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Heat Exchanger Temperature Control: A Comprehensive Review of Modelling, Classical, Robust, Intelligent, and Data-Driven Control Strategies

* Ahmed Khamees[1] and Mohamed Abdulgader Matoug[2]
[1]College of science and technology. Umm al-aranib
[2]Computer Department - Faculty of Education – Fezzan University

Abstract
Accurate temperature regulation is essential for the safe and energy-efficient operation of heat exchangers. Maintaining the desired outlet temperature is challenging because process dynamics vary with flow rate, inlet temperature, fluid properties, fouling, transport delay, and actuator characteristics. This review provides a comprehensive overview of temperature-control strategies for heat exchanger systems. It first summarizes the mathematical models used for controller design, including energy-balance, lumped-parameter, distributed-parameter, first-order-plus-dead-time, state-space, and data-driven models. Classical approaches, such as PI, PID, cascade, feedforward, anti-windup, fuzzy-tuned, and optimization-based PID controllers, are then reviewed, followed by robust techniques including sliding-mode control, higher-order sliding modes, adaptive control, disturbance observers, and robust model predictive control. Intelligent methods based on fuzzy logic, artificial neural networks, hybrid control, and data-driven prediction are also discussed. The reviewed studies are compared using tracking accuracy, settling time, overshoot, disturbance rejection, computational cost, tuning effort, and implementation requirements. The literature shows that PID controllers remain the dominant industrial solution because of their simplicity, whereas robust and intelligent methods achieve better performance under nonlinear and uncertain conditions. However, limited experimental validation, the absence of standardized benchmarks, controller complexity, chattering, and real-time implementation continue to present important research challenges.

Keywords: Heat exchanger; Temperature control; Process modelling; PID control; Sliding mode control; Intelligent control; Artificial neural networks; Data-driven control

1. Introduction

Heat exchangers are used in power plants, chemical industries, petroleum refineries, refrigeration systems, and thermal energy storage to transfer heat between fluids at different temperatures[1], [2]. Their performance depends on accurate outlet-temperature control. In practice, this task is difficult because the operating conditions change continuously. Variations in flow rate, inlet temperature, and fluid properties modify the process dynamics, while fouling reduces the heat-transfer coefficient and changes the thermal behavior of the exchanger [3], [4]. Thermal inertia and transport delay further slow the response, making temperature regulation more difficult [4].

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PID control is widely used because of its simple structure and ease of implementation [5]. However, a controller tuned for one operating condition may not provide the same performance when the process characteristics change. Variations in process gain, time delay, and measurement noise can increase overshoot, prolong the settling time, and reduce control accuracy. Actuator saturation may also cause integral windup and degrade the transient response [6], [7], [8], [9]. Feedforward compensation, anti-windup methods, and adaptive tuning have been introduced to improve PID performance under changing operating conditions [4]. Optimization and intelligent algorithms have also been used to tune PID parameters automatically [10]. For example, the CB-BPP strategy combines offline optimization with online parameter adjustment and reduced the Integral of Absolute Error (IAE) by up to 45% compared with a conventional PID controller [11]

Several studies have also investigated advanced control methods for heat exchangers. ANN models have been used to represent the nonlinear behaviour of the process, while MPC has improved temperature regulation under fouling conditions by providing more accurate process models [12], [13]. Dynamic studies have shown that fouling changes the thermal response of the exchanger, indicating that controller parameters should be adjusted as operating conditions change [14].

The limitations of PID control have encouraged the use of sliding-mode control (SMC), which is less sensitive to parameter variations and external disturbances [15], [16]. The main drawback of first-order SMC is chattering, which can increase actuator wear and excite unmodeled dynamics [17], [18], [19]. Higher-order sliding-mode methods reduce chattering while preserving the robustness of SMC. Hybrid controllers that combine SMC with PID, backstepping, or adaptive techniques have also been reported to improve tracking performance and reduce oscillations [18], [20], [21].

2. Heat-Exchanger Dynamics

2.1. Operating Principle

A heat exchanger transfers thermal energy between fluids at different temperatures [22]. In most industrial units, the fluids remain physically separated while heat passes through a solid wall. The controlled variable is usually the outlet temperature of the hot or cold stream. In some applications, wall temperature or heat duty may also be regulated [23].

The outlet temperature depends on the inlet temperatures, fluid flow rates, thermophysical properties, overall heat-transfer coefficient, effective surface area, exchanger configuration, and heat loss to the surroundings [24]. A change in one of these quantities shifts the operating point and alters the process response.

Temperature is commonly regulated by changing the hot- or cold-fluid flow rate through a valve or variable-speed pump [25]. Steam-valve position, pump speed, electrical heating power, and bypass flow may also serve as manipulated inputs. In bypass control, part of the fluid passes around the exchanger and is then mixed with the treated stream. This arrangement changes the final outlet temperature without changing the overall exchanger flow [26].

PID, feedback, and feedforward controllers have been used for outlet-temperature regulation. PID control remains common because its structure is simple and its parameters have a clear physical interpretation. However, its performance depends on the tuning method and the operating range [12]. Figure 1 illustrates the basic operating principle of a typical shell-and-tube heat exchanger together with the main manipulated variables and control objectives. The outlet temperature is commonly

regulated by adjusting the hot- or cold-fluid flow rate, steam-valve opening, pump speed, bypass flow, or electrical heating power. Depending on the application, the controller aims to maintain the desired outlet temperature, wall temperature, or heat duty despite variations in operating conditions.

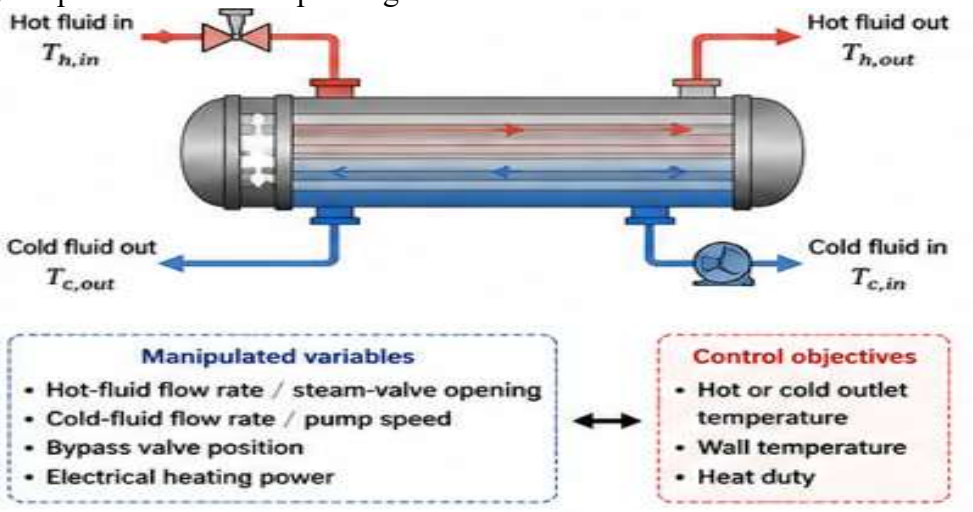


Fig. 1. Operating principle of a shell-and-tube heat exchanger, manipulated variables, and typical temperature-control objectives.

2.2. Nonlinear Characteristics

The dynamic response of a heat exchanger is nonlinear. The heat-transfer coefficient changes with flow velocity, Reynolds number, fluid regime, surface condition, and temperature. Valves and pumps also have nonlinear input–output characteristics, particularly near their operating limits [27].

The driving temperature difference varies along the exchanger and changes as the inlet conditions and flow rates vary. As a result, a model identified at one operating point may not remain accurate over the full operating range. This loss of accuracy affects controller tuning and may lead to a slower response, steady-state error, or oscillation [28]. The process dynamics of a heat exchanger depend strongly on the operating conditions. Changes in flow rate, temperature, fluid properties, and actuator characteristics alter the process response and reduce the accuracy of linear models identified around a single operating point. Figure 2 illustrates the main nonlinear characteristics that influence heat exchanger temperature control.

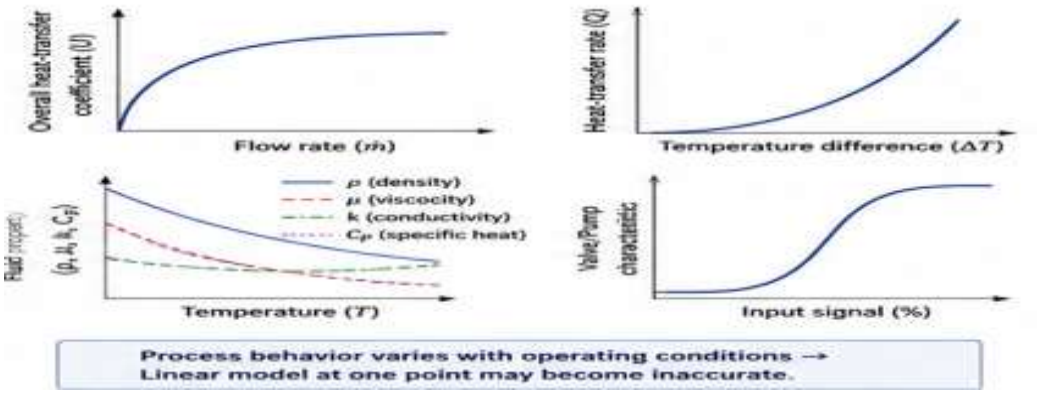


Fig. 2. Typical nonlinear characteristics influencing heat exchanger dynamics and temperature-control performance.

2.2.1. Variable Heat-Transfer Coefficients

The convective heat-transfer coefficient depends on the flow regime and local thermal conditions. Changes in flow rate can therefore alter both the process gain

and the response time [29]. Takagi–Sugeno fuzzy models have been used to represent these changes across different flow rates and temperatures. Such models divide the operating range into local regions and combine the corresponding model outputs through fuzzy weighting [30].

3.2.2. Temperature-Dependent Fluid Properties

Fluid density, viscosity, thermal conductivity, and specific heat vary with temperature. These variations affect pressure drop, convective heat transfer, residence time, and stored thermal energy [31], [32].

Viscosity changes are particularly important for oils and fluids with high Prandtl numbers. Under these conditions, temperature-dependent properties can alter turbulent transport and reduce the Nusselt number relative to constant-property predictions [33].

2.2.3. Nonlinear Modelling Approaches

Nonlinear process models are used when a single linear model cannot describe the exchanger over the required operating range. Hammerstein models represent the process as a static nonlinearity followed by linear dynamics. This structure can describe nonlinear actuator behavior together with the thermal dynamics of the exchanger [34].

Artificial neural networks have also been applied to heat-exchanger modelling. They can estimate nonlinear relations among operating conditions, overall heat-transfer coefficient, and required surface area without imposing a fixed analytical structure [35].

2.3. Thermal Inertia

Part of the supplied heat is stored in the fluids, exchanger wall, pipes, and temperature sensors before it affects the outlet temperature [36]. This stored energy slows the process response after a change in the control input [37]. Thermal inertia can filter short disturbances, but it also increases the settling time and limits how rapidly the outlet temperature can be changed [38]. Thermal inertia introduces a delay between a change in the control input and the corresponding outlet-temperature response. Because part of the supplied energy is stored within the fluids, exchanger wall, pipes, and sensors, the temperature changes gradually rather than instantaneously. Figure 3 illustrates the influence of thermal inertia on the transient response of a heat exchanger.

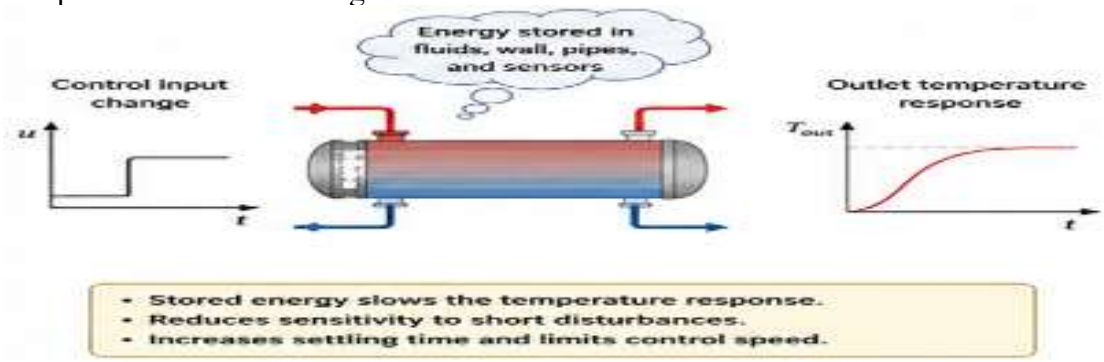


Fig. 3. Effect of thermal inertia on the dynamic response of a heat exchanger.

2.4. Transport Delay

Transport delay in control systems, particularly in thermal processes, significantly impacts system stability and performance [39]. Delays arise from various sources, including fluid travel time, sensor and actuator response, and communication lags [40]. These delays can lead to reduced stability margins and potential oscillations,

especially when they vary with flow rates or operating conditions. Therefore, effective controller design must account for the expected delays and their variations [41]. Transport delay is an inherent feature of heat exchanger systems and arises from several physical and measurement processes. Delays introduced by fluid transport, actuator dynamics, sensor response, and communication reduce the speed of the closed-loop response and may degrade control performance. Figure 4 summarizes the major sources of transport delay and illustrates their effect on the transient outlet-temperature response.

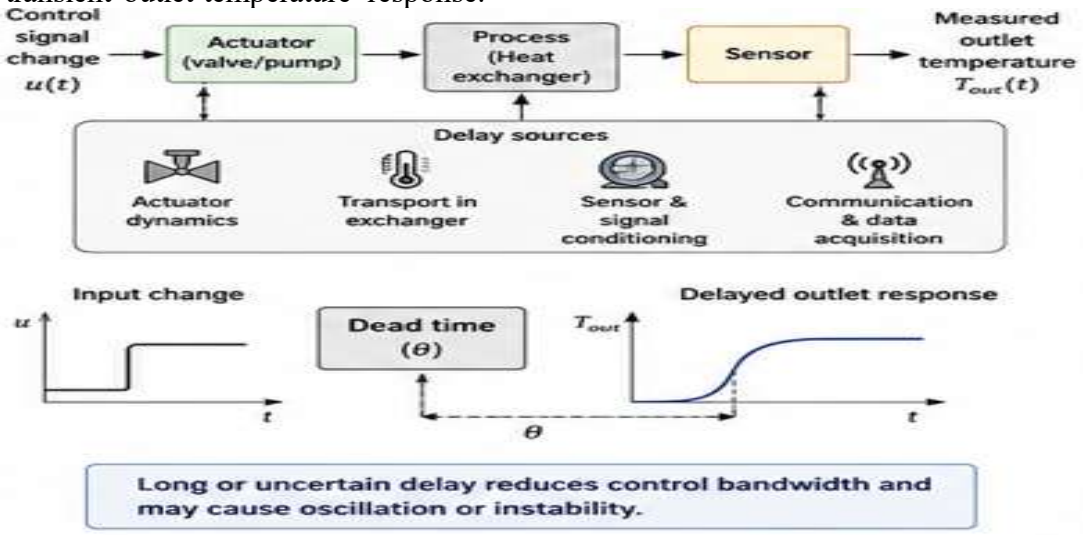


Fig. 4. Schematic representation of transport delay in a heat exchanger, showing the main delay sources and the resulting dead-time in the outlet-temperature response.

Sources of Transport Delay

- Fluid Dynamics: The time taken for fluid to travel through exchangers and pipes contributes to the overall delay, affecting the system's response time [42].
- Sensor and Actuator Delays: Delays in sensor readings and actuator responses can exacerbate the overall system delay, complicating control efforts [43], [44].
- Communication Lags: Data acquisition and communication links introduce additional delays that can affect real-time control decisions [43], [45].

Control Strategies

- Gain Scheduling and Feedforward Compensation: Implementing gain scheduling and feedforward compensators can enhance control performance by synchronizing transportation delays, as demonstrated in electric flow heater systems [46].
- Bode Plot Techniques: Simplified design procedures using Bode plots allow for effective controller design in the presence of transport delays, ensuring satisfactory performance [47].

2.5. Disturbances and Uncertainty

Heat exchangers face significant challenges due to disturbances and uncertainties in operational conditions [48]. These variations can stem from changes in inlet temperature, fluid flow, and other factors, necessitating robust control strategies to maintain desired outlet temperatures. Effective control mechanisms must account for these disturbances to minimize oscillations and control effort. The following sections outline key strategies and methodologies for managing these challenges. Temperature regulation in heat exchangers is continuously influenced by external disturbances and model uncertainties. Disturbances such as changes in inlet temperature, flow rate, and thermal load alter the operating conditions, whereas

uncertainty arises from heat-transfer variations, actuator nonlinearities, sensor imperfections, and unmodeled process dynamics. Figure 5 illustrates the principal disturbance sources and uncertainties that must be addressed to achieve reliable temperature control.

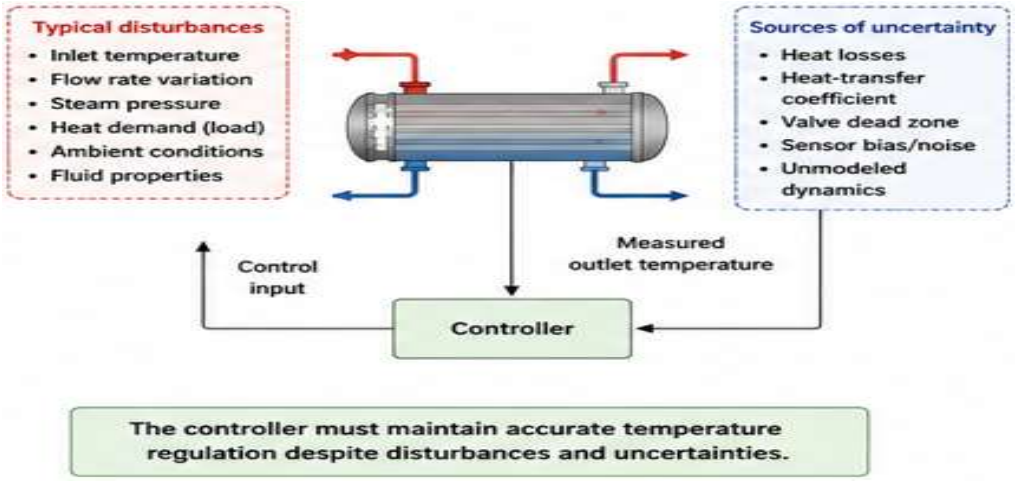


Fig. 5. Disturbances and uncertainty sources influencing heat exchanger temperature regulation and closed-loop control performance.

Disturbance Propagation Evaluation

A rigorous model evaluates how disturbances propagate through heat exchanger networks, using the effectiveness-NTU methodology to represent each exchanger algebraically [49] Gouda et al. (2019) proposed a computationally efficient linear model to evaluate disturbance propagation in heat exchanger networks by predicting outlet-temperature deviations caused by inlet disturbances. The model successfully identified disturbance propagation paths and maximum temperature deviations in benchmark HENs, although it is limited to linear systems without bypass configurations and is not intended for controller design or flexibility analysis[50].

Control Strategies

To maintain accurate outlet-temperature regulation under nonlinear dynamics, model uncertainties, and external disturbances, a wide range of advanced control strategies has been proposed in recent years [51]. Fractional-order control has received considerable attention because it introduces additional tuning flexibility and generally provides better tracking performance and disturbance rejection than conventional PID control. Dong and Deng (2022) combined operator theory with a fractional-order PID controller to improve robustness against model uncertainties and external disturbances, achieving stable temperature tracking in simulations [52]. Tang et al. (2023) further enhanced disturbance rejection by integrating fractional-order active disturbance rejection control with nonlinear feedback and feedforward compensation, resulting in faster response and improved robustness compared with PID, ADRC, and conventional fractional-order ADRC [53].

Industrial implementation has also attracted increasing interest. Tomar et al. (2024) developed a PLC–SCADA-based temperature-control framework that combined cascade control, feedforward control, Smith prediction, and optimized PID and fractional-order PID controllers. Their experimental results showed that the fractional-order PID controller tuned using the ant colony optimization algorithm produced the shortest settling time, lower overshoot, and stronger disturbance rejection than the conventional PID controller. More recently, adaptive and observer-based control methods have been introduced to address parameter uncertainty and unknown dynamics [54]. Mechhoud and Belkhatir (2025) proposed an adaptive

output-feedback controller with an adaptive boundary observer for a parallel-flow heat exchanger, enabling online estimation of distributed states and uncertain parameters while guaranteeing closed-loop stability under input constraints [55] .
Advanced robust control techniques have also evolved beyond conventional fractional-order PID controllers. Bai et al. (2024) employed composite learning together with a disturbance observer to improve uncertainty estimation and tracking performance in fractional-order nonlinear systems [56]. Similarly, Li et al. (2025) combined fractional-order super-twisting sliding mode control with active disturbance rejection control to reduce chattering, accelerate convergence, and improve robustness against parameter variations and external disturbances [57]. Collectively, these studies indicate that recent research is moving toward adaptive, observer-based, and fractional-order control architectures that can simultaneously improve tracking accuracy, disturbance rejection, and robustness. However, many of these approaches rely on simulation-based validation, involve relatively high computational complexity, and require careful parameter tuning before practical industrial deployment.
Table1 summarizes recent studies on advanced control strategies developed for heat exchangers and related thermal systems operating under model uncertainties, nonlinear dynamics, external disturbances, and input constraints. The comparison highlights the objective, methodology, strengths, limitations, and major findings of each study, providing an overview of recent developments beyond conventional PID-based temperature control.

Table 1. Comparison of Recent Advanced Control Strategies for Heat Exchanger and Thermal Process Temperature Control under Uncertainties and Disturbances

Re	Aim	Purpose	Advantages	Disadvantages	Main Result
[52]	Develop an operator-based fractional-order PID nonlinear robust controller for heat exchangers under uncertainties and disturbances.	Improve temperature tracking and robustness by integrating operator theory with fractional-order PID control.	Strong tracking performance, effective disturbance rejection, improved robustness to uncertainties, verified through MATLAB simulation.	Requires manual/offline tuning of fractional-order parameters, higher implementation complexity, validated only by simulation, further robustness improvements are needed.	Achieved stable tracking and robust disturbance rejection in simulation despite uncertainties, but parameter tuning remains a limitation.
[53]	Develop an improved fractional-order active disturbance rejection	Improve temperature-control performance by combining	Faster response, improved tracking accuracy, stronger	Controller design is relatively complex, fractional-order parameters still require	The proposed FOADRC outperformed PID, ADRC, and conventional

Table 1. Comparison of Recent Advanced Control Strategies for Heat Exchanger and Thermal Process Temperature Control under Uncertainties and Disturbances

Re	Aim	Purpose	Advantages	Disadvantages	Main Result
	controller for nonlinear reactor temperature systems with uncertainties and disturbances.	reactor modeling with a fractional-order observer, nonlinear feedback, and feedforward compensation.	disturbance rejection, higher robustness, validated by simulations and experiments, applicable to other nonlinear systems.	optimization, and broader industrial validation is needed.	FADRC by providing faster response, improved robustness, and more effective disturbance rejection while maintaining accurate reactor temperature control.
[54]	Develop a PLC–SCADA-based framework for real-time heat exchanger temperature control using optimized PID and FOPID controllers.	Integrate advanced control strategies and optimization algorithms to automate, monitor, and improve temperature regulation under nonlinearities, delays, and external disturbances.	Real-time PLC–SCADA implementation, multiple control strategies, anti-windup compensation, metaheuristic optimization, experimental validation, improved disturbance rejection, and superior FOPID performance.	High hardware cost and system complexity, dependence on optimization quality, component failures can affect the whole system, SCADA communication latency, and need for further optimization using newer algorithms.	FOPID outperformed PID in both simulations and real-time experiments. ACO achieved the most balanced controller tuning, providing faster settling, lower overshoot, improved steady-state performance, and effective disturbance rejection within the PLC–SCADA framework.
[56]	Develop a composite learning fuzzy controller for fractional-order	Improve tracking accuracy and uncertainty estimation by	More accurate uncertainty estimation than AFC, improved tracking	Conservative controller assumptions, performance may degrade when the	The proposed CLFC outperformed conventional AFC by providing more

Table 1. Comparison of Recent Advanced Control Strategies for Heat Exchanger and Thermal Process Temperature Control under Uncertainties and Disturbances

Re	Aim	Purpose	Advantages	Disadvantages	Main Result
	nonlinear systems with uncertainties and time-varying disturbances.	integrating fuzzy logic, a serial-parallel estimation model, and a fractional-order disturbance observer.	performance, enhanced robustness, effective disturbance estimation, closed-loop stability, and better composite learning performance demonstrated by simulation.	actual control input differs significantly from the ideal input, validation is limited to simulations, and further extensions to constrained systems and finite-time stabilization are required.	accurate estimation of system uncertainties and better tracking performance under time-varying disturbances while maintaining closed-loop stability.
[57]	Develop a fractional-order super-twisting sliding mode active disturbance rejection controller for electro-hydraulic position servo systems operating under nonlinear dynamics, uncertainties, and external disturbances.	Improve tracking accuracy, suppress chattering, accelerate convergence, and compensate for unknown disturbances by integrating fractional-order operators, super-twisting sliding mode control, and ADRC.	Reduced chattering, faster convergence, improved disturbance rejection, accurate real-time disturbance estimation, additional tuning flexibility, high tracking precision, and robustness validated under ±15% parameter variations.	Increased computational burden due to fractional-order approximation, manual parameter tuning, simulation-only validation, and the need for optimization-based tuning methods in future work.	The proposed controller achieved a 37.25% faster rise time, a 0.008 mm steady-state error, an 18.37% reduction in sinusoidal tracking error, and maintained stable performance under ±15% parameter uncertainties, demonstrating superior robustness and tracking performance.

Table 1. Comparison of Recent Advanced Control Strategies for Heat Exchanger and Thermal Process Temperature Control under Uncertainties and Disturbances

Re	Aim	Purpose	Advantages	Disadvantages	Main Result
[55]	Develop an adaptive output-feedback bounded bilinear controller for PDE-based parallel-flow heat exchangers with uncertain parameters and input constraints.	Regulate outlet temperature while estimating distributed states and unknown parameters online and ensuring closed-loop stability under actuator constraints.	Handles input constraints, estimates unknown parameters online, reconstructs distributed states, guarantees exponential stability, achieves convergence of tracking and estimation errors, and is extendable to other hyperbolic PDE systems.	Evaluated only through simulations, does not address external disturbances or uncertain boundary parameters, involves high computational complexity, and MPC implementation remains future work.	The proposed controller successfully regulated outlet temperature, achieved accurate online state and parameter estimation, ensured exponential closed-loop stability, and demonstrated satisfactory tracking performance in numerical simulations.

As summarized in Table 1, recent research has progressively shifted from conventional PID control toward more advanced strategies, including fractional-order control, active disturbance rejection control, adaptive control, fuzzy composite learning, sliding mode control, and observer-based approaches. These methods consistently improve tracking accuracy, disturbance rejection, and robustness under nonlinear operating conditions and model uncertainties. Fractional-order controllers generally outperform conventional PID controllers because they provide additional tuning flexibility and better dynamic performance. Likewise, adaptive observers and disturbance estimation techniques improve state estimation and compensate for unknown dynamics, resulting in enhanced closed-loop stability. Despite these advantages, most reported methods increase controller complexity, require extensive parameter tuning, and are primarily validated through numerical simulations rather than industrial implementation. Consequently, developing control strategies that simultaneously achieve high robustness, low computational complexity, simple tuning, and real-time applicability remains an important research challenge for heat exchanger temperature control.

2.6. Fouling

Fouling on heat-transfer surfaces is a significant challenge in maintaining the efficiency of heat exchangers [58], [59]. As deposits accumulate, they introduce thermal resistance, reduce the overall heat-transfer coefficient, and increase pressure drops, ultimately affecting process

dynamics [58], [60]. This gradual fouling necessitates a reevaluation of control strategies over time, as controllers tuned for clean conditions may become less effective. The following sections elaborate on the implications of fouling in heat exchangers [59], [60], [61]. Fouling is a gradual process that continuously alters the thermal behavior of heat exchangers during operation. The accumulation of deposits increases thermal resistance, reduces the overall heat-transfer coefficient, and raises the pressure drop, resulting in changes to the process dynamics and control characteristics. Figure 6 summarizes the influence of fouling on heat transfer and highlights its impact on temperature-control performance.

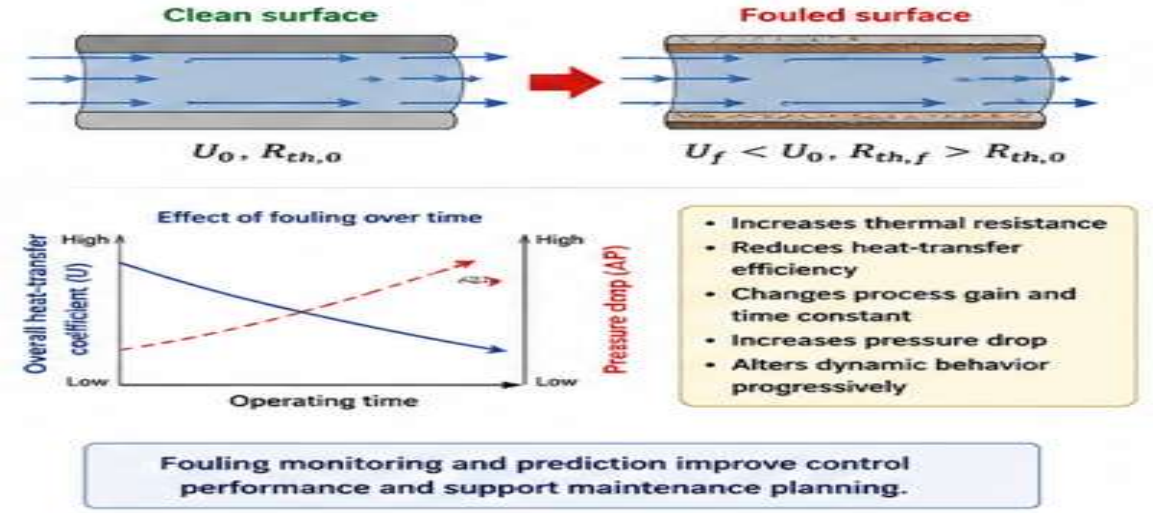


Fig. 6. Progressive effects of fouling on heat-transfer performance, pressure drop, and heat exchanger dynamics.

3. Mathematical Models of Heat Exchangers

3.1. Energy-Balance Model

The energy-balance model describes the thermal behavior of a heat exchanger using the conservation of energy. The change in stored thermal energy depends on the heat entering and leaving the system, the heat exchanged between the fluids, and the heat lost to the surroundings. For a well-mixed control volume, the model is written as [24], [48], [62], [63] :

$$mc_p \frac{dT}{dt} = \dot{m}c_p(T_{in} - T) + UA(T_{other} - T) - Q_{loss}, \quad (1)$$

where $m$is the fluid mass, $c_p$is the specific heat capacity, $\dot{m}$is the mass flow rate, $U$is the overall heat-transfer coefficient, $A$is the heat-transfer area, and Q_{loss} is the heat exchanged with the surroundings.

The model relates the process variables to the outlet temperature through an energy balance. Its accuracy is affected by the assumptions made during modelling, including complete mixing, uniform temperature inside the control volume, simplified wall dynamics, and estimated heat losses.

3.2. Lumped-Parameter Model

The lumped-parameter model assumes a uniform temperature inside each control volume [64]. Under this assumption, the governing equations become ordinary differential equations. The resulting model is simple and requires little computational effort. For this reason, it is often used for controller design, parameter estimation, and real-time simulation [65].

The assumption of uniform temperature is not always valid. Prediction errors become larger when temperature changes along the exchanger length, especially in

long heat exchangers, at high flow rates, or during rapid operating changes [66], [67].

3.3. Distributed-Parameter Model

The distributed-parameter model represents temperature as a function of both time and position. Partial differential equations are used to describe heat transfer along the exchanger length [68].

This model captures convection, transport delay, and spatial temperature variation more accurately than a lumped model [69]. The improvement in accuracy requires more model parameters, numerical discretization, and higher computational effort [70]. In many control applications, reduced-order models are used to decrease the computational load [71].

3.4. First-Order Plus Dead-Time (FOPDT) Model

The first-order plus dead-time (FOPDT) model is widely used in industrial heat exchanger studies. Its transfer function is:

$$mG(s) = \frac{Ke^{-Ls}}{\tau s + 1}, \tag{2}$$

where $K$is the process gain, $\tau$is the time constant, and $L$is the transport delay. Only three parameters are required to describe the process, making the model easy to identify from experimental data [72]. It is therefore common in PID tuning and controller design. The model describes the process around one operating condition, so its parameters may change with flow rate, inlet temperature, or fouling [73].

3.5. State-Space Model

The state-space model represents heat exchanger dynamics as:

$$\dot{x} = f(x, u, d, \theta), \tag{3}$$
$$y = h(x),$$

where $x$contains the system states, $u$is the control input, $d$represents external disturbances, and θcontains uncertain model parameters.

Linear state-space models are obtained by linearizing the nonlinear equations around an operating point. They are often used in observer design and optimal control [74]. Nonlinear state-space models retain the nonlinear process dynamics and are suitable for adaptive control, sliding-mode control, nonlinear model predictive control, and learning-based methods [75].

3.6. Data-Driven Model

Data-driven models use measured input-output data instead of detailed physical equations. Common examples include autoregressive models, artificial neural networks, recurrent neural networks, long short-term memory networks, Gaussian process regression, and hybrid physics-based learning models. These models are useful when physical parameters are unavailable or difficult to estimate. Their accuracy depends on the quality and range of the training data. Prediction errors usually increase when the operating conditions differ from those used during model training [76], [77].

4. Classical Temperature Controllers

The studies summarized in Table 2 indicate that conventional PI and PID controllers remain the most widely adopted solutions for heat exchanger temperature control because of their simple structure and straightforward implementation. Recent research has focused on improving these controllers through advanced tuning methods, cascade architectures, feedforward compensation, fuzzy adaptation, optimization algorithms, and PLC–SCADA implementation rather than replacing

them with entirely new control structures. These modifications generally improve transient response, reduce overshoot, shorten settling time, and enhance disturbance rejection. However, fixed controller gains remain sensitive to changes in operating conditions, transport delay, fouling, and process nonlinearities. Additional control loops and optimization algorithms improve performance but increase design complexity, tuning effort, and hardware requirements. Overall, the literature shows that classical controllers continue to provide reliable solutions for many industrial applications, while adaptive tuning and auxiliary compensation techniques are increasingly adopted to maintain stable performance under varying operating conditions.

Table 2. Comparison of Classical and PID-Based Temperature-Control Strategies Applied to Heat Exchanger Systems

Ref.	Controller	Purpose	Advantages	Disadvantages
[78]	PSO-tuned PID	To tune a PID controller for a cross-flow heat exchanger using a CFD-based identified model and particle swarm optimization.	Uses a process model obtained from CFD data; optimizes PID gains systematically; improves tracking and transient response compared with manual tuning.	Depends on the accuracy of the identified model; PSO requires repeated simulations; no reported industrial implementation.
[79]	Cascaded PI with feedforward signal compensation	To improve temperature control in an industrial heat-exchange system affected by steam-pressure, ambient-temperature, and water-quality variations.	Retains a simple PI structure; compensates for unmodeled dynamics; uses measured process information; improves disturbance rejection without replacing the cascade architecture.	Requires calculation of the compensation signal; depends on reliable measurements; the design is more complex than standard cascade PI control.
[80]	PID with Ziegler–Nichols, Cohen–Coon, and Chien et al. tuning	To model a shell-and-tube heat exchanger and compare three PID tuning methods for outlet-temperature control.	Direct comparison under the same model; simple implementation; considers inverse response and large overshoot; reports numerical transient indices.	Simulation-based study; fixed controller gains; performance may change outside the identified operating condition; limited treatment of disturbances and actuator constraints.
[81]	Experimental PID with trial-and-error and direct-synthesis tuning	To regulate the cold-water outlet temperature of a heat-exchanger prototype by manipulating the hot-water flow rate.	Prototype implementation; Arduino-based control; direct process measurements; compares trial-and-error tuning with direct synthesis.	Hunting occurred near the setpoint; the valve approached full opening at the higher reference; tuning was partly empirical; the response was relatively slow.
[82]	Fuzzy self-tuning PID	To design an outlet-temperature controller for a shell-and-tube heat exchanger exposed to corrosion-risk operating conditions.	Combines a dynamic heat-exchanger model with online PID-gain adjustment; addresses changing process behavior; gives faster control than fixed tuning in simulation.	Validated only in MATLAB; fuzzy rules require expert selection; quantitative comparison with several classical tuning methods was limited; industrial tests were not reported.

[83]	Fuzzy PID compared with conventionally tuned PI	To reduce settling time and overshoot in shell-and-tube heat-exchanger temperature control.	Adjusts PID action through fuzzy reasoning; improves transient performance; compares the proposed method with PI controllers using several tuning rules.	Based on simulation; requires fuzzy membership-function and rule design; computational demand is higher than that of a conventional PI controller.
[84]	Classical PID, GA-tuned PID, and fuzzy PID	To compare classical PID tuning rules with genetic-algorithm tuning under specified overshoot constraints and fuzzy PID structures.	Examines Ziegler–Nichols and AMIGO methods; includes 2%, 5%, and 10% overshoot constraints; uses an explicit ISE objective; compares classical and intelligent tuning.	GA tuning has a higher computational cost; fuzzy topologies need design choices; the study is model- and simulation-based; results depend on the imposed optimization constraints.
[85]	PI/PID cascade control using frequency-domain specifications	To regulate shell-side outlet temperature using an outer temperature loop and an inner flow-control loop.	Uses a cascade structure; the inner loop reacts faster to flow disturbances; controller design is based on frequency-domain requirements; PI and PID designs are compared on the same benchmark system.	Relies on an FOPDT approximation; requires two-loop tuning.
[86]	Feedforward cascade compound control with predictive functional control and incremental PID	To improve outlet-temperature control in a heat exchanger with long delay and weak disturbance rejection.	Combines measured-disturbance compensation, cascade control, prediction, and PID action; addresses large delay; improves tracking and anti-disturbance performance.	More complex than classical PI/PID control; requires a predictive model; controller calculations and tuning are heavier; model mismatch may reduce feedforward accuracy.
[87]	Classical P, PI, and PID comparison	To derive a shell-and-tube heat-exchanger model and compare several classical controllers in MATLAB.	Direct comparison of classical controllers; simple implementation; examines settling time and percentage overshoot; useful as a baseline study.	Simulation-only validation; limited treatment of noise, actuator limits, uncertainty, and operating-point changes; tuning details are not fully evident from the abstract.
[54]	PLC–SCADA PID and FOPID with metaheuristic tuning	To implement and compare PID and fractional-order PID controllers for real-time heat-exchanger temperature regulation.	Real-time PLC–SCADA implementation; simulation and experimental testing; anti-windup control; several optimization algorithms; evaluates ISE, IAE, and ITAE.	Higher hardware and software complexity; optimization results depend on algorithm settings; FOPID needs more parameters; communication and component faults may affect operation.
[88]	PID and first-order sliding-mode control	To compare PID control with first-order sliding-mode control	Uses PID as a clear classical benchmark; allows direct comparison of	PID performance depends on fixed gains; first-order sliding mode can produce

		for heat-exchanger liquid-temperature regulation.	conventional and robust nonlinear control; examines tracking under nonlinear heat-exchanger behavior.	chattering; practical performance depends on sampling, noise, and actuator limits; conference-level validation.

The studies listed in Table 2 show that conventional PI and PID controllers remain common in heat exchanger temperature-control systems because they are simple and easy to implement. Recent work has focused less on introducing new classical structures and more on improving PID performance through cascade loops, feedforward compensation, fuzzy gain adjustment, optimization algorithms, anti-windup methods, and PLC–SCADA implementation. Classical tuning methods remain useful as baseline approaches, but their fixed gains limit performance when the heat exchanger operates under changing flow rates, delays, fouling conditions, and external disturbances. Cascade and feedforward structures improve disturbance rejection, although they require additional measurements, process models, and tuning effort. Experimental studies also show that poor tuning or actuator saturation may lead to hunting, overshoot, and slow settling. Thus, classical controllers remain practical, but modified and automatically tuned PID structures are generally more reliable when heat exchanger dynamics change during operation.

5. Robust Controllers

Heat-exchanger models contain uncertainties arising from varying heat-transfer coefficients, changing flow conditions, fouling, heat losses, and actuator behavior. Robust control methods are designed to maintain stability and acceptable tracking performance despite these uncertainties. Sliding-mode control is particularly attractive because it can provide disturbance rejection and reduced sensitivity to matched uncertainties [89], [90].

Recent studies on robust heat-exchanger control have mainly focused on reducing sensitivity to model uncertainty, transport delay, communication latency, bounded disturbances, actuator constraints, and changes in inlet conditions [91], [92]. Table 3 summarizes original studies published between 2020 and 2026 and compares their control objectives, reported advantages, limitations, and principal findings. Particular attention is given to robust predictive control, first- and higher-order sliding-mode methods, time-varying sliding surfaces, terminal sliding modes, and adaptive gain mechanisms.

Table 3. Comparison of Recent Robust Control Strategies for Heat Exchanger Temperature Regulation

Ref.	Controller	Purpose	Advantages	Disadvantages	Main Result
[93]	Robust model predictive control and convex-lifting-based robust control	To achieve offset-free temperature tracking and reduce energy consumption in a laboratory plate heat exchanger while accounting for uncertainty and input constraints.	Handles process and actuator constraints; considers model uncertainty; substantially reduces online computational effort compared with conventional RMPC; experimentally validated.	Requires an uncertain process model and offline optimization; controller construction is more involved than PI or PID design; robustness depends on the selected invariant sets.	The proposed convex-lifting controllers reduced settling time by up to 70% and increased energy savings by 82% relative to the tested RMPC implementation.

[94]	Higher-order networked sliding-mode control based on the super-twisting algorithm	To regulate heat-exchanger temperature in the presence of process delay, random communication delay, and model uncertainty.	Attenuates chattering; compensates for network and process delays; provides faster convergence than the conventional reaching-law controller; includes a Lyapunov-based stability condition.	Evaluated through simulation rather than experimental implementation; requires delay-related assumptions and suitable super-twisting gains; network measurements and communication quality affect performance.	The controller maintained temperature regulation under random delays and uncertainty while producing less chattering and faster convergence than the benchmark sliding-mode reaching law.
[95]	Time-varying sliding-mode control optimized by the dragonfly algorithm	To improve convergence and reduce chattering in a plate heat exchanger under bounded disturbances and input constraints.	Uses a time-varying sliding surface; includes actuator constraints through an auxiliary system; optimizes controller parameters automatically; establishes stability using Lyapunov analysis.	Optimization adds computational cost; performance depends on the dragonfly-algorithm settings; evidence is simulation-based; implementation under sensor noise was not reported.	The optimized controller regulated the outlet temperature under bounded disturbances and achieved faster convergence and lower chattering than the quasi-sliding-mode benchmark.
[96]	Adaptive barrier-function-based sliding-mode control	To regulate the outlet cold-water temperature of a double-pipe heat exchanger partly filled with metal foam while reducing settling time and hot-water demand.	Requires only the measured cold-water temperature; adapts the switching gain without requiring a fixed disturbance bound; considers changes in inlet temperature; Lyapunov stability is established; combines thermal enhancement with robust control.	Contains additional design parameters; validation is numerical; barrier-function tuning affects transient control effort; practical sensor noise and actuator dynamics require further testing.	The controller maintained accurate temperature regulation under inlet-temperature variation. With a metal-foam diameter ratio of 1.2, settling time was reduced by one half and the required hot-water temperature by 17.3%; larger ratios produced further reductions.
[97]	Data-based adaptive second-order terminal sliding-mode	To control nonlinear discrete-time systems without an explicit plant	Does not require detailed model information; combines terminal convergence with	Requires online data-driven linearization and predictive calculations;	The study showed bounded tracking and sliding variables

	predictive control	model and validate the method on a steam–water heat exchanger.	predictive control; uses disturbance-delay estimation; reduces chattering through a second-order sliding function; proves boundedness of the tracking error.	parameter selection is more involved than standard SMC; the heat-exchanger evaluation is based on a practical simulation rather than a reported physical experiment.	and demonstrated effective temperature regulation in the steam–water heat-exchanger example under disturbance and model-free operating conditions.

The studies in Table 3 show a clear movement toward recent studies that use higher-order, terminal, and adaptive sliding-mode controllers to reduce chattering and improve temperature tracking under uncertainty. However, most results are still based on simulation, and practical performance depends on gain selection, actuator limits, noise, and process delay.

6 Intelligent Controllers

6.1 Fuzzy Logic Control

Fuzzy logic control is a powerful approach that leverages human reasoning through linguistic rules rather than precise mathematical models. This method is particularly effective in scenarios where system behavior is variable or when accurate models are unavailable. The controller typically processes inputs such as temperature error and its rate of change, converting them into fuzzy values to generate control signals. The following sections elaborate on the key aspects of fuzzy logic control. Fuzzy PID controllers improve the performance of conventional PID control by adapting the control action according to the current operating conditions. The temperature error and its derivative are processed by a fuzzy inference system, while optimization algorithms such as particle swarm optimization can further refine the controller parameters. Figure 7 presents the overall framework of a fuzzy PID temperature-control system applied to a heat exchanger.

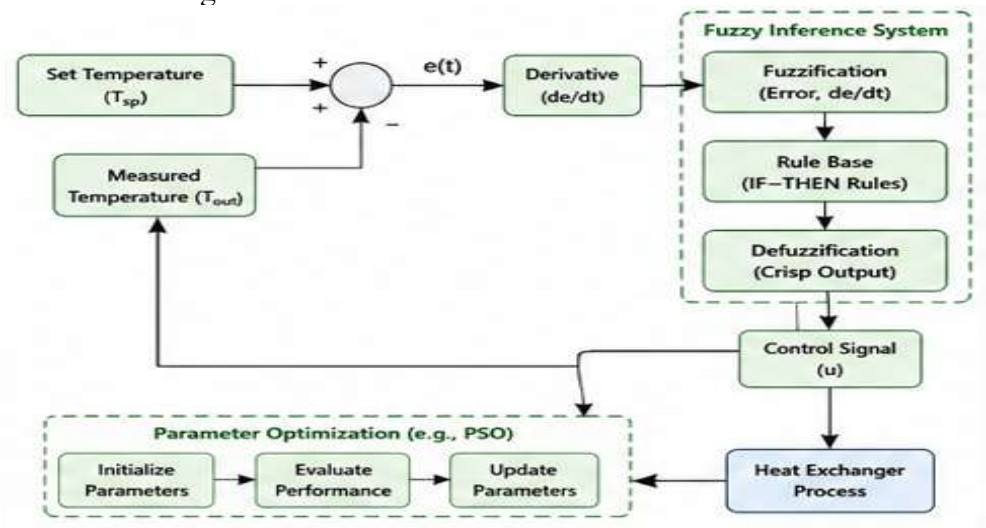


Fig. 7. Block diagram of a fuzzy PID temperature-control system incorporating fuzzy inference and parameter optimization.

Advantages of Fuzzy Logic Control

- **Model Independence**: Fuzzy controllers do not require a mathematical model, making them suitable for complex systems where traditional modeling is challenging [98].

- **Linguistic Representation**: Control actions are based on qualitative descriptions, allowing for intuitive design and implementation [99].
- **Adaptability**: Fuzzy logic can effectively manage systems with changing dynamics, providing robust performance across various operating conditions [100]

Optimization Techniques

- **Particle Swarm Optimization (PSO)**: Recent studies have employed PSO to optimize fuzzy control parameters, enhancing performance metrics such as rise time and overshoot [101].
- **Heuristic Knowledge Integration**: The design process allows for the incorporation of expert knowledge, improving the controller's responsiveness and accuracy [102].

6.2 Fuzzy PID Control

Fuzzy PID control integrates fuzzy logic with traditional PID control to enhance performance, particularly in dynamic environments. This approach allows for real-time adjustments of PID parameters based on current operating conditions, leading to improved stability and reduced error in control systems. However, the complexity of tuning and the reliance on the quality of fuzzy rules and membership functions present significant challenges. Self-tuning fuzzy PID controllers improve the adaptability of conventional PID control by updating the controller gains according to the process error and its rate of change. Instead of generating the control signal directly, the fuzzy inference system continuously adjusts the proportional, integral, and derivative gains to maintain satisfactory performance under varying operating conditions. Figure 8 presents the general architecture of a fuzzy gain scheduling PID controller for heat exchanger temperature regulation.

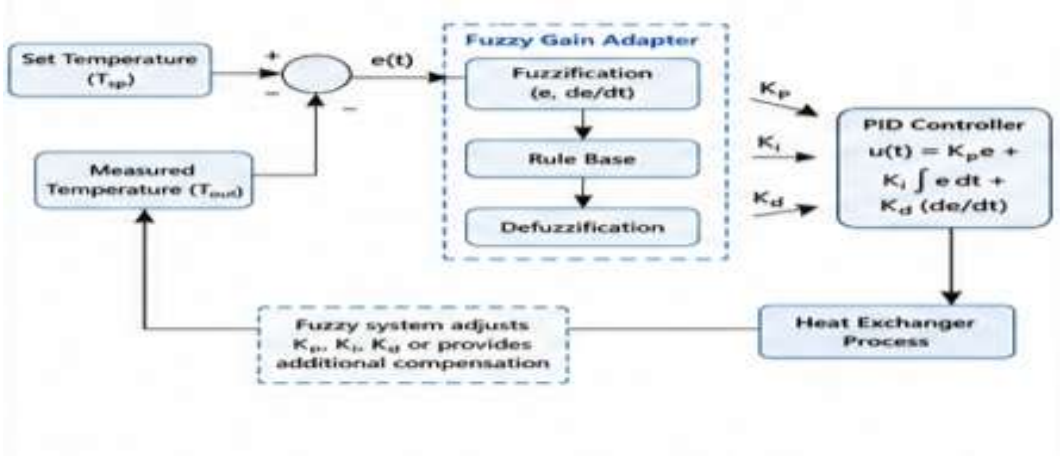


Fig. 8. General architecture of a fuzzy gain scheduling PID controller for adaptive heat exchanger temperature regulation.

Advantages of Fuzzy PID Control

- **Dynamic Adjustment**: Fuzzy PID controllers can modify proportional (Kp), integral (Ki), and derivative (Kd) gains in response to changing system dynamics, improving performance over fixed-gain controllers [103].
- **Enhanced Performance**: Studies show that fuzzy PID controllers outperform conventional PID controllers in terms of rise time and overshoot, particularly in nonlinear systems [104].
- **Expert Knowledge Integration**: Fuzzy logic allows for the incorporation of expert knowledge, making it easier to handle uncertainties in process control [103].

Limitations of Fuzzy PID Control

- **Parameter Complexity**: The design of fuzzy PID controllers involves numerous parameters, complicating the tuning process [105].
- **Dependence on Fuzzy Rules**: The effectiveness of the controller is heavily reliant on the quality of the fuzzy rules and membership functions, which can vary significantly [106]

6.3 Artificial Neural Networks

Artificial neural networks (ANNs) are increasingly utilized for modeling and predicting outlet temperatures in various thermal processes [107]. Their effectiveness hinges on the choice of network architecture, with feedforward networks suitable for static mappings, while recurrent networks (RNNs) and long short-term memory (LSTM) networks excel in dynamic scenarios.

Network Architectures

- **Feedforward Networks**: Commonly used for static nonlinear mappings, these networks are effective in simpler temperature control tasks [108].
- **Recurrent Networks and LSTMs**: These are designed for dynamic systems, capturing time-dependent behaviors, as demonstrated in heat exchanger applications where they achieved high prediction accuracy [109], [110].

Training Data Importance

- The performance of ANNs is contingent on the training data's breadth. For instance, models trained on limited operational ranges may yield unreliable predictions when faced with new conditions [111].
- Continuous data monitoring and model adjustments are crucial for maintaining accuracy, as shown in studies where models adapted to changing conditions improved prediction reliability [12]. Neural network models have been widely adopted for heat exchanger temperature control because they can represent nonlinear process behavior without requiring explicit physical equations. Depending on the control objective, they may serve as predictors, inverse models, disturbance estimators, soft sensors, adaptive compensators, or PID gain schedulers. Figure 9 summarizes the general structure of neural-network-based approaches and their common applications in heat exchanger control.

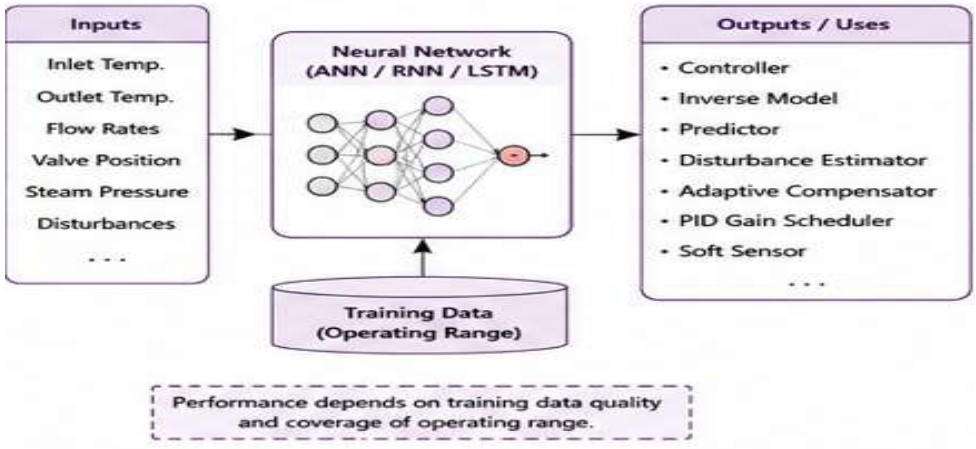


Fig. 9. General architecture of neural-network-based temperature control, showing typical process inputs, training data, and common industrial applications.

6.4 Neural Network-Assisted Control

The integration of neural networks with conventional controllers presents a robust approach to managing nonlinear systems and external disturbances. This hybrid methodology leverages the strengths of both paradigms, ensuring closed-loop stability through conventional control while utilizing neural networks to adaptively

estimate complex behaviors. The following sections outline the key aspects of this approach.

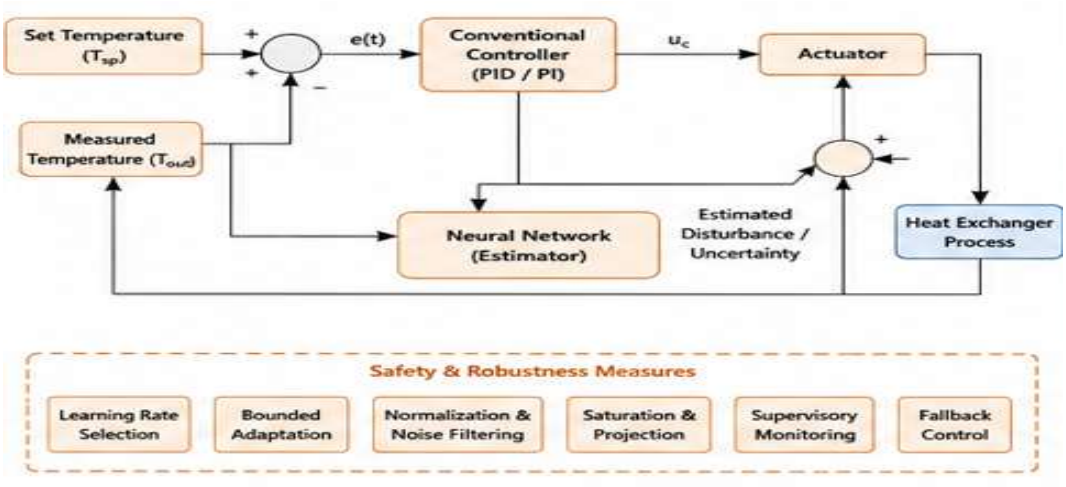


Fig. 10. Hybrid neural-network-assisted control framework for heat exchanger temperature regulation, incorporating disturbance estimation and practical safety mechanisms.

Hybrid Control Mechanism

- **Stability Maintenance**: Conventional controllers provide stability even when neural network estimates are inaccurate, preventing system failure [112]. Hybrid neural-network-assisted control combines conventional feedback control with data-driven estimation to improve temperature regulation under nonlinear and uncertain operating conditions. The neural network estimates unmodeled dynamics and external disturbances, while the conventional controller maintains closed-loop stability. Additional safety mechanisms, including bounded adaptation, noise filtering, saturation handling, supervisory monitoring, and fallback control, improve the reliability of practical implementations. Figure 10 presents the general architecture of a neural-network-assisted control system for heat exchanger temperature regulation.
- **Nonlinearity Handling**: Neural networks excel in managing nonlinearities and can generalize across various operating conditions, enhancing control accuracy [113], [114].

Practical Implementation Considerations

- **Learning Rate and Parameter Limits**: Careful selection of learning rates and parameter constraints is crucial for effective training and performance of the neural network[115]
- **Safety Features**: Incorporating saturation limits and supervisory functions enhances system safety, ensuring that control actions remain within safe operational bounds [116]

6.5 Adaptive Neuro-Fuzzy Inference System

The ANFIS is a hybrid intelligent system that integrates the qualitative reasoning of fuzzy logic with the learning capabilities of neural networks. This combination allows ANFIS to effectively model and control complex nonlinear systems, making it suitable for applications such as temperature prediction, process modelling, and controller design. The ANFIS's adaptability and robustness make it a preferred choice over traditional control methods like PID controllers. However, its computational cost increases with the number of inputs or membership functions,

and the quality of the model heavily depends on the training data, which can lead to overfitting issues.

Advantages of ANFIS

- **Hybrid Approach**: Combines fuzzy logic's qualitative reasoning with neural networks' learning capabilities, allowing for effective modelling of complex systems under uncertainty [117].
- **Control Applications**: Demonstrates improved dynamic performance and robustness in control applications compared to classical PID and other controllers[118]
- **Versatility**: Successfully applied in various domains, including thermal comfort and production management, showcasing its adaptability [119].

Limitations of ANFIS

- **Computational Complexity**: Faces challenges with large input spaces due to the curse of dimensionality and increased computational expense [120]
- **Overfitting Risks**: The model's accuracy is highly dependent on the quality of training data, which can lead to overfitting if not managed properly [121].

Solutions and Future Directions

- **Architectural Modifications**: Proposals exist to reduce computational complexity through architectural changes and efficient training procedures [120].
- **Efficient Rule Generation**: ANFIS can efficiently convert PID control experiences into fuzzy control rules, addressing difficulties in generating and adjusting membership functions and fuzzy rules[122]. ANFIS integrates fuzzy inference with neural-network learning to model nonlinear process behavior and improve controller adaptation. During training, the membership functions, fuzzy rules, and consequent parameters are updated from process data, allowing the model to capture complex input–output relationships while maintaining an interpretable rule base. Figure 11 presents the general structure of an ANFIS-based system and its common applications in heat exchanger modelling, prediction, controller design, and PID tuning.

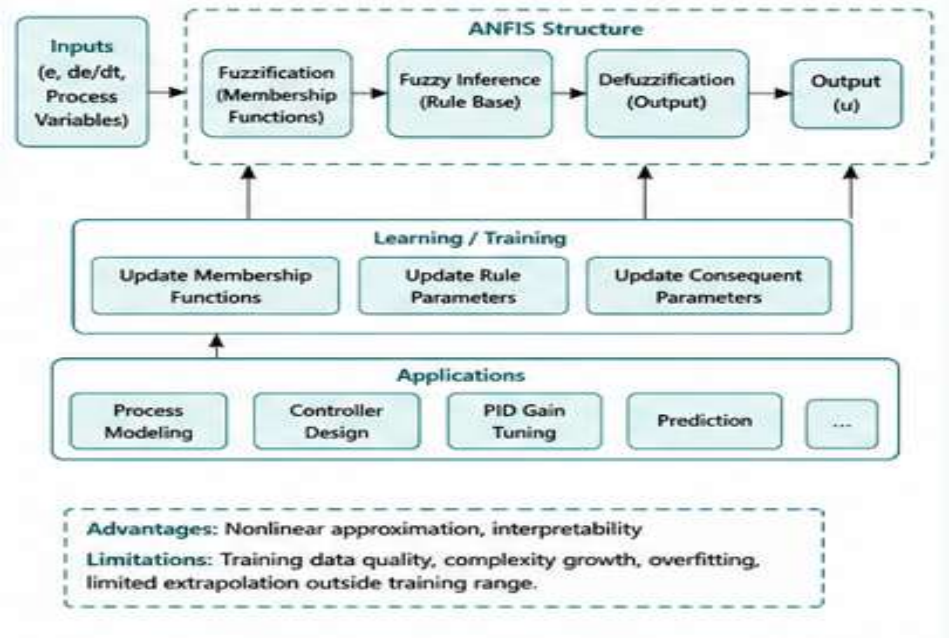


Fig. 11. General architecture of an adaptive neuro-fuzzy inference system (ANFIS) and its applications in heat exchanger modeling and temperature control.

6.6 Hybrid Intelligent Controllers

Hybrid intelligent controllers integrate multiple control strategies to enhance performance in complex systems [123]. These controllers leverage the strengths of various methodologies, such as fuzzy logic, neural networks, and optimization algorithms, to achieve superior tracking accuracy and disturbance rejection compared to traditional single-method controllers. However, their design complexity and resource demands pose challenges for real-time applications [124].

Key Features of Hybrid Intelligent Controllers

- **Integration of Control Methods**: Hybrid controllers combine fuzzy logic, neural networks, and PID control, allowing for adaptive and robust performance in nonlinear environments [123].
- **Optimization Techniques**: Algorithms like genetic algorithms and simulated annealing are employed to fine-tune controller parameters, enhancing system responsiveness and stability [125]
- **Real-World Applications**: These controllers have been successfully implemented in various fields, demonstrating improved performance in complex, real-time scenarios [126]

Challenges in Implementation

- **Increased Complexity**: The integration of multiple control strategies necessitates careful design and tuning, which can complicate the implementation process [127].
- **Resource Intensive**: Hybrid controllers often require more computational power and memory, making them less suitable for resource-constrained environments [128].

Recent research has increasingly focused on hybrid control architectures that combine conventional, intelligent, and optimization-based methods within a unified framework. By integrating complementary control strategies, these approaches seek to improve robustness, disturbance rejection, nonlinear adaptation, and tracking accuracy beyond what can be achieved by individual controllers. Figure 12 summarizes common hybrid controller architectures reported in the literature together with their potential benefits and practical implementation challenges.

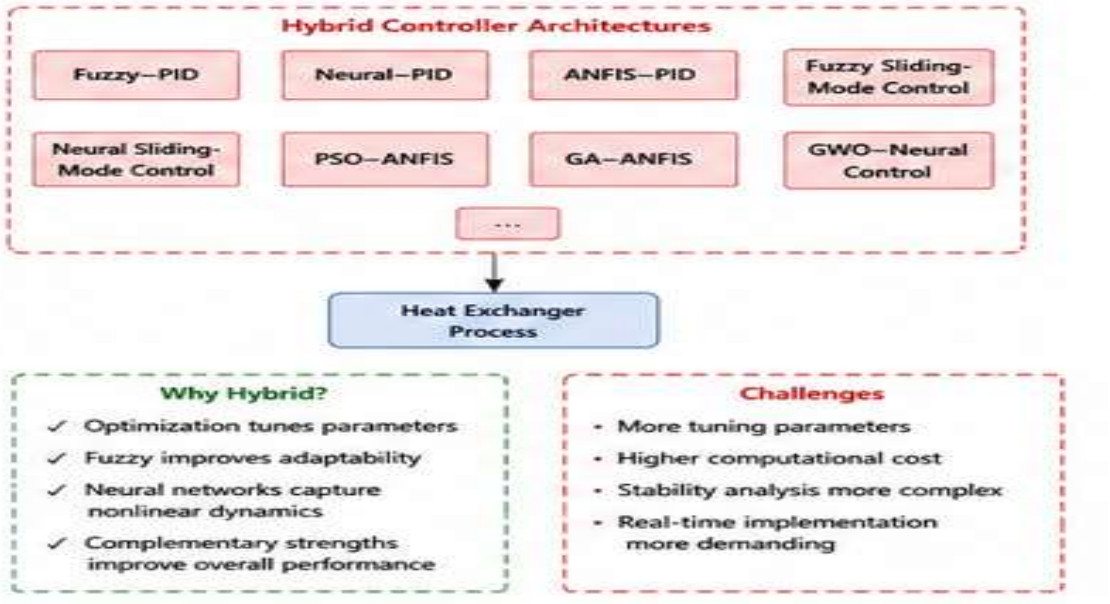


Fig. 12. Representative hybrid intelligent control architectures, highlighting their potential advantages and implementation challenges for heat exchanger temperature control.

7. Comparative Evaluation of Control Strategies

Controller performance should be verified under realistic operating conditions rather than only under nominal simulations. Typical test cases include changes in inlet temperature, flow rate, heat-transfer coefficient, transport delay, measurement noise, actuator limits, fouling, and model uncertainty. Good tracking under ideal conditions does not guarantee reliable operation in practice. A controller should maintain stable and accurate temperature regulation when disturbances and parameter variations are present.

Table 4 summarizes how recent original studies have evaluated temperature-control strategies for heat exchanger systems. Rather than comparing controllers alone, the table highlights the performance indices, robustness tests, fairness of the evaluation procedure, and the principal conclusions reported in each study.

Table 4. Comparison of Recent Experimental Evaluation Criteria Used for Heat Exchanger Temperature Controllers

Ref.	Controller Evaluated	Performance Criteria	Robustness Evaluation	Main Finding
[93]	Robust MPC	IAE, ISE, energy consumption, settling time	Model uncertainty, actuator constraints	Robust MPC improved energy efficiency while maintaining temperature regulation.
[79]	Cascade PI	Overshoot, settling time, IAE	Steam-pressure disturbance, inlet-temperature variation	Feedforward compensation improved disturbance rejection.
[80]	PID	Rise time, settling time, overshoot, steady-state error	Different tuning methods	Chien tuning produced the best transient response.
[81]	PID	Rise time, settling time, overshoot	Experimental operating conditions	Direct synthesis reduced oscillation compared with trial-and-error tuning.
[82]	Fuzzy PID	Overshoot, settling time, tracking error	Nonlinear operating conditions	Online fuzzy tuning improved tracking accuracy.
[86]	Feedforward Cascade + PFC	IAE, ITAE, overshoot	Long delay, disturbances	Compound control reduced delay effects and improved tracking.
[54]	PID / FOPID	ISE, IAE, ITAE, overshoot	Load disturbance, real-time PLC implementation	FOPID achieved better overall performance than PID.

The studies summarized in Table X indicate that the evaluation methodology has become more comprehensive in recent years. Early studies mainly focused on transient characteristics such as overshoot and settling time, whereas recent work also considers tracking accuracy, energy consumption, computational cost, and robustness under practical operating conditions. Nevertheless, the reported results are often obtained under different heat exchanger models, operating conditions, and disturbance scenarios, making direct numerical comparison difficult. A consistent benchmarking framework based on common performance indices and identical testing conditions is therefore essential for objective assessment of temperature-control strategies.

8. Practical Challenges

Heat exchanger performance is strongly influenced by changing operating conditions, model uncertainty, and practical implementation constraints. These factors make accurate temperature

regulation challenging and have encouraged the development of more advanced control strategies. One of the main sources of performance degradation is fouling, which reduces the heat-transfer rate and increases pressure loss. Incorporating fouling models into predictive control frameworks, such as model predictive control (MPC), has been shown to improve control accuracy and increase overall performance by more than 24% [13]. Learning-based controllers provide another way to address process uncertainty. Neural-network-based methods can learn complex system dynamics directly from operating data and maintain satisfactory temperature regulation under changing conditions [129]. More recent approaches, such as the CB-BPP framework, combine offline optimization with online adaptation to improve tracking accuracy and disturbance rejection [11]. In industrial applications, controller performance is determined not only by control accuracy but also by computational efficiency and implementation feasibility [130]. Practical control systems must therefore remain reliable in the presence of sensor noise, actuator limitations, and continuously changing operating conditions [131].

9. Future Research Directions

Future research should prioritize controllers that maintain reliable performance under changing operating conditions rather than at a single design point. Adaptive control, online parameter estimation, and robust tuning methods are expected to improve temperature regulation in the presence of process uncertainty, transport delay, measurement noise, and actuator constraints.

Fouling also deserves greater attention because it gradually changes heat-transfer characteristics and pressure loss. Integrating fouling estimation with temperature control and condition monitoring could improve energy efficiency while reducing unnecessary maintenance.

Although sliding-mode control offers strong robustness, further work is needed to reduce chattering and verify its performance under realistic industrial conditions. Likewise, learning-based methods require larger and more diverse industrial datasets, together with hybrid physical–data models, to improve reliability and generalization.

Digital twins provide a promising platform for controller development and testing, but their accuracy should be validated using experimental data and real-time hardware. Finally, standardized benchmark models, common disturbance scenarios, and unified performance metrics are needed to enable fair and reproducible comparisons among classical, robust, intelligent, and learning-based control strategies.

10. Conclusions

Maintaining the outlet temperature of a heat exchanger is difficult because its dynamics change with operating conditions, fluid properties, transport delay, fouling, thermal inertia, and actuator limitations. These variations reduce the accuracy of fixed control designs and increase the need for controllers that remain effective over a wide operating range.

Model selection has a direct influence on control performance. Lumped-parameter and first-order-plus-dead-time models are widely used because they are simple and computationally efficient. They are well suited to many industrial applications but usually represent only a limited operating region. Nonlinear, distributed, and data-driven models capture process behavior more accurately, although they require additional process information and higher computational effort.

PI and PID controllers remain the most common solutions in industry because they are straightforward to tune and implement. Sliding-mode control, model predictive control, and adaptive techniques improve disturbance rejection and maintain better performance when system parameters change. Fuzzy logic, neural networks, and hybrid approaches extend these capabilities to highly nonlinear processes, but their practical use is still restricted by computational cost, training requirements, and limited experimental validation.

No single control method performs best under all operating conditions. The choice of a controller should reflect the characteristics of the heat exchanger, the required control accuracy, and the available computational resources. More experimental studies, common benchmark models, and consistent evaluation procedures would make published results easier to compare and help advanced control methods move beyond simulation into routine industrial applications.

References

[1] R. K. Shah and D. P. Sekulic, "Heat exchangers," *Handb. heat Transf.*, vol. 3, 1998.

[2] P. Barmavatu, P. Rani, M. K. Das, and S. A. Deshmukh, "Critical review of heat exchangers for thermal energy storage (TES) and conservation systems," *J. Therm. Anal. Calorim.*, vol. 150, no. 14, pp. 10609–10626, 2025.

[3] B. John, "Automation of Heat Exchanger System Using DCS: Enhancing Efficiency and Control," 2025.

[4] J.-K. Ahn, G.-B. So, J.-Y. Lee, Y.-H. Lee, M.-O. So, and G.-G. Jin, "PID control of a shell and tube heat exchanger system incorporating feedforward control and anti-windup techniques," *J. Inst. Control. Robot. Syst.*, vol. 20, no. 5, pp. 543–550, 2014.

[5] A. Badavath and Y. V Hote, "Internal model control-based design of PID, PIDA, and PID-II controllers for networked control systems," *IETE Tech. Rev.*, vol. 43, no. 1, pp. 34–57, 2026.

[6] A. J. Prado, M. Herrera, X. Dominguez, J. Torres, and O. Camacho, "Integral windup resetting enhancement for sliding mode control of chemical processes with longtime delay," *Electronics*, vol. 11, no. 24, p. 4220, 2022.

[7] P. A. M. Devan, R. Ibrahim, M. Omar, K. Bingi, M. Nagarajapandian, and H. Abdulrab, "A novel fractional-order dead-time compensating controller for the wireless networks," *Sci. Rep.*, vol. 13, no. 1, p. 17658, 2023.

[8] H. Xingqi, H. Guolian, and T. Wen, "Tuning of PIDD 2 controllers for oscillatory systems with time delays," *Front. Control Eng.*, vol. 3, p. 1083419, 2023.

[9] S. Charkoutsis, "A Novel Nonlinear PID Controller for Improved Performance and Robust Control of Nonlinear Systems," 2025, *Liverpool John Moores University (United Kingdom)*.

[10] R. S. Patil, S. P. Jadhav, and M. D. Patil, "Review of intelligent and nature-inspired algorithms-based methods for tuning PID controllers in industrial applications," *J. Robot. Control*, vol. 5, no. 2, pp. 336–358, 2024.

[11] L. Zhao and C. Zhang, "CFPSO-driven predictive and adaptive PID control for heat exchanger temperature regulation," *Eng. Res. Express*, vol. 7, no. 4, p. 0452d5, 2025.

[12] S. Khan, *Modeling and temperature control of heat exchanger process*. LAP LAMBERT Academic Publishing, 2017.

[13] R. M. PK and J. Subbaiah, "Iterative quality weighted interpolation for LPV-MPC control of industrial heat exchanger under varying fouling conditions," *Asia-Pacific J. Chem. Eng.*, vol. 17, no. 5, p. e2811, 2022.

[14] C. Borges de Carvalho, E. P. Carvalho, and M. A. S. S. Ravagnani, "Dynamic analysis of fouling buildup in heat exchangers designed according to TEMA standards," *Ind. Eng. Chem. Res.*, vol. 57, no. 10, pp. 3753–3764, 2018.

[15] S. J. Gambhire, D. R. Kishore, P. S. Londhe, and S. N. Pawar, "Review of sliding mode based control techniques for control system applications: SJ Gambhire et al.," *Int. J. Dyn. Control*, vol. 9, no. 1, pp. 363–378, 2021.

[16] A. K. Junejo, W. Xu, M. A. Abido, M. Hamouda, J. R. Perez, and Y. Tang, "Recent Developments in Sliding Mode Control for Electric Drives: Performance Assessment, and Comparative Evaluation with Conventional Techniques," *IEEE Trans. Power Electron.*, 2026.

[17] Z. Li, K. Luo, L. Tao, and Y. Zhou, "Adaptive sliding mode control via multiscale super-twisting algorithm," *IEEE Access*, 2026.
[18] A. J. Koshkouei, K. Burnham, and A. Zinober, "Flatness, backstepping and sliding mode controllers for nonlinear systems," in *Modern Sliding Mode Control Theory: New Perspectives and Applications*, Springer, 2008, pp. 269–290.
[19] D. Tong, C. Xu, Q. Chen, and W. Zhou, "Sliding mode control of a class of nonlinear systems," *J. Franklin Inst.*, vol. 357, no. 3, pp. 1560–1581, 2020.
[20] L. Wu, J. Liu, S. Vazquez, and S. K. Mazumder, "Sliding mode control in power converters and drives: A review," *IEEE/CAA J. Autom. Sin.*, vol. 9, no. 3, pp. 392–406, 2021.
[21] Y. Liang, D. Zhang, G. Li, and T. Wu, "Adaptive chattering-free PID sliding mode control for tracking problem of uncertain dynamical systems," *Electronics*, vol. 11, no. 21, p. 3499, 2022.
[22] M. Momeni and A. Fartaj, "Numerical thermal performance analysis of a PCM-to-air and liquid heat exchanger implementing latent heat thermal energy storage," *J. Energy Storage*, vol. 58, p. 106363, 2023.
[23] A. M. Flynn, T. Akashige, and L. Theodore, *Kern's process heat transfer*. John Wiley & Sons, 2019.
[24] D. P. Sekulic and R. K. Shah, *Fundamentals of heat exchanger design*. John Wiley & Sons, 2023.
[25] V. F. Rahmadini, A. Ma'arif, and N. S. Abu, "Design of water heater temperature control system using PID control," *Control Syst. Optim. Lett.*, vol. 1, no. 2, pp. 111–117, 2023.
[26] W. L. Luyben, "Heat-exchanger bypass control," *Ind. Eng. Chem. Res.*, vol. 50, no. 2, pp. 965–973, 2011.
[27] B. P. Rasmussen, C. Price, J. Koeln, B. Keating, and A. Alleyne, "HVAC system modeling and control: Vapor compression system modeling and control," in *Intelligent Building Control Systems: A Survey of Modern Building Control and Sensing Strategies*, Springer, 2017, pp. 73–103.
[28] J. Wang, C. Li, L. Zeng, T. Fu, and K. Liu, "Thermal performance analysis of a heat exchanger with a novel turbulator insert by using machine learning method," *Case Stud. Therm. Eng.*, vol. 72, p. 106412, 2025.
[29] P. Duda, "Heat transfer coefficient distribution—a review of calculation methods," *Energies*, vol. 16, no. 9, p. 3683, 2023.
[30] C. Ruiz-Mercado, A. Pacheco-Vega, and G. Torres-Chavez, "A Takagi-Sugeno fuzzy dynamic model of a concentric-tubes heat exchanger," *Chem. Prod. Process Model.*, vol. 4, no. 2, 2009.
[31] F. Asiri, S. Rehman, T. Saidani, and T. Orlova, "Numerical simulation for heat and mass transfer of MHD non-Newtonian fluid flow in a channel subject to temperature-dependent thermophysical features," *Int. J. Mod. Phys. B*, vol. 39, no. 20, p. 2550177, 2025.
[32] D. Kurmanova, N. Jaichibekov, A. Karpenko, and K. Volkov, "Modelling and simulation of heat exchanger with strong dependence of oil viscosity on temperature," *Fluids*, vol. 8, no. 3, p. 95, 2023.
[33] C. Irrenfried and H. Steiner, "Modulation of turbulence flux budgets by varying fluid properties in heated high Prandtl number flow," *Flow, Turbul. Combust.*, vol. 112, no. 1, pp. 147–164, 2024.
[34] F. Evangelista, "Dynamics Of Double Pipe Heat Exchangers: Explicit Time Domain Solutions," 2007, *ResearchGate*.
[35] J. A. Hernández-Gil, D. Colorado-Garrido, F. A. Alaffita-Hernández, and B. A. Escobedo-Trujillo, "Heat exchanger design considering variable overall heat transfer

coefficient: An artificial neural network approach," *Heat Transf.*, vol. 51, no. 3, pp. 2488–2509, 2022.
[36] H. N. Chaudhry, B. R. Hughes, and S. A. Ghani, "A review of heat pipe systems for heat recovery and renewable energy applications," *Renew. Sustain. Energy Rev.*, vol. 16, no. 4, pp. 2249–2259, 2012.
[37] S. Govindan, D. Wang, A. Sivasubramaniam, and B. Urgaonkar, "Leveraging stored energy for handling power emergencies in aggressively provisioned datacenters," in *Proceedings of the seventeenth international conference on Architectural Support for Programming Languages and Operating Systems*, 2012, pp. 75–86.
[38] H. Shi, S. Pan, K. Liu, T. Wan, C. Li, and B. Niu, "Optimizing Control Chain Latency in Liquid Cooled Data Center for Load Responsive Operation," *Buildings*, vol. 16, no. 9, p. 1752, 2026.
[39] S. Bysko, K. Łakomiec, and K. Fujarewicz, "Conservation-Consistent Modeling of Time-Varying Transfer Delays with Applications in Energy Systems," *Energies*, vol. 19, no. 5, p. 1262, 2026.
[40] H. Sun, L. Chuanchao, T. Songxiang, and S. Tao, "Adaptive Control for UAV Speed Tracking with Multi-Delay Compensation Using Smith Predictor and Fuzzy PID Tuning," *Electronics*, vol. 14, no. 16, p. 3288, 2025.
[41] A. Arora, M. Bhadu, and A. Kumar, "Simultaneous damping and frequency control in AC microgrid using coordinated control considering time delay and noise," *Trans. Inst. Meas. Control*, vol. 46, no. 12, pp. 2436–2463, 2024.
[42] J. PAL, S. K. Nagar, and J. D. Sharma, "Digital controller design for systems with transport lag," *Int. J. Syst. Sci.*, vol. 23, no. 12, pp. 2385–2392, 1992.
[43] R. Sipahi, S.-I. Niculescu, C. T. Abdallah, W. Michiels, and K. Gu, "Stability and stabilization of systems with time delay," *IEEE Control Syst. Mag.*, vol. 31, no. 1, pp. 38–65, 2011.
[44] B. Ai, L. Sentis, N. Paine, S. Han, A. Mok, and C.-L. Fok, "Stability and performance analysis of time-delayed actuator control systems," *J. Dyn. Syst. Meas. Control*, vol. 138, no. 5, p. 51005, 2016.
[45] G. Zhao, M. A. Imran, Z. Pang, Z. Chen, and L. Li, "Toward real-time control in future wireless networks: Communication-control co-design," *IEEE Commun. Mag.*, vol. 57, no. 2, pp. 138–144, 2018.
[46] P. Nowak, P. Grelewicz, M. Fratczak, J. Musial, and J. Pospiech, "Efficient Heat Source Control with Transportation Delay Synchronization," in *2024 28th International Conference on Methods and Models in Automation and Robotics (MMAR)*, IEEE, 2024, pp. 82–87.
[47] S. Biswas, S. Mahata, P. K. Roy, and K. Chatterjee, "Application of empirical bode analysis for delay-margin evaluation of fractional-order pi controller in a renewable distributed hybrid system," *Fractal Fract.*, vol. 7, no. 2, p. 119, 2023.
[48] K. Thulukkanam, *Heat exchangers: Operation, performance, and maintenance*. CRC Press, 2024.
[49] P. J. Heggs and F. Vizcaino, "A rigorous model for evaluation of disturbance propagation through heat exchanger networks," *Chem. Eng. Res. Des.*, vol. 80, no. 3, pp. 301–308, 2002.
[50] M. M. Gouda, M. Kaoud, and S. M. Aly, "Evaluation of Disturbance Propagation through Heat Exchanger Networks," *Int. J. Comput. Appl.*, vol. 975, p. 8887, 2019.
[51] M. Fanoodi, F. Abdollahi, M. A. Shoorehdeli, and M. Maboodi, "Fault-Tolerant Temperature Control of HRSG Superheaters: Stability Analysis Under Valve Leakage Using Physics-Informed Neural Networks," *arXiv Prepr. arXiv2512.00990*, 2025.
[52] G. Dong and M. Deng, "Operator & Fractional Order Based Nonlinear Robust Control

for a Spiral Counter-flow Heat Exchanger with Uncertainties and Disturbances," *Machines*, vol. 10, no. 5, p. 335, 2022.
[53] X. Tang, B. Xu, and Z. Xu, "Reactor temperature control based on improved fractional order self-anti-disturbance," *Processes*, vol. 11, no. 4, p. 1125, 2023.
[54] B. Tomar, N. Kumar, and M. Sreejeth, "PLC and SCADA based temperature control of heat exchanger system through fractional order PID controller using metaheuristic optimization techniques," *Heat Mass Transf.*, vol. 60, no. 9, pp. 1585–1602, 2024.
[55] S. Mechhoud and Z. Belkhatir, "Adaptive Bounded Bilinear Control of a Parallel-Flow Heat Exchanger," *Int. J. Adapt. Control Signal Process.*, vol. 39, no. 2, pp. 320–331, 2025.
[56] Z. Bai, S. Li, and H. Liu, "Fuzzy composite learning control of uncertain fractional-order nonlinear systems using disturbance observer," *IEEE Trans. Emerg. Top. Comput. Intell.*, vol. 9, no. 1, pp. 1078–1090, 2024.
[57] L. Yuesong, L. Huixuan, M. Long, S. Nao, X. Jiali, and P. Zhiguang, "Fractional-order super-twisting sliding mode active disturbance rejection control for electro-hydraulic position servo systems," *Nonlinear Eng.*, vol. 14, no. 1, p. 20250173, 2025.
[58] M. M. Awad, *Fouling of heat transfer surfaces*. INTECH Open Access Publisher London, 2011.
[59] M. Varnaseri and S. M. Peyghambarzadeh, "Basic Concepts of Fouling in Heat Transfer System," in *Scale Formation in Heat Exchangers*, Springer, 2024, pp. 1–51.
[60] S. N. Kazi, "Fouling and fouling mitigation on heat exchanger surfaces," in *Heat Exchangers-Basics Design Applications*, Intechopen, 2012.
[61] B. Setyoko, "Evaluasi kinerja heat exchanger dengan metode fouling faktor," *Teknik*, vol. 29, no. 2, pp. 148–153, 2008.
[62] S. Kakaç, H. Liu, and A. Pramuanjaroenkij, *Heat exchangers: selection, rating, and thermal design*. CRC press, 2002.
[63] F. P. Incropera, D. P. DeWitt, T. L. Bergman, and A. S. Lavine, *Fundamentals of heat and mass transfer*, vol. 6. Wiley New York, 1996.
[64] D. Csemány and R. Kovács, "Comparative analysis of lumped parameter and one-dimensional continuum models for droplet evaporation at elevated pressures and temperatures," *Int. Commun. Heat Mass Transf.*, vol. 169, p. 109547, 2025.
[65] J. Till, V. Aloi, and C. Rucker, "Real-time dynamics of soft and continuum robots based on Cosserat rod models," *Int. J. Rob. Res.*, vol. 38, no. 6, pp. 723–746, 2019.
[66] E. Heim *et al.*, "Comparison of simulation tools for optimizing borehole heat exchanger field operation," *Geotherm. Energy*, vol. 12, no. 1, p. 24, 2024.
[67] C. Brown, N. Cassidy, S. Egan, and D. Griffiths, "Numerical modelling of deep coaxial borehole heat exchangers in the Cheshire Basin, UK," *Comput. Geosci.*, vol. 152, p. 104752, 2021.
[68] T. Maier and M. Stripf, "Distributed parameter model of a novel heat pump adsorber design using 3D-FEM," *Appl. Therm. Eng.*, vol. 278, p. 126963, 2025.
[69] S. J. Granella, "Anomalous diffusion in drying: A fractional calculus perspective on modeling and applications in agro-food systems," *Food Phys.*, p. 100088, 2026.
[70] X. Chen *et al.*, "Progress and challenges of integrated machine learning and traditional numerical algorithms: Taking reservoir numerical simulation as an example," *Mathematics*, vol. 11, no. 21, p. 4418, 2023.
[71] J. Lorenzetti, A. McClellan, C. Farhat, and M. Pavone, "Linear reduced-order model predictive control," *IEEE Trans. Automat. Contr.*, vol. 67, no. 11, pp. 5980–5995, 2022.
[72] M. Wild *et al.*, "Lithium sulfur batteries, a mechanistic review," *Energy Environ. Sci.*, vol. 8, no. 12, pp. 3477–3494, 2015.
[73] S. H. Jadhav and R. V Sarwadnya, "Modeling of pine sleek PID control system in AC

heat exchanger," *J. Ambient Intell. Humaniz. Comput.*, vol. 14, no. 12, pp. 16159–16171, 2023.

[74] Z. Li, Y. Liu, W. Tan, and S. Bi, "Model predictive control for nonlinear system with feedback linearization and extended state observer," *Int. J. Syst. Sci.*, vol. 57, no. 9, pp. 2745–2759, 2026.

[75] J. Iqbal, M. Ullah, S. G. Khan, B. Khelifa, and S. Ćuković, "Nonlinear control systems - A brief overview of historical and recent advances," *Nonlinear Eng.*, vol. 6, no. 4, pp. 301–312, 2017.

[76] E. Lavasa *et al.*, "Hybrid Intelligence: The Fusion of Science-Based and Machine Learning Models," in *Artificial Intelligence, Data and Robotics: Foundations, Transformations and Future Directions*, Springer, 2026, pp. 137–173.

[77] S. Kasilingam, R. Yang, S. K. Singh, M. A. Farahani, R. Rai, and T. Wuest, "Physics-based and data-driven hybrid modeling in manufacturing: a review," *Prod. Manuf. Res.*, vol. 12, no. 1, p. 2305358, 2024.

[78] O. K. Sallam, A. T. Azar, A. Guaily, and H. H. Ammar, "Tuning of PID controller using Particle Swarm Optimization for cross flow heat Exchanger based on CFD System Identification," in *International Conference on Advanced Intelligent Systems and Informatics*, Springer, 2019, pp. 300–312.

[79] Y. Jia, T. Chai, H. Wang, and C.-Y. Su, "A signal compensation based cascaded PI control for an industrial heat exchange system," *Control Eng. Pract.*, vol. 98, p. 104372, 2020.

[80] F. D. Olana and T. A. Abose, "PID temperature controller design for shell and tube heat exchanger," *Int. J. Eng. Manuf.*, vol. 11, no. 1, pp. 1–5, 2021.

[81] A. S. Wardhana, H. A. Azizah, and C. N. Hamdani, "Testing of Temperature Control System on Prototype of Heat Exchanger Based on PID," *J. Otomasi Kontrol dan Instrumentasi*, vol. 13, no. 2, pp. 81–91.

[82] H.-Z. Jin, Y. Gu, and G.-F. Ou, "Corrosion risk analysis of tube-and-shell heat exchangers and design of outlet temperature control system," *Pet. Sci.*, vol. 18, no. 4, pp. 1219–1229, 2021.

[83] C. S. Reddy and K. Balají, "A fuzzy-PID controller in shell and tube heat exchanger simulation modeled for temperature control," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 21, no. 3, pp. 1364–1371, 2021.

[84] M. E. Çimen, Z. Garip, M. Emekli, and A. F. Boz, "Fuzzy Logic PID Design using Genetic Algorithm under Overshoot Constrained Conditions for Heat Exchanger Control," *J. Inst. Sci. Technol.*, vol. 12, no. 1, pp. 164–181, 2022.

[85] K. R. A. Govind and S. Mahapatra, "Design of PI/PID control algorithm for a benchmark heat exchanger system using frequency domain specifications," in *2022 IEEE International Power and Renewable Energy Conference (IPRECON)*, IEEE, 2022, pp. 1–5.

[86] W. Miao and B. Xu, "Application of feedforward cascade compound control based on improved predictive functional control in heat exchanger outlet temperature system," *Appl. Sci.*, vol. 13, no. 12, p. 7132, 2023.

[87] Z. A. Khalaf, M. R. Jassim, F. Q. Mohammed, and T. F. Hasan, "Simulation of Heat Exchanger Dynamics and Its Control Study By Using MATLAB," *Samarra J. Eng. Sci. Res.*, vol. 2, no. 1, pp. 1–11, 2024.

[88] H. Altinkaya, A. Khamees, E. Yaghoubi, and E. Yaghoubi, "Control of Heat Exchanger Liquid Temperature Using PID Control and first Order Sliding Mode Control System," in *2024 International Conference on Electrical, Computer and Energy Technologies (ICECET*, IEEE, 2024, pp. 1–6.

[89] T. Jeon, S. Kim, and Y. Lee, "Integral sliding mode control for ship main cooling

systems," *J. Adv. Mar. Eng. Technol.*, vol. 49, no. 6, pp. 525–535.

[90] P. Ziółkowski, M. Drosińska-Komor, J. Głuch, and Ł. Breńkacz, "Review of methods for diagnosing the degradation process in power units cooperating with renewable energy sources using artificial intelligence," *Energies*, vol. 16, no. 17, p. 6107, 2023.

[91] Y. Xu and M. Deng, "Particle filter design for robust nonlinear control system of uncertain heat exchange process with sensor noise and communication time delay," *Appl. Sci.*, vol. 12, no. 5, p. 2495, 2022.

[92] C. Ren, J. Han, C. Chen, and C. Yang, "Multi-period optimization embedded dynamic path-constrained model predictive control for heat exchanger networks under fouling conditions," *Appl. Therm. Eng.*, p. 128220, 2025.

[93] J. Oravec, M. Horváthová, and M. Bakošová, "Energy efficient convex-lifting-based robust control of a heat exchanger," *Energy*, vol. 201, p. 117566, 2020.

[94] D. Shah, A. Shah, and A. Mehta, "Higher order networked sliding mode controller for heat exchanger connected via data communication network," *Eur. J. Control*, vol. 58, pp. 301–314, 2021.

[95] A. Boonyaprapasorn, S. Kuntanapreeda, P. S. Ngiamsunthorn, T. Kumsaen, and T. Sethaput, "Time-varying sliding mode controller for heat exchanger with dragonfly algorithm," *Int. J. Electr. Comput. Eng.*, vol. 13, no. 4, pp. 3958–3968, 2023.

[96] L. F. Ali, S. A. AL-Samarraie, and A. J. Humaidi, "Performance of double pipe heat exchanger—partially occupied by metal foam—is better enhanced using robust adaptive barrier function-based sliding mode control," *Energies*, vol. 18, no. 17, p. 4671, 2025.

[97] W. Xu, X. Liu, X. Liu, and T. Wang, "Data-based adaptive second-order terminal sliding mode predictive control for nonlinear SISO systems with discrete-time dynamics," *Int. J. Syst. Sci.*, vol. 57, no. 4, pp. 1186–1199, 2026.

[98] M. Coban and M. Fidan, "Fuzzy Logic Based Temperature Control," in *2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, IEEE, 2019, pp. 1–4.

[99] R. Aguilar, V. Muñoz, and Y. Callero, "Control application using fuzzy logic: Design of a fuzzy temperature controller," *Fuzzy Inference Syst. Appl.*, pp. 379–396, 2012.

[100] J. I. García-Sucerquia and C. Palacio-Gómez, "ojs2 has produced an error Message: CAUGHT EXCEPTION: Non-static method Locale:: getLocalePrecedence () should not be called statically, assuming $ this from incompatible context In file:/home/rcfonline/revcolfis. org/ojs/lib/pkp/classes/core/DataObject. inc. php At line: 31 Stacktrace: Server info: OS: Linux PHP Version: 5.6. 40 Apache Version: N/A DB Driver: mysql DB server version: 5.7. 28-log Control de Temperatura Utilizando Lógica Difusa," *ojs2 has Prod. an error Messag. CAUGHT Except. Non-static method Locale getLocale should not be Call. statically, assuming $ this from incompatible Context file/home/rcfonline/revcolfis. org/ojs/classes/journal/Journal. inc. php line 320 Stacktrace Serv. info OS Linux PHP Version 5.6. 40 Apache Version N/A DB Driv. mysql DB Serv. version 5.7. 28-log ojs2 has Prod. an error Messag. CAUGHT Except. Non-*static method DAORegistry getDAO should not be Call. statically, assuming $ this from *incompatible Context file/home/rcfonline/revcolfis. org/ojs/classes/journal/Journal. inc. php line 335 Stacktrace Serv. info OS Linux PHP Version 5.6. 40 Apache Version N/A DB Driv. mysql DB Serv. version 5.7. 28-log ojs2 has Prod. an error Messag. CAUGHT Except. Non-static method DAORegistry getDAOs should not be Call. statically, assuming $ this from incompatible Context file/home/rcfonline/revcolfis. org/ojs/lib/pkp/classes/db/DAORegistry. inc. php line 59 Stacktrace Serv. info OS Linux PHP Version 5.6. 40 Apache Version N/A DB Driv. mysql DB Serv. version 5.7. 28-log ojs2 has Prod. an error Messag. CAUGHT Except. Non-static method Regist. get should not be Call. statically, assuming $ this from incompatible Context*

file/home/rcfonline/revcolfis. org/ojs/lib/pkp/classes/db/DAORegistry. inc. php line 30 Stacktrace Serv. info OS Linux PHP Version 5.6. 40 Apache Version N/A DB Driv. mysql DB Serv. version 5.7. 28-log ojs2 has Prod. an error Messag. CAUGHT Except. Non-static method Regist. getRegistry should not be Call. statically, assuming $ this from incompatible Context file/home/rcfonline/revcolfis. org/ojs/lib/pkp/classes/core/Registry. inc. php line 38 Stacktrace Serv. info OS Linux PHP Version 5.6. 40 Apache Version N/A DB Driv. mysql DB Serv. version 5.7. 28-log *Rev. Colomb. Física*, vol. 42, no. 3, p. 378, 2011.

[101] W. Cai, L. Jia, Y. Zhang, N. Ni, and P. Gao, "Research on optimization of fuzzy control rules based on particle swarm optimization algorithm," in *The 2nd International Conference on Information Science and Engineering*, IEEE, 2010, pp. 5341–5343.

[102] K. Das Sharma, A. Chatterjee, and A. Rakshit, "Fuzzy controller design I: stochastic algorithm-based approach," in *Intelligent Control: A Stochastic Optimization Based Adaptive Fuzzy Approach*, Springer, 2018, pp. 37–75.

[103] D. Jha, A. Ahmed, S. Kumar, and D. Roy, "Fuzzy-PID and interpolation: a novel synergetic approach to process control.," *Int. J. Optim. Control Theor. Appl.*, vol. 14, no. 4, 2024.

[104] A. A. Khan and N. Rapal, "Fuzzy PID controller: design, tuning and comparison with conventional PID controller," in *2006 IEEE International Conference on Engineering of Intelligent Systems*, IEEE, 2006, pp. 1–6.

[105] G. M. de Almeida, V. V. R. e Silva, E. G. Nepomuceno, J. Denti Filho, and R. Yokoyama, "Tuning PID Control: A Hybrid Approach using Fuzzy Logic and Genetic Programming".

[106] A. Varshney and V. Goyal, "Re-evaluation on fuzzy logic controlled system by optimizing the membership functions," *Mater. Today Proc.*, 2023.

[107] D. R. E. Ewim, M. O. Okwu, E. J. Onyiriuka, A. S. Abiodun, S. M. Abolarin, and A. Kaood, "A quick review of the applications of artificial neural networks (ANN) in the modelling of thermal systems," 2021.

[108] N. Patil and D. R. Patil, "Implementation of Artificial Neural Network on Temperature Control Process," in *2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS)*, IEEE, 2018, pp. 93–97.

[109] N. Rimac and Ž. Ujević Andrijić, "Monitoring of heat exchangers in preheat trains using neural networks," *Pet. Sci. Technol.*, vol. 43, no. 19, pp. 2609–2627, 2025.

[110] P. Wang and F. Si, "Dynamic prediction of the thermal nonlinear process based on deep hybrid neural network," in *E3S Web of Conferences*, EDP Sciences, 2020, p. 1007.

[111] A. Tlatelpa-Becerro, L. Castro-Gómez, G. Urquiza, and R. Rico-Martínez, "Prediction of the outlet temperature of an experimental heat exchanger using artificial neural networks," *WIT Trans Model Simul*, vol. 59, pp. 213–220, 2015.

[112] P. I. Doerschuk, E. Sarrafian, M. Mekic, and D. O. Doerschuk, "Hybrid neural network/conventional control of a benchmark process control problem," in *Proceedings of the 2002 International Joint Conference on Neural Networks. IJCNN'02 (Cat. No. 02CH37290)*, IEEE, 2002, pp. 97–101.

[113] M. Kharrat and P. Mercorelli, "A comprehensive review of adaptive control for nonlinear systems with nonlinearities and faults using fuzzy logic and neural network techniques," *Mathematics*, vol. 14, no. 8, p. 1256, 2026.

[114] B. Zhu, H. R. Karimi, L. Zhang, and X. Zhao, "Neural network-based adaptive reinforcement learning for optimized backstepping tracking control of nonlinear systems with input delay: B. Zhu et al.," *Appl. Intell.*, vol. 55, no. 2, p. 129, 2025.

[115] Y. Wu *et al.*, "Demystifying learning rate policies for high accuracy training of deep neural networks," in *2019 IEEE International conference on big data (Big Data)*, IEEE,

2019, pp. 1971–1980.
[116] N. Rajender, G. R. Ginni, K. M. Rayudu, K. S. Bharathi, A. V. L. Devi, and S. S. Rani, "Adaptive self-supervised learning for real-time problem solving in autonomous systems," *Sci. Rep.*, 2026.
[117] Y. Tan, C. Shuai, L. Jiao, and L. Shen, "An adaptive neuro-fuzzy inference system (ANFIS) approach for measuring country sustainability performance," *Environ. Impact Assess. Rev.*, vol. 65, pp. 29–40, 2017.
[118] M. Mubeena, S. Mullai Venthan, M. S. Nisha, P. Senthil Kumar, P. Vijayakumar, and G. Rangasamy, "A survey of autopilot control systems: From classical pid to intelligent adaptive controllers," *Int. J. Aeronaut. Sp. Sci.*, vol. 27, no. 2, pp. 1086–1111, 2026.
[119] G. Naadimuthu, D. M. Liu, and E. S. Lee, "Application of an adaptive neural fuzzy inference system to thermal comfort and group technology problems," *Comput. Math. with Appl.*, vol. 54, no. 11–12, pp. 1395–1402, 2007.
[120] M. N. M. Salleh, N. Talpur, and K. Hussain, "Adaptive neuro-fuzzy inference system: Overview, strengths, limitations, and solutions," in *International conference on data mining and big data*, Springer, 2017, pp. 527–535.
[121] C. Aliferis and G. Simon, "Overfitting, underfitting and general model overconfidence and under-performance pitfalls and best practices in machine learning and AI," *Artif. Intell. Mach. Learn. Heal. care Med. Sci. Best Pract. pitfalls*, pp. 477–524, 2024.
[122] H. Altınkaya and D. Ekmekci, "Tuning of PID Controller in PLC-Based Automatic Voltage Regulator System Using Adaptive Artificial Bee Colony–Fuzzy Logic Algorithm," *Electronics*, vol. 13, no. 24, p. 5039, 2024.
[123] N. W. Madebo, "Hybrid adaptive PID control strategy for UAVs using combined neural networks and fuzzy logic," *PLoS One*, vol. 20, no. 8, p. e0331036, 2025.
[124] A. N. Zulkifili, I. Ishak, and M. A. Zakaria, "Adaptive Control in Mobile and Autonomous Robotics: A Unified Taxonomy and Comparative Review," *IEEE Access*, 2026.
[125] S. S. Ram, C. Kumar, R. Saravanakumar, and D. Banjerdpongchai, "System identification and robust PID controller tuning of quarter car suspension system using hybrid optimization techniques," *Sci. Rep.*, vol. 15, no. 1, p. 24195, 2025.
[126] X. Zhao, Y. Sun, Y. Li, N. Jia, and J. Xu, "Applications of machine learning in real-time control systems: a review," *Meas. Sci. Technol.*, vol. 36, no. 1, p. 12003, 2025.
[127] Z. Yuan, B. Chen, G. Sin, and R. Gani, "State-of-the-art and progress in the optimization-based simultaneous design and control for chemical processes," *AIChE J.*, vol. 58, no. 6, pp. 1640–1659, 2012.
[128] K. Nguyen, S. Schoedel, A. Alavilli, B. Plancher, and Z. Manchester, "Tinympc: Model-predictive control on resource-constrained microcontrollers," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*, IEEE, 2024, pp. 1–7.
[129] S. Sundar and S. Salapaka, "Data Driven Temperature Control of Heat Exchangers," University of Illinois, 2018.
[130] L. G. Tugashova and A. V Zatonskiy, "Comparison of methods for heat exchanger control," *Theor. Found. Chem. Eng.*, vol. 55, no. 1, pp. 53–61, 2021.
[131] C. Manchikatla, "Optimization and control of heat exchanger network under uncertainty," 2022.
[132] Shakra, A. S. A. (2026). Utilizing Geothermal Energy in Waw an-Namus, South Libya, for Electricity Generation Using Binary Cycle Technology. *مجلة جامعة فزان العلمية*, 77–91. استرجع في من https://fezzanu.edu.ly/fusj/index.php/FUAJ/article/view/785
[133] Mezyed, H. N. A., & El-Khozondar, H. J. (2026). A Cost-Efficient Dual-Stage MPPT Solar Charge Controller with IoT Integration for Reliable Energy Storage in Power-Deficient Regions. *مجلة جامعة فزان العلمية*, 92–108. استرجع في من

https://fezzanu.edu.ly/fusj/index.php/FUAJ/article/view/786

[134] Irhouma, M. A., Ihmiudah, M. E. E., Fakher, M. A., & Nassar, Y. (2026). Design, Modeling, and Simulation of an Off-Grid Hybrid Energy System Integrating Solar Photovoltaics, Diesel Generators, and Batteries for Brack Al-Shatti Area, Libya. *مجلة جامعة فزان العلمية*, 180–201. استرجع في من https://fezzanu.edu.ly/fusj/index.php/FUAJ/article/view/791

[135] Imbayah, I., F. Nassar, Y., Khaleel, M., El-Khozondar, H. J., & Elmnifi, M. (2026). Design of a Hybrid Photovoltaic-Battery-Diesel System for Green Hydrogen Production. *مجلة جامعة فزان العلمية*, 1–22. استرجع في من https://fezzanu.edu.ly/fusj/index.php/FUAJ/article/view/781

[136] E. Yaghoubi, E. Yaghoubi, A. Khamees, and A. H. Vakili, "A systematic review and meta-analysis of artificial neural network, machine learning, deep learning, and ensemble learning approaches in field of geotechnical engineering," *Neural Computing and Applications*, vol. 36, pp. 12655–12699, 2024, doi: 10.1007/s00521-024-09893-7.

[137] A. Khamees and H. Altınkaya, "Data-driven LSTM-HHO optimization framework for strategic V2G connection sitting," Scientific Reports, vol. 16, Art. no. 19702, 2026, doi: 10.1038/s41598-026-49699-2

[138] xE. Yaghoubi, E. Yaghoubi, A. Khamees, and A. Alharam, "A novel control strategy for centralized and decentralized microgrids in response to cyber-physical attacks using a frequency sensitivity approach," *Journal of Applied Technology and Innovation*, vol. 9, no. 3, pp. 18–33, 2025, doi: 10.65136/jati.v9i3.8.

[139] E. Yaghoubi, E. Yaghoubi, A. Khamees, and A. Alharam, "A novel control strategy for centralized and decentralized microgrids in response to cyber-physical attacks using a frequency sensitivity approach," *Journal of Applied Technology and Innovation*, vol. 9, no. 3, pp. 18–33, 2025, doi: 10.65136/jati.v9i3.

[140] A. Khamees and A. Alharam, "Sliding mode control-based modeling and analysis of permanent magnet DC motors," *Journal of Applied Technology and Innovation*, vol. 9, no. 2, pp. 1–12, 2025, doi: 10.65136/jati.v9i2.18

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Authors' Contributions

N.	Author Name and Emai and ORCID link	Study Conception / Idea	Data Collection or Contribution to Data Collection	Contribution to Previous Studies / Literature Review	Study Methodology	Conducting Analyses (Practical Aspect)	Data Analysis	Interpretation and Discussion of Results	Approval of Final Version
1	Ahmed Khamees ahmed_khm340@yahoo.com	√		√	√	√	√	√	√
2	**Mohamed Abdulgader Matoug moh.matoug@fezzanu.edu.ly**		√			√			√