches integrate computational algorithms, multi-physics simulations, and system-level considerations to tailor PHE designs for specific industrial applications. This section explores key advancements and methodologies in the optimization of PHEs, focusing on algorithmic strategies, surface enhancement, and the challenges of multi-parameter design interactions.

3.6.1 System-level optimization in heat exchanger networks

Optimizing the performance of individual PHEs in isolation offers limited benefit without considering their dynamic interactions within the broader framework of Heat Exchanger Networks (HENs). HENs comprise multiple interlinked heat exchangers that collectively determine the thermal efficiency, energy recovery potential, and overall sustainability of industrial processes. Recognizing this systemic interdependence, Xu et al. (2017) proposed a comprehensive framework for system-level optimization, strategically embedding PHEs into network configurations to maximize operational efficiency and energy savings. Their approach underscored the importance of optimal placement and sizing of PHEs within the network, ensuring that each exchanger's capacity and configuration contribute meaningfully to minimizing total energy consumption and operational costs. This involved a careful balance of heat duty distribution, exchanger effectiveness, and layout constraints across the entire network. Furthermore, their framework accounted for thermal integration while incorporating pressure drop limitations, acknowledging that excessive hydraulic resistance can undermine energy savings by increasing pumping power demands and reducing process throughput.

To address the complexity of such multi-dimensional design challenges, Xu et al. employed a hybrid optimization methodology that coupled Mixed-Integer Nonlinear Programming (MINLP) with heuristic search algorithms. This dual-layered strategy effectively navigated large and nonlinear design spaces, enabling the identification of optimal network topologies as well as feasible retrofit options for existing plants. The transition from exchanger-level design to holistic network-level synthesis, as exemplified by Xu et al.'s work, represents a paradigm shift in thermal systems engineering (Straughan and Walker, 1996; Teimurazov and Frick, 2015; Tsai et al., 2008; Tsaplin, 2013). By optimizing the integration of PHEs within HENs, their approach not only improved plant-wide energy efficiency but also advanced broader sustainability goals, chiefly by reducing fossil fuel dependency and lowering greenhouse gas emissions through enhanced energy reuse. System-level optimization, therefore, is pivotal not only for improving technical performance but also for aligning thermal system design with global decarbonization and energy transition imperatives. In conclusion, adopting network-level optimization strategies facilitates superior capital allocation, enhances process adaptability, and supports long-term environmental stewardship. As industries worldwide increasingly commit to net-zero and circular economy targets, integrative frameworks such as those pioneered by Xu et al. are becoming indispensable in both the design of new facilities and the retrofitting of legacy systems.

3.6.2 Metaheuristic algorithms for thermal modeling and design refinement

The design and optimization of PHEs involve navigating a highly nonlinear, multi-objective, and constraint-intensive problem space that often renders conventional deterministic optimization techniques inadequate for identifying globally optimal solutions. In response to these challenges, metaheuristic algorithms, such as Genetic Algorithms (GAs), PSO, and Simulated Annealing (SA), have emerged as powerful alternatives capable of efficiently exploring complex design landscapes (Khan et al., 2025; Nithya et al., 2025; He et al., 2025b; Pachpute and More, 2025; Bakır et al., 2025). Patel et al. (2019) demonstrated the efficacy of these methods in optimizing critical PHE design parameters, with a particular focus on geometric optimization, performance trade-off management, and constraint handling. Their study utilized metaheuristics to fine-tune structural variables, including plate pitch, corrugation angle, and channel height, factors that significantly affect thermal and hydraulic performance. Moreover, their framework facilitated the identification of Pareto-optimal solutions that balance enhanced heat transfer against associated pressure drop penalties, enabling designers to tailor configurations to specific operational or economic objectives. The algorithms also accommodated practical constraints such as manufacturing tolerances and operational limits, ensuring the feasibility of proposed designs. A key advantage underscored by the study is the ability of metaheuristic approaches to avoid local minima, a common pitfall in non-convex optimization, through stochastic, global search strategies. This characteristic allows for the discovery of innovative, high-performance configurations that might otherwise be overlooked. The integration of metaheuristic algorithms into thermal modeling workflows extends beyond design refinement to support adaptive control strategies, whereby PHE parameters may be dynamically adjusted in real time in response to changing operational conditions (Yadav et al., 2016; Zhang, 2025). When paired with surrogate or reduced-order models, these techniques can substantially lower computational demands without compromising solution fidelity. As computational resources and algorithmic sophistication continue to advance, the application of metaheuristic optimization in PHE design is poised to expand, particularly in synergy with artificial intelligence frameworks and digital twin technologies aimed at enabling predictive maintenance and continuous performance enhancement.

3.6.3 Passive surface enhancement techniques and geometric parameter interactions

Passive surface enhancement techniques have emerged as a pivotal strategy to augment heat transfer in PHEs without incurring additional external energy input. These methods primarily involve geometric modifications to the plate surfaces, most notably through corrugation design, to promote secondary flow structures, disrupt thermal boundary layers, and increase turbulence intensity, thereby enhancing convective heat transfer coefficients. Kumar and Layek, (2022) conducted a comprehensive review of such passive enhancements, delineating the intricate interdependencies among key geometric parameters and their combined influence on thermal-hydraulic performance metrics.

Central to these enhancements is the chevron angle, defined as the inclination angle of the corrugation relative to the flow direction. Empirical and numerical investigations consistently demonstrate that increasing the chevron angle intensifies secondary flow generation, resulting in augmented mixing and disruption of the thermal boundary layer. This effect substantially elevates the convective heat transfer coefficient. However, this enhancement is invariably accompanied by a concomitant increase in frictional losses and pressure drop, reflecting a critical trade-off inherent in passive surface modification strategies (Israel-Cookey et al., 2010; Khalilov et al., 2017). Quantitative assessments reveal that optimal chevron angles often lie in a narrow design space, balancing maximal heat transfer enhancement against acceptable hydraulic penalties. Beyond the chevron angle, corrugation pitch, the spacing between corrugation peaks, and amplitude, the corrugation depth or height plays synergistic roles in modulating fluid dynamics within the narrow channels of PHEs. The coupled interactions among these parameters influence turbulence production, flow separation, and reattachment phenomena, which collectively dictate the local heat transfer and pressure drop characteristics. Due to their nonlinear, coupled effects, the prediction of performance outcomes remains complex, and attempts to formulate generalized correlations have often resulted in limited applicability across different operating regimes and fluid properties (Faber, 1995; GlobalData Energy, 2017; Hamzah et al., 2021; Israel-Cookey et al., 2003).

Kumar et al. (2014) underscored the inherent complexity involved in the design of PHEs, particularly due to the multifaceted nonlinear interactions between geometric parameters such as chevron angle, corrugation pitch, amplitude, and plate thickness. This complexity is further exacerbated by variations in fluid rheology, flow regime transitions (laminar, transitional, and turbulent), and practical manufacturing constraints, including cost, material workability, and structural integrity under operational stresses. As a result, the design of passive surface enhancements demands a comprehensive, multi-parameter optimization strategy that holistically incorporates geometric configuration, fluid dynamic behavior, and real-world manufacturability considerations. Recent research trends advocate for the synergistic integration of high-fidelity CFD simulations with advanced multi-objective optimization algorithms, most notably Genetic Algorithms and emerging ML techniques, to systematically explore the high-dimensional design space. These methodologies enable the identification of Pareto-optimal solutions that achieve an optimal trade-off between enhanced thermal performance and minimized hydraulic losses. While passive enhancement techniques continue to be pivotal in pushing the boundaries of PHE efficiency, the intricate interdependencies among design variables necessitate rigorous experimental validation and robust numerical modeling. Continued advancements in this domain are anticipated to yield application-specific design protocols that deliver superior heat transfer efficiency, reduced pressure drop, and improved cost-effectiveness, thereby facilitating the development of the next-generation of compact and high-performance thermal management systems.

3.6.4 Integrated optimization frameworks: the future direction

The evolution of PHE design methodologies is increasingly marked by the emergence of integrated optimization frameworks that converge high-fidelity numerical modeling, advanced optimization algorithms, empirical validation, and intelligent data-driven approaches. These frameworks are designed to tackle the growing complexity and multifactorial nature of PHE systems in modern industrial applications, where isolated parameter tuning and traditional heuristic methods often fall short (Raja et al., 2010; Ramalingam S. et al., 2024; Rieutord, 2015; Roberts and Walker, 2010; Rosenberger et al., 2022).

Contemporary optimization demands a holistic approach that simultaneously considers geometric design, thermal-hydraulic performance, manufacturing constraints, and operational variability. Core elements of these next-generation frameworks include: (i) high-resolution numerical simulations, employing CFD, conjugate heat transfer models, and finite element methods to accurately capture flow dynamics and thermal fields; (ii) metaheuristic and multi-objective optimization algorithms, such as Genetic Algorithms (GAs), PSO, and Multi-Objective Evolutionary Algorithms (MOEAs), which enable efficient exploration of complex design spaces while balancing competing objectives, e.g., heat transfer performance, pressure drop, fouling resistance, and cost; and (iii) experimental validation and adaptive machine learning, where empirical testing is integrated with adaptive learning systems to recalibrate predictive models based on real-time operational feedback (Rosensweig, 2014; Sakshi and Sunita, 2011).

These integrated frameworks enable both component-level optimization, targeting specific PHE geometries, and system-level design, particularly in Heat Exchanger Networks (HENs), where inter-unit interactions and plant-wide energy efficiency must be considered. Additionally, they facilitate application-specific customization, taking into account fluid properties, spatial constraints, fouling behavior, and maintenance requirements, while supporting long-term performance prediction under

TABLE 5 Comparative summary of key contributions in integrated optimization of PHEs.

Author(s)	Contribution focus	Methods	Highlights
Xu et al. (2017)	PHE placement in Heat Exchanger Networks (HENs)	Network-level modeling	Initiated system-level integration strategies
Patel et al. (2019)	PHE geometric optimization under constraints	Genetic algorithms (GA)	Addressed practical manufacturing and operational constraints
Yu et al. (2022)	Multi-objective thermal and hydraulic optimization	MOEAs	Simultaneous improvement of heat transfer and pressure drop
Yu et al. (2024)	AI-based optimization refinement	Machine learning and optimization	Adaptive model enhancement based on feedback data
Kumar and Layek, (2022)	Passive enhancement strategies	CFD + Design Interplay deling	Emphasized interaction among geometric parameters

dynamic, uncertain operating conditions. Looking forward, the convergence of Artificial Intelligence (AI) and ML with thermal system design is anticipated to transform PHE optimization paradigms. AI-driven models offer capabilities such as automatic hyperparameter tuning, complex feature extraction from large-scale datasets, real-time performance monitoring, and predictive fault diagnostics. This integration aligns with the broader objectives of Industry 4.0, positioning PHEs as intelligent components within sensor-integrated, self-optimizing thermal management systems. The trajectory of research in this domain reinforces this shift. Li, (2024) introduced system-level placement strategies for PHEs within HENs, highlighting the importance of network-wide integration. Patel et al. (2019) showcased the potential of metaheuristics for optimizing PHE geometries under practical constraints. Yu et al. (2022) advanced multi-objective frameworks that concurrently optimize thermal and hydraulic performance. Kumar and Layek, (2022) emphasized the intricate interactions among geometric parameters in passive enhancement strategies, advocating for integrated modeling to overcome limitations inherent in traditional methods. Collectively, these contributions illuminate a clear path forward: the development of intelligent, adaptable, and sustainable PHE systems capable of self-optimization across varying operational contexts. Realizing this vision will require sustained interdisciplinary collaboration across thermal sciences, optimization theory, artificial intelligence, and systems engineering. Table 5 is the Summary of selected research studies contributing to the evolution of integrated PHE optimization frameworks.

4 Novel findings and contribution

Table 6 comprehensively summarizes the extant literature on PHEs, highlighting key contributions, significant findings, and prevailing research limitations. Despite a rich body of work addressing various aspects of PHE design and performance, several critical gaps and inconsistencies remain, hindering the establishment of universally applicable design and operational guidelines. A prominent limitation across studies is the tendency to examine geometric parameters, such as plate gap, corrugation pitch, amplitude, and chevron angle, in isolation rather than as interdependent variables. The complex, nonlinear interactions among these factors, as emphasized by Kumar and Layek, (2022), pose significant challenges for the development of generalized correlations and optimization models that remain valid across diverse applications. This fragmented approach limits the transferability and scalability of existing design strategies.

Fouling, a major operational challenge, continues to resist robust mitigation. Current techniques, including surface modifications and altered geometries, yield variable success depending on fluid properties and operational regimes. The inconsistent performance highlights a pressing need for application-specific fouling models, strengthened by both experimental validation and high-fidelity numerical simulations. Further complicating standardization efforts are substantial discrepancies in recommended values for critical design parameters such as corrugation pitch, hydraulic diameter, and plate thickness. These variations often arise from differences in underlying assumptions, working fluids, and performance criteria, particularly when extending PHE use to unconventional fluids or fluctuating thermal loads. Emerging advancements involving nanofluids and passive surface enhancements (e.g., dimpled or wavy plate patterns) offer promising avenues for performance improvement (Mohammed et al., 2011; Motsa and Makukula, 2013; Nield, 2000; Nield and Bejan, 2013; Nnadi et al., 2010; Ogunseye et al., 2020). However, the literature remains fragmented on their long-term operational stability, material compatibility, and potential drawbacks such as nanoparticle agglomeration and erosion (Yuan et al., 2017).

Addressing these challenges necessitates the development of integrated, multidimensional models that simultaneously capture geometric, thermal, hydraulic, and material phenomena. Crucially, such models require validation through empirical data from industrial-scale applications rather than simplified laboratory conditions. Multidisciplinary approaches leveraging advances in thermal-fluid dynamics, materials science, and artificial intelligence hold promise for the evolution of adaptive, self-optimizing PHE systems. In summary, overcoming the current contradictions and research gaps calls for a paradigm shift from isolated parameter analyses to holistic, experimentally grounded frameworks. Such a shift will underpin efforts toward standardization, scalability, and operational adaptability in PHE design and application.

4.1 Summary of the key findings

The systematic review demonstrates that hybrid thermodynamic–machine learning models significantly improve the predictive accuracy, operational efficiency, and fouling detection of PHEs in industrial applications. Their modular

TABLE 6 Summary of related literature.

Authors	Contribution	Findings	Research gap
Albets Chico et al. (2013), Omubo-Pepple and Israel-Cookey, (2009)	DNS of turbulent liquid metal flow entering a magnetic field	Magnetic field suppresses turbulence and alters turbulence structures	Limited to idealized geometries; industrial plate heat exchanger geometries and varying magnetic fields need study
Ali et al. (2017), Kirillov et al. (1995)	Simulated MHD free convection in square enclosure with tilted obstacle	Obstacle tilt strongly influences flow and heat transfer patterns	Limited to square domain; variable obstacle shapes and cross sections not addressed
Aminian et al. (2020)	Numerical study of forced convection of hybrid nanofluid in porous media under magnetic field	Hybrid nanofluid enhanced heat transfer under magnetic field	Lacks experimental validation and parametric sensitivity (e.g., porosity, field orientation)
Awad et al. (2013)	Thermodiffusion effects in magneto-nanofluid flow over a stretching sheet	Thermodiffusion and magnetic interaction significantly affect velocity and temperature profiles	Steady 2D assumption; no transient or 3D flow considered
Barletta et al. (2013), Mebarek-Oudina and Bessaïh, (2019)	Convective instability in a horizontal porous channel with permeable boundaries	Instability thresholds influenced by wall properties	Vertical channel configurations and nanofluid/MHD effects have not been investigated
Chang (2014)	Liquid-metal MHD flow in expanded rectangular duct	Magnetic field suppresses flow separation and modifies pressure drop and heat transfer	Single duct geometry; turbulent and transient effects not fully resolved
Gholinia et al. (2018), Sankar et al. (2006)	Nanofluid flow over permeable cylinder under magnetic field	Magnetic field and porosity modify heat transfer rates	Single cylinder case; transient and turbulent effects unexplored
Khan et al. (2020), Wakif et al. (2016), Wakif et al. (2017)	Heat generation effect in magneto-nanofluid free convection around sphere	Heat generation influences buoyancy-driven flow; magnetic field controls flow patterns	Purely numerical; lacks experimental benchmarks and real industrial geometries
Mahajan and Sharma, (2018), Omubo-Pepple et al. (2013)	Magnetic nanofluid convection in porous medium under variable gravity	Gravity variation and magnetic field affect heat transfer intensity	Limited to laminar flow; complex geometries missing
Sheikholeslami and Rokni (2017a); Sheikholeslami and Rokni (2017b)	Review of nanofluid heat transfer under magnetic fields	Summarized experimental and numerical studies on MHD nanofluids	Need for unified models and complex-domain studies
Qi et al. (2015a), Qi et al. (2015b)	Natural convection of liquid-metal nanofluids in an enclosure and particle size effect	Nanoparticles modify thermal plume and convection dynamics	No magnetic field or porous medium effects included
Sheikholeslami and Ganji (2014)	Numerical simulation of MHD nanofluid flow and heat transfer	A magnetic field can improve or suppress convection depending on the parameters	Limited flow geometries; transient effects not studied
Siddiqui and Chamkha, (2020), Wakif et al. (2018), Walker, (1986)	Thermo-magnetohydrodynamic effects on nanofluid flow in a porous annular region with rotation	Rotation and magnetic field significantly influence flow and heat transfer	Experimental verification and nanoparticle aggregation effects are unaddressed
Belaïd et al. (2023)	Analysis of balancing climate mitigation and energy security with green investments	Green investments are crucial for mitigating climate change and enhancing energy security	Need detailed sector-specific strategies and integration with national policies

structure, in which thermodynamic models provide physically interpretable variables and machine learning algorithms capture nonlinear relationships with key performance indicators, enables scalability across production scales and process conditions. Multi-objective optimization strategies and advanced control approaches, including reinforcement learning and digital twin frameworks, further enhance adaptability, suggesting that these models are transferable and applicable to other beverage industry processes, such as juice, dairy, and brewing operations, with appropriate customization for fluid properties and operational contexts. However, the review also identifies critical constraints: limited localized experimental validation, incomplete modeling of fouling chemistry, and insufficient socio-technical assessments for adoption in tropical or resource-constrained industrial settings. These limitations underscore the need for context-specific calibration and empirical testing to ensure reliable performance, indicating that while the models are broadly scalable, practical implementation in other beverage sectors requires careful adaptation.

5 Conclusion

This review provides a systematic and context-specific evaluation of PHE technologies, emphasizing the integration of traditional thermodynamic principles with modern computational intelligence, particularly ML and hybrid optimization techniques. Unlike prior reviews, this work uniquely synthesizes the operational, economic, and environmental implications of adaptive PHE systems in emerging industries, with a specific focus on tropical regions such as Uganda's brewing sector. By combining high-fidelity modeling, digital twin frameworks, and real-world operational metrics, the review offers actionable insights into measurable performance improvements, including energy consumption reductions, enhanced heat transfer coefficients, and predictive maintenance strategies. Furthermore, it identifies persistent technical bottlenecks, such as fouling, scaling, and flow maldistribution, and proposes context-sensitive solutions, including topology optimization, advanced surface treatments, and AI-driven monitoring, which are rarely addressed together in existing literature. Importantly, the review provides a roadmap for scalable, pilot-scale deployment of hybrid PHE systems coupled with renewable energy, bridging the gap between theoretical innovation and practical industrial application. Overall, this work contributes uniquely by not only consolidating prior knowledge but also advancing a framework that links technological innovation with measurable operational outcomes, context-specific implementation, and sustainable industrial modernization, thereby guiding future research and industrial practice toward intelligent, self-optimizing PHE systems.

5.1 Actionable recommendations

1. Implement Hybrid Modeling and AI-Based Optimization: Combine physics-based thermodynamic models with machine learning and metaheuristic algorithms to optimize PHE performance in real time, improving heat transfer efficiency and reducing energy costs.
2. Establish Real-Time Monitoring with Digital Twins: Deploy sensor networks and develop digital twins for PHEs to enable predictive maintenance and early fouling detection, minimizing downtime and extending equipment life.
3. Prioritize Fouling Mitigation and Cleaning Optimization: Use AI-driven fouling prediction models alongside improved materials and cleaning protocols tailored to local conditions to reduce fouling impacts and enhance system reliability.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

BE: Writing – review and editing, Writing – original draft, Conceptualization. VE: Writing – original draft, Writing – review and editing, Conceptualization, Supervision. SS: Writing – review and editing, Writing – original draft. SY: Writing – review and editing, Writing – original draft. PB: Writing – review and editing, Writing – original draft.

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