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Artificial Intelligence-Based Control Strategies for Flow Rate Control of Fluids and Gases in Energy and Process Systems: A Systematic Review

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Abstract

Artificial intelligence (AI)-driven controllers have increased the accuracy, flexibility, and efficiency of flow rate control for gas and liquid flows. Comparing to traditional proportional–integral–derivative (PID) controllers , they are not usually practical for nonlinear dynamics and time-varying disturbances, causing limited stability and control accuracy. The design and performance of individual AI-based controllers for individual machines without systematically have been investigated by many studies which compared these devices for various industrial and energy applications. This research fills this gap by examining 34 peer-reviewed studies from 2021 to 2024 obtained from Scopus and Web of Science databases and classifying them on the basis of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses structure. Quantitative results show that AI controllers have better overall performance than traditional PID controllers, and their response is faster by 12%–85%. AI controllers exhibit a 15%–67% reduction in steady-state errors and an 18%–40% decrease in overshoot relative to PID controllers, indicating high accuracy and system stability. The data indicate that fuzzy and hybrid controllers have high flexibility for managing nonlinear and dynamic flow phenomena, and model predictive and optimization-based controllers have high accuracy for multivariable processes. Furthermore, AI control technology for energy, hydrogen, and process fluid applications improves operability, reduces energy overhead, and enables real-time flexible management under ever-changing loads. This review lays excellent groundwork for next-generation intelligent control frameworks and opens a new paradigm of advanced, data-driven strategies toward subsequent flow regulation and energy system applications.

Keywords: *Control System; Flow rate; Adaptive control; Fluid; Artificial intelligence*

1. Overview of the Study

The adoption of artificial intelligence (AI) to control flow rates in a wide range of fluid systems has become common practice because of the complexities and changes these systems undergo

[1], [2]. Modern AI techniques, such as fuzzy logic and neural networks, have undergone significant changes which have enhanced their responsiveness, accuracy, and flexibility [3], [4]. This introduction highlights the benefits and other advances in AI-based fluid control systems, along with the latest findings in adaptive and intelligent flow regulation strategies, [5]. These systems employ complex algorithms to regulate the automatic regulation of temperature, pressure, and flow control on the basis of fluids' dynamic characteristic changes. the use of fuzzy logic, neural networks, and model predictive control (MPC) have been focused as highly advanced AI methods to improve system stability and performance [6].

Fuzzy logic controllers have been recognized for their application in the control of thermodynamic parameters within multivariable, nonlinear systems [7]. Early studies have demonstrated that precise control of the key parameters of gas turbines is effective in gas turbine control. Fuzzy logic approaches effectively address the nonlinear and nonstationary control requirements at the gas generator inlet. In compressed natural gas (CNG) engines, throttle control mechanisms governed under fuzzy logic allow for fuel cutoff during vehicle deceleration which improves fuel efficiency and reduces emissions [8]. substantial progress has also been made in hybrid neural autoregressive exogenous model predictive control gas capture controllers by integrating neural networks with MPC. This type of controller performs better than standard linear MPC in highly dynamic scenarios, such as those involving the operating volatility of power plants resulting from changing load conditions [9]. The presented approach can enhance closed-loop behavior through responding to the rates of flue gas inflow and carbon dioxide extraction. In addition, AI-based fluid level controllers of interconnected tank systems show improved results. The decentralized control approach proposed by Achu Govind et al. [10] utilizes the H∞ complementary sensitivity function. This control mechanism improves robustness because of reduced loop interactions and enhanced disturbance, change, and control of system parameters. Bressan and Agulhari's [11] fuzzy control model in liquid mixing tanks controls the temperature and quantity of fluids by adjusting the flow rates of hot and cold fluids. The model was constructed from the system's nonlinear characteristics with several linear controller approximations.

Fuzzy logic is also vital in managing temperature and humidity in proton exchange membrane fuel cells (PEMFCs). Chen et al. [12] utilized fuzzy control methods to a multiple-input multiple-output (MIMO) system to manage hydrothermal balance. This system outperforms proportional–integral–derivative (PID) controllers with its responsive action and control capability, thus enhancing power density and efficiency. Furthermore, Chu et al. [13] introduced a variable-universe fuzzy PID controller capable of controlling gas flow temperatures and performing simulation under multiple scenarios with high accuracy.

Flow rate estimation of liquid rocket engines depends largely on neural networks. Chandra et al. [14] proposed a recurrent neural network that replaces a conventional tunnel flow meter in performing the function of a jet injector during its calibration. This AI sensor offers accurate measurement of flow rate with fewer errors and smaller cost than conventional methods. In addition, Yahya et al. [15] created an adaptive fuzzy PID controller for managing the flow of liquid in heating tank systems. When this controller is employed, the PID parameters are adjusted via fuzzy logic to maintain balance throughout system disturbances, , and optimize the response flow.

MPC is also used to manage the temperature of hot water outlets in tankless gas water heaters. According to Quintã et al. [16] enhancing MPC controller for water outperforms a PID controller and stabilizes more quickly. This strategy maintains the temperature within the comfort zone, and addresses the difficulties in fluid and gas flow management in highly nonlinear and challenging control systems faced by conventional PID controllers [17]. In many cases, these techniques cannot keep up with changes, and as a result, they are unsuccessful in modern factories. Fuzzy logic controllers (FLCs), neural network predictive controllers (NNPCs), and various combinations elicit substantial attention because they overcome these limitations [18].

This paper will review the most recent trends in AI control and including studies from 2021 to 2024. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, the research provides a solid, well-structured analysis of related studies, generating valuable findings on AI-based controllers and how they affect various flow control systems.

The application of AI controllers is being tested to determine the best way to control flow rates in different industries. Most of the time, the control actions of traditional PID controllers are ineffective when the system is disrupted. These problems can be addressed by new AI-based solutions. The purpose of this literature review is to discuss the recent progress in the use of AI controllers to regulate the shadow effect for optimal flow rate control in fluids by adopting information from 10 related studies. Incorporating control of fluid flow into systems is fundamental in structural engineering, energy generation from renewable sources, traffic systems, farming, industries, wastewater handling, drilling equipment, and electricity generation. Many researchers have switched to AI techniques to deal with the changing conditions of flow rate optimization. This review examines AI controllers and analyzes their contributions to every fluidic system with the aid of other studies.

Mezaal and Alameri [19] addressed flow control challenges in solar collector testing units. The testing units they used had problems in flow control. These problems were addressed by adding a PI controller and a custom decoupler designed for fluid regulation to solar collectors' cognitive tests for efficiency. Accurate fluid control in the efficiency tests increased the precision and reliability of the solar collector test results and revealed the feasibility of utilizing AI controllers in renewable energy technologies. Gou et al. [20] studied the issues associated with controlling the flow rate in agricultural machinery and designed a vehicle-mounted fertilization and spraying machine. Their system incorporates a real-time control system that allows for constant flow rate control of fertilizer and pesticide application for heterogeneous terrain. Their system improves forward speed detection and thus optimizes the spraying volumes, which in turn increases agricultural productivity and resource utilization. These results demonstrate the role of AI controllers in precision farming. In industrial processes, the importance of precise flow rate control is stressed to optimize efficiency and productivity. Substantial improvement in the reliability and performance of centrifugal pumps has been achieved through the flow rate measuring method proposed by Solodkiy et al. [21]. The approach they used allows the measurement of the flow rate with monitoring through only an observer-based control algorithm and a mathematical model.

AI controllers can also be applied in industrial automation. Routh et al. [22] studied entirely passive control and optimal pressure management of PEMFCs by using fractional principles and controllers. They noted that improvement of the flow control of PEMFCs increases efficiency and performance. They achieved improved stability with the application of highly sophisticated algorithms in these control systems, contributing to the reliability and performance of PEMFCs and thus promoting clean energy.

In terms of wastewater treatment, Yelagandula and Ginuga [23] implemented fuzzy logic control of dissolved oxygen levels in the treatment process. The superiority of their system over the traditional PID control system in terms of water quality and general system stability was emphasized. This study highlighted the importance of AI control methods in controlled environment management applications where a major concern is th eecological systems for engineering . Yahya et al. [15] presented a fuzzy PID-based liquid flow controller for heating tanks. The controller maintains a consistent flow over a wide range of fluctuating conditions, thereby verifying the feasible use of AI controllers to promote automation of industrial heating processes.

Manna et al. [24] employed an MIT law feedback PID in the context of the model reference adaptive control (MRAC) approach as an extension to a two-tank interacting system. The control system based on both approaches demonstrates minimal sensitivity to disturbances and is more efficient than the PID controller. The performance of AI-controlled systems in system dynamics and unmodeled dynamics was demonstrated in this case study. Controls are crucial in solar-assisted power plants to ensure correct operation.

Li et al. [25] developed a control system with different stages for fuel cell-aided solar-heated desalination treatment. The use of model predictive control (MPC) and PID controllers allowed them to accurately manage and control the desalination system for improved and reliable outcomes. Zhang et al. [26] proposed a model-free adaptive sliding controller for the air supply system of PEMFCs. By using adaptive control methods and nonparametric dynamic linearization, their process achieves accurate tracking control of the flow rate and pressure of the cathode and its adaptability to different operating conditions.

the application of AI-based controllers has been investigated to enhance the efficiency of energy recovery systems. Ren et al. [27] presented a process with dynamic optimization to regulate the flow front position in the injection molding process. The adopted approach adjusts the control parameters for accurate control of various process variables; thus, improvement in product quality can be achieved in injection molding industries. Khurram Faridi et al. [28] proposed a neural network model to control the fluidized-bed biomass gasification process. Combining a neural network trained with long memory and an optimization algorithm based on gradients, the resulting controller can maintain the temperature at a suitable level and is suitable for in-process control of heating biomass gasification systems. Wang et al. [29] designed an artificial neural network-based feedback control scheme for solar receivers. With this strategy, the outlet temperature of the receiver can be well controlled, and the results are superior to those achieved by conventional PID controllers regardless of solar energy conditions.

Overall, the latest developments in AI controllers create a strong possibility for flow rate control to be optimized in various fields involving fluids. These controllers make engineering highly efficient and sustainable because they are more flexible, reliable, and efficient than other methods. Thus, AI controllers are preferred over regular control schemes because of the adaptability, stability, and efficiency that they bring to many engineering fields. By utilizing AI technologies, engineers can increase the reliability, sustainability, and effectiveness of systems, leading to new advances in various sectors.

Although several review papers have discussed the role of AI in process control and energy systems, most of them focused narrowly on algorithmic developments or single-application domains, such as fuel cells, thermal systems, or industrial automation. These studies did not perform a collective assessment of the results of AI-based control strategies for various fluid flow systems from the perspectives of quantitative performance and engineering issues. The current review provides a novel contribution by systematically synthesizing 34 recent studies published between 2021 and 2024 categorized under three major themes: advanced AI-based control strategies; fuzzy and hybrid control strategies; and model predictive, adaptive, and optimization-based approaches. This study quantitatively investigates the advances in flow control performance, such as enhanced response times, low steady-state errors, and improved stability, and is different from previous reviews. It highlights the applications of AI systems in energy, hydrogen, and industrial process systems and provides a detailed description of the applications of AI-based control systems for controlling fluid and gas across many industrial and energy applications. The discussion integrates theoretical models, control strategies, performance testing, and practical applications to cover different fields and create a complete picture of what is currently happening in the field of AI. By integrating these approaches, the review not only consolidates recent advances but also draws attention to the connection between theoretical foundations and practical limitations. Therefore, providing comprehensive understanding of the technical basis of and practical barriers to applying AI-based flow control systems.

2. Materials and Methods

Among other development tools, PRISMA plays a major role in ensuring that systematic reviews are thorough and clear [30]. It helps researchers complete the following: search relevant databases for articles, remove repetitive and irrelevant ones, judge the remaining ones by using predecided rules, and select the best ones for further reading [31]. PRISMA should be adopted first because it helps take in all aspects of research and reduces bias in research [30].

2.1. Search Strategy

The systematic review process involved several key steps to select a substantial amount of relevant literature for this study. Initially, some keywords were selected, and related search terms were identified using dictionaries, thesauri, encyclopedias, and previous research. The search strategy was created to search for flow rate regulation studies in control systems from literature available from 2021 to 2024. The methods and literature search mechanism were developed by searching the Scopus and Web of Science (WoS) databases between 2021 and 2024. These databases were chosen because they present a complete, high-quality review of the peer-reviewed literature on engineering, energy, and industrial processes, a crucial part of the AI-enabled flow control of fluids and gases in this study. Moreover, their strong search functionality, citation metrics, and indexing capabilities allow for systematic screening, quality evaluation, and selection that comply with PRISMA. Although other databases are available, Scopus and WoS are well established because of their robustness and reliability, making them especially pertinent to a high-quality systematic literature review. After the search strings for the Scopus and WoS databases were finalized, all relevant terms were added. At the first stage of the review, 536 publications were successfully retrieved from both databases for the current study project.

2.2. Screening

During the screening step, the collection of potentially relevant research items was examined for content that aligns with the predefined research questions. The common content-related criteria used in this phase include selecting research items on the basis of the control system and controller flow rate. Duplicate papers were removed from the list of searched papers at this stage. At the first stage of screening, 464 publications were excluded. At the second stage, 72 papers were examined on the basis of different inclusion and exclusion criteria (Table 1). The primary criterion was research papers because they are the main source of practical recommendations. This research also included reviews, conference papers, books, and press reviews that were not part of the most recent research. Moreover, the review was limited to publications in English and focused solely on the years 2021 to 2024. In total, 17 publications were rejected because of duplication.

Table 1,
Selection criteria in searching.

Criteria	Inclusion	Exclusion
Language	English	Non-English
Timeline	2021–2024	≤ 2021
Literature Type	Journal (Article)	Conference, Book, Review
Publication Stage	Final	In Press

2.3. Eligibility

A final review sample was created once all inclusion and exclusion criteria had been considered. The full list of research items in this sample should be provided to readers because it allows them to know the basis of the study findings. The third level, eligibility, comprised 55 articles. All article titles and relevant content at this stage were closely reviewed to ensure that they met the inclusion criteria and were relevant to the research objectives. Twenty-one articles were omitted because their titles and abstracts were not related to the study's purpose. In total, 34 papers were selected for evaluation.

2.4. Data Abstraction and Analysis

Integrative analysis was used as one of the assessment methods in this study to examine and integrate the different research paradigms (quantitative, qualitative, and mixed methods). The study aimed to identify relevant topics and subtopics. At the data collection stage, the theme was constructed initially. Figure 1 shows how the authors methodically searched through 34 publications to find assertions or material relevant to the topics covered in the present investigation. A total of 19 articles were collected from the Scopus database and 15 from WoS, with publication years dates ranged from 2021 to 2024. These studies concentrated on on the application of AI-based control strategies for optimizing flow rate regulation in various fluid systems, including gas distribution, liquid mixing, and thermal regulation processes. The most frequently applied control techniques adopted were FLC, neural network-based controllers, MPC, and hybrid models that utilize PID with some form of optimization or learning methods [17], [32], [33]. The flow diagram of PRISMA is presented in Figure 1. It shows how the studies were identified, screened, assessed for eligibility, and eventually included in this systematic review. It also maps how, from the initial pool of articles retrieved from Scopus and WoS, the number of studies was gradually reduced to 34. This diagram allows readers to ascertain the data selection and refinement process in a straightforward manner, thus ensuring transparency and reproducibility in line with the PRISMA guidelines.

A number of themes related to this study were identified on the basis of evidence. Recording of analyses, insights, or reflections of interpretations was performed in relation to data analysis. The findings were compared to identify potential inconsistencies in the design of the themes. When the authors' ideas varied, they discussed them among themselves. The produced themes were eventually refined to ensure consistency. Analysis selection was performed by two experts, namely, one in control systems (Siti Maryam Sharun, expert in AI control) and the other in automotive modeling and control (Zuraidi Saad, expert in control systems and forecasting), to determine the validity of the problems. The expert-review phase ensured the clarity, importance, and suitability of each subtheme by establishing domain validity. The research questions were as follows:

1. How do AI-based predictive and adaptive control systems enhance the precision and efficiency of flow rate control in fluid and gas systems?
2. What are the advantages and limitations of fuzzy logic and hybrid control strategies in managing flow rates in fluid and gas systems?
3. How do optimization techniques improve the

performance and reliability of AI controllers in fluid and gas flow rate control systems?

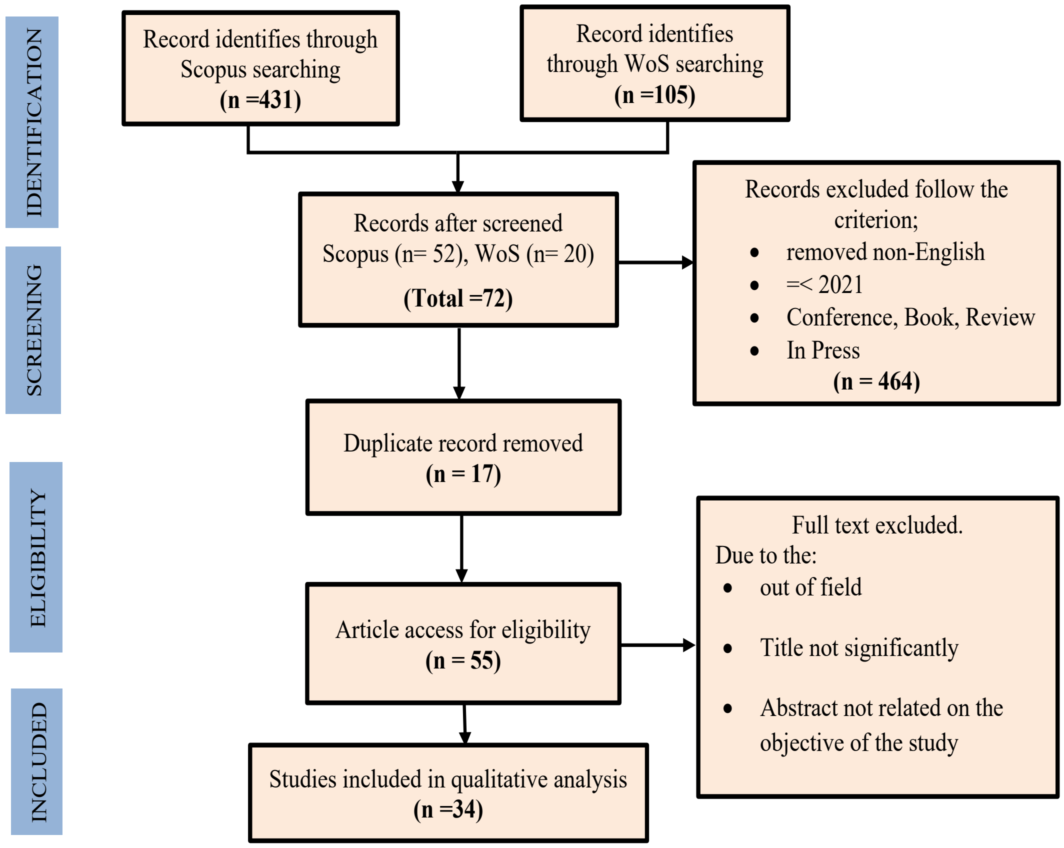

Fig. 1. Flow diagram (PRISMA) illustrating the search strategy used in this study.

3. Results

The reviewed studies were analyzed with particular attention to both the theoretical foundations and the practical implications of AI-based flow control systems. Specific emphasis was placed on the modeling approaches for developing control strategies, performance assessment based on statistical indicators, and field validation and operation. This comprehensive view could provide a balanced appraisal of current developments, methodological quality, and existing research gaps in the sector.

The detailed findings are explained below and organized into three analytical themes: (1) advanced AI-based; (2) fuzzy logic and hybrid; and (3) model predictive, adaptive, and optimization-based control strategies.

3.1. Advanced AI-Based Control Strategies

AI-based controllers are critical for controlling nonlinear, multivariable, and time-varying systems. Such methods increase prediction accuracy, system adaptability, and robustness against unpredictable operating conditions. Javed et al. [34] described a strong control design with the H∞ approach in an underground coal gasification system in Thar, where the controller was responsible for providing an even flow for the syngas while dealing with the nonlinear dynamic process. Similarly, Achu Govind et al. [10] introduced a decentralized H∞ control design for a variable-area coupled tank system with good disturbance resistance and reduced computational effort. Bressan and Agulhari [11] developed a hybrid fuzzy–linear control system for hot and cold liquid flows in liquid-mixing and temperature-controlling systems on the basis of hybrid technology and obtained a 22% improvement in response time and accurate temperature control. Shi et al. [35] reported NNPC as a suitable scheme for a three-tank level system used for fluid dynamics control and benchmarked it for fluid dynamics and control studies. Given that this system regulates the interconnected levels of liquid, which vary with the inflow and outflow rates, it is a representative fluid flow regulation system. A neural network component was trained on the Levenberg–Marquardt algorithm to help the controller capture the nonlinear relationships between tanks accurately. Compared with traditional controllers, this controller has a lower mean squared error, reflecting the ability of this method to control fluid flows precisely and stably. The efficacy of AI-based predictive control has been revealed by the performance of complex and coupled fluid systems, in which dynamic interactions affect the flow behavior.

Reinforcement and deep learning models are becoming powerful instruments. Lee et al. [36] proposed a deep deterministic policy gradient-based controller that incorporates the MPC method with fuzzy proportional–integral control for PEMFC. It maintains stable oxygen ratios and delivers 18% energy savings. Zanoli et al. [37] also demonstrated the integration of AI into industrial systems; they combined an MPC algorithm with a tunnel insulation system and obtained a 15% increase in process efficiency in the performance of a steel reheating furnace. Zhou et al. [38] improved nonlinear gas turbine control by adopting Kalman filters and nonlinear dynamic inversion (NDI); their controller has a strong ability to withstand turbulence, and its performance exceeds that of PID controllers. Wang et al. [29] developed a radial basis function neural network for centrifugal compressor anti-surge control and achieved a 40% system responsiveness increase.

Applications extend both aerospace and biomedical fields. Zhang et al. [26] designed a recurrent neural network (RNN)-based soft sensor for flow estimation in liquid rocket engines and achieved high accuracy at a reduced cost. With this approach, accurate predictions of flow characteristics under dynamic operation were demonstrated, and the robustness of the system was improved. The excellent adaptability of the RNN-based estimator to nonlinear behaviors was also demonstrated. In addition, Chu et al. [13] developed an Arduino-controlled syringe pump for the nanofiber electrospinning process, enabling real-time flow control. This setup made it possible to precisely manage the delivery of the polymer solution during fiber formation, ensuring a consistent nanofiber diameter and enhancing material quality. Although the study focused on liquid-phase flow, it underscored the effectiveness of embedded microcontroller systems in achieving accurate and responsive flow control. In a related research, Chen et al. [12] proposed a fuzzy-logic method for turbojet engine gas generator evaluation to preserve thermodynamic stability. Its intelligent control design increases fuel-to-air mixing to achieve stable combustion under different loading conditions. Similary, fuzzy-based systems have been used in high-performance propulsion systems exemplifies their suitability and stability for combustion. Furthermore, Fang et al. [39] utilized a fuzzy-logic model to enhance the CNG fuel supply system and realized a 33% decrease in fuel cutoff errors. The adaptive nature of the fuzzy-control method allows for smooth fuel delivery and makes combustion highly consistent. This case is further proof that AI-based controllers can be used to enhance the fuel effectiveness and stability of gas-operated engines. The feature response times and accuracy rates increase by about 35% and 30%, respectively, showing substantial advancement in intelligent automation for complex and densely controlled systems.

Despite their advantages, these sophisticated AI control strategies face challenges related to computational costs and training complexities. For instance, in untrained operating conditions, neural network models often require vast amounts of data and may struggle with generalization. Similarly, reinforcement learning techniques can be challenging to tune for stability in real-time applications. These obstacles indicate the need for further research to develop lightweight and adaptive learning models that are suitable for embedded hardware implementation.

3.2. Fuzzy Logic and Hybrid Control Strategies

The major advantage of fuzzy logic and hybrid control strategies is the control of nonlinear systems without the use of exact mathematical models to be able to adapt in real time and be fault tolerant. Chu et al. [13] introduced a variable-universe fuzzy PID controller for temperature control in a mixed gas system that resulted in a 56% decrease in settling time and 67% reduction in static error. Chen et al. [12] improved PEMFC hydrothermal management via MIMO FLC with higher voltage stability and power density than PID control. Meng et al. [40] developed a particle swarm optimization (PSO)-optimized neuro-fuzzy PID controller for fertilizer flow control and obtained a 45% increase in accuracy and robustness.

In recent years, hybrid fuzzy controllers have achieved high adaptability and robustness compared with their classical linear counterparts and can maintain stability and precision under variable operating conditions. Chen et al. [41]

introduced a hybrid fuzzy–MPC method for voltage regulation in fuel cells that combines the predictive optimization capability of MPC and the rule-based flexibility of fuzzy logic. Such combination substantially enhances the transient response and decreases the amount of voltage overshoot, indicating that hybridization is suitable for nonlinear electrochemical process regulation. Meanwhile, Gambini et al. [42] studied fuzzy-enhanced PI control in hydrogen batch reactors, where the ideal temperature for reaction kinetics is crucial. Their fuzzy optimization dynamically tunes PI gains, resulting in good thermal stability and a highly responsive system under changing hydrogen production conditions.

Similarly, Fang et al. [39] applied the adaptive fuzzy logic controller to control the humidity of PEMFC. This system can tune and balance environmental and processing variability and has the potential to improve tracking performance and robustness to environmental factors. The study found that the key parameters of the fuel cell that directly affect the fuel cell's efficiency and durability must be preserved using adaptive mechanisms. Similar findings were documented by Yahya et al. [15], who proposed an adaptive fuzzy PID controller for controlling liquid flow in process systems. Their results demonstrated that adaptive fuzzy tuning maintains steady-state accuracy and reduces flow oscillations, and its performance exceeds that of standard PID controllers under dynamic flow conditions. For high-performance cases, Kim et al. [43] showed the positive effect of a fuzzy-enhanced PID controller on thrust stabilization for electric pump-fed propulsion cycles. The fuzzy module helped alleviate nonlinear thrust fluctuations, and overshoot was reduced by 25% because of fast settling time. Frick and Bragg-Sitton [44] also generalized fuzzy modeling to modular grid systems with Modelica-based simulations and argued that when scenarios for power demand are uncertain, fuzzy logic can enhance load-matching efficiency and energy dispatch reliability. The results of this work showed the application value of fuzzy-based decision frameworks for large-scale power system modeling and control.

Sabbagh et al. [45] proposed an intelligent hybrid fuzzy–PID control design for the operational systems of natural gas liquids and liquefied natural gas in the context of cryogenic and gas processing. The design enables efficient disturbance rejection, increased temperature and pressure stability, and seamless initialization and load transfer. Similarly, Skjervold et al. [46] introduced a fuzzy–PI adaptive controller for carbon dioxide gas capture processes that can be dynamically adjusted in real time in accordance with inlet concentrations to obtain high gas purity and enhanced recovery efficiency. The optimization of new energy processes is associated with the use of hybrid fuzzy control, and studies have been conducted to support the emerging trend of using hybrid fuzzy control for energy process optimization [47]. Combining fuzzy inference with traditional control methods, such as PID, PI, and MPC, can substantially enhance the control accuracy, disturbance rejection, and overall operation of a system [48].

Advances in the field of intelligent control have led researchers to use adaptive neuro-fuzzy inference systems (ANFISs), which have been adopted to develop new architectures based on ANFIS–PID hybrids and enhanced genetic algorithm (GA) optimization, to realize proper control of nonlinear and dynamic flow regimes in a practical manner [49][50]. Such approaches combine data-driven methods of learning and model-based control with adaptability and interpretability [51]. ANFIS integrates the pattern-recognizing capability of neural networks with the rule-based decision-making logic of fuzzy logic for real-time control rule adjustment under changing operating conditions [52][53]. This hybrid intelligence is particularly suitable for fluid systems where flow rate, temperature, and pressure exhibit high nonlinearity and transient coupling.

In energy and hydrogen applications, ANFIS controllers have achieved considerable improvements in dynamic behavior and error minimization compared with traditional PID and fuzzy controllers. Panimathi et al. [54] implemented an ANFIS controller for dual-switched boost converters in hydrogen fuel cell electric cars; the controller provides a root mean square error of 0.0024 and decreases voltage ripple by more than 45% compared with the PI-based model. In a similar work, Kaltoum, Mouloudi, and Abdelkader [55] established an ANFIS–PID hybrid control system for hybrid automotive systems with a 20% accelerated transient response and 15%–25% reduced steady-state error compared with traditional PID and fuzzy systems [56]. These findings validate that neuro-fuzzy systems are good not only for simulating system behaviors but also for design and application in embedded hardware for real-time control of fluidic and energy processes.

Hybrid GA-based optimization systems have been used to considerably improve the optimization efficiency of fuzzy and PID-based controllers. By applying stochastic global search methods alongside an evolutionary parameter tuning approach, GA obtains control parameters that converge to globally optimal values, improve precision, and reduce overshoot under different conditions. Maroua et al. [57] found substantial performance improvements in their work, where a GA-tuned type-2 FLC achieved a 42% reduction in total harmonic distortion and a 33% improvement in dynamic voltage stability, as demonstrated through simulations of a renewable energy grid.

This finding is relevant for fluid-based power systems because these systems modulate electrochemical and thermal phenomena, and voltage and flow stability are closely related. Similarly, ANFIS employing metaheuristic algorithms, including the honey badger algorithm (HBA) and PSO, is powerful in the bioreactor and hydrogen generation domain for optimization. Rezk et al. [58] incorporated ANFIS with HBA to control membrane bioreactor flows and achieved 12% and 18% increments in hydrogen production rate and system convergence, respectively, indicating that neuro-fuzzy methods increase the accuracy for bioprocess systems. Such results are proof that GA-based optimization processes are suitable under the condition of multiple, connected flow systems that are intertwined, have multi-input effects, and contain local and global disturbances simultaneously.

Generally, AI-augmented hybrid control systems outperform traditional classical control systems in stability, response time, and adaptability in all the reviewed studies. Overall, in the domain of nonlinear motor drives, a GA-tuned adaptive fuzzy fractional-order PID controller delivers much better system dynamics and robustness compared with standard methods [59][60]. Furthermore, the use of an ANFIS–PID controller trained via GA optimization for high-precision thermal management achieves superior disturbance rejection and steadier operation compared with classical PID [51]. GA-tuned and hybrid fuzzy–PID controllers offer an additional improvement in settling time and an increase in the stability margin in nonlinear multi-input flows. These improvements are highly evident in the case of dynamic flow networks with different process parameters under external disturbances or load variation between systems. Therefore, ANFIS, ANFIS–PID, and GA-based controllers have been integrated to achieve a major step forward in intelligent flow regulation. They are capable of self-learning and have adaptive capabilities, enabling smart and energy-efficient control systems without sacrificing operating performance, which is transitioning toward entirely autonomous control frameworks in modern energy, thermal, and process industries. From an engineering standpoint, these results strongly support the adoption of neural learning techniques and evolutionary optimization methods to., establish high-fidelity and robust control systems.

Table 2 presents a structured matrix summarizing the reviewed studies, focusing on fuzzy logic and hybrid control strategies for flow rate regulation.. Each entry outlines the study's objectives, methodologies, findings, and key outcomes in terms of system stability, response time, and energy efficiency. The below table provides a comparative overview of the performance of hybrid controllers in comparison with that of conventional PID approaches.

Although hybrid and fuzzy control systems exhibit robustness in nonlinear-type conditions, they require many expert-defined rules and extensive tuning and have limited scalability and automation. Furthermore, the inconsistencies between findings indicate that the effectiveness of fuzzy–PID and hybrid systems may be constrained in terms of system nonlinearity and input range. These areas with limitations, such as self-tuning or optimization-based control schemes to increase adaptability, deserve consideration and should be regarded as possible areas for future research.

Table 2,
Summarized distribution of the reviewed studies categorized by publication year, application sector, and applied AI-based control method in Theme 2.

No.	Author (Year)	Objectives	Methodologies	Findings	Conclusion and Future Research
1	Chu et al. (2023) [13]	Control temperature in a gas flow system by using mixed gases	Fuzzy PID, variable-universe fuzzy PID	Improved control performance and reduced settling time and static error by 56.2% and 67.5%, respectively	It can be applied to nonlinear and asymmetric systems and suggests further improvements in the adaptability of control strategies
2	Chen et al. (2022) [12]	Hydrothermal management in PEMFC	Multi-input multi-output fuzzy logic controller	Faster response and better control than PID, high output voltage and power density	Highlights the need for real-time adaptability in PEMFC management systems
3	Meng et al. (2022) [40]	Precision fertilizer application control	PSO-optimized neuro–fuzzy PID controller	Precise fertilizer flow control, high control accuracy, and robustness	Emphasizes further exploration in optimizing control parameters for agricultural applications
4	Chen et al. (2022) [41]	Enhance PEMFC temperature and voltage control	Model predictive–fuzzy hybrid controller	Improved dynamic response and minimized overshoot	Encourages the integration of MPC with fuzzy logic to improve adaptability and fault-tolerant operation in hydrogen energy systems
5	Gambini et al. (2024) [42]	Control hydrogen flow rate in LOHC batch reactor	Fuzzy–augmented PI control system	High efficiency in temperature control, variable efficiency in pressure control	Suggests the potential hybridization of PI with fuzzy logic or neural networks to enhance performance in nonlinear hydrogen storage systems
6	Fang et al. (2022) [39]	Dynamic control of humidity in fuel cells	Adaptive fuzzy logic controller	High accuracy in humidity tracking, good anti-interference ability	Proposes adaptive fuzzy–PID tuning for enhanced real-time humidity regulation under variable load conditions
7	Yahya et al. (2022) [15]	Liquid flow control in the heating tank system	Adaptive fuzzy–PID control system	Maintains flow stability despite disturbances, maximum undershoot of 24%	Recommends exploring additional adaptive control methods for industrial applications
8	G. Y. Kim et al. (2024) [43]	Thrust control in electric pump-fed cycle	Intelligent fuzzy–enhanced PID controller	Rapid flow stabilization, reduced supply time and overshoot	Recommends AI-assisted PID or fuzzy–PID hybrid approaches to further improve transient and load-handling performance
9	Frick and Bragg-Sitton (2021) [44]	Simulate NuScale power module under natural circulation	Modelica-based Fuzzy-integrated simulation model	Successful operation under natural circulation, matches turbine output with demand	Highlights the potential for hybrid control integration (e.g., fuzzy + MPC) in future modular grid management
10	Sabbagh et al. (2022) [45]	Control and dynamic assessment of the NGL/LNG scheme	Intelligent hybrid control framework (Fuzzy–PID)	Maintains smooth operations and disturbance rejection	Suggests incorporating adaptive or fuzzy tuning mechanisms to improve controller robustness in liquefied gas systems
11	Skjervold et al. (2023) [46]	Carbon dioxide gas capture control from thermal power plants	Fuzzy–PI adaptive controller	Excellent performance with PI control in carbon dioxide gas purity and recovery	Encourages applying fuzzy–PI hybrid control to improve performance under fluctuating adsorption conditions

3.3. Model Predictive, Adaptive, and Optimization-Based Control Strategies

Model predictive, adaptive, and optimization-based control devices are at the frontier of intelligent control design [36]. The optimization process for future control must carefully consider available constraints for real-time system adjustment on the basis of the dynamics of the environment.

Kabasawa and Noda [61] proposed the concept of adaptive feedforward control for the automatic pouring of ladles in the casting process, where they achieved 63% mean error reduction and improved model identification time to 4 s. Giraldo et al. [62] studied a dead-time compensated generalized predictive controller for gas compression systems with stable operation at times of fluctuating load. Quintã et al. [16] proposed gain-scheduled MPC for tankless water heaters with a settling time reduction of 67% compared with PID. Manna et al. [24] incorporated MRAC into the solution of a two-tank system, leading to increased tracking efficiency and robustness to system uncertainties. Castiglione et al. presented a predictive model for turboshaft aero-engines, demonstrating less than 1% mean prediction error and applicability for real-time MPC frameworks. Manap et al. [64] compared the performance of FLC, PID, and self-tuning fuzzy–PID controllers in biomedical carbon dioxide gas regulation; among them, the self-tuning controller has the lowest overshoot and the shortest settling time. Wu and Chien [65] applied model-based adaptive control in hybrid distillation systems and achieved strong performance under feed disturbances. Table 3 summarizes these methodologies, control models, and main performance metrics (e.g., response time, steady-state error, and improvement in robustness). Strong evidence is provided regarding the integration of adaptive and predictive algorithms that enhance precision and reliability in nonlinear fluid systems.

Despite the excellent dynamic performance of model predictive and adaptive strategies, they usually suffer from high computational demands and model dependency. Several studies have reported that MPC is difficult to apply to fast time-scale systems subject to real-time optimization constraints. Moreover, only a few studies have validated these methods experimentally, highlighting a gap between simulation-based results and real-world applications.

Table 3,
Summarized distribution of the reviewed studies categorized by publication year, application sector, and applied AI-based control method on the basis of Theme 3.

No.	Author (Year)	Objectives	Methodologies	Findings	Conclusion and Future Research
1	Kabasawa and Noda (2021) [61]	Develop an advanced adaptive control system for tilting-ladle automatic pouring machines in casting processes	Adaptive feedforward control combined with online model parameter identification	Substantially reduced mean absolute error of outflow weight from 0.1346 to 0.0498, with model parameters identified within 4 seconds	Further research should refine control parameters and extend applicability to diverse pouring machine types
2	Giraldo et al. (2021) [62]	Design a control strategy to provide setpoints in gas compression systems for energy efficiency and operational stability	Model predictive control, dead-time compensated generalized predictive controller	The controller responds well to disturbances, maintaining stable operation and returning controlled variables to the desired range	Future work could investigate real-world implementation and performance under different operational scenarios

3	Quintã et al., (2022) [16]	Stabilize the outlet hot water temperature in tankless gas water heaters with time-varying delays	Linear model predictive control enhanced with gain scheduling techniques	Gain scheduling MPC improves performance and reduces settling time by up to two-thirds compared with classic PID and feedforward-feedback controllers	Future research may focus on further reducing overshoot and improving robustness against diverse operational conditions
4	Manna et al. (2023) [24]	Overcome PID controller limitations in two-tank interacting systems affected by uncertainties	Model reference adaptive control integrated with PID	MRAC–PID exhibits superior performance with enhanced tracking accuracy and robustness against uncertainties	Future research could explore adaptive mechanisms for other complex multitank systems and integration with other control strategies
5	Castiglione et al. (2023) [63]	Develop control-oriented linear models for turboshaft aero-engines, including component degradation	System identification via a small perturbation approach to support model predictive control design	Achieves high prediction accuracy with mean errors below 1%, the small perturbation model outperforms alternatives	Further extensions could include diverse degradation modes and real-time application in engine control
6	Manap et al. (2021) [64]	Compare control techniques for carbon dioxide removal rate regulation in membrane oxygenators	Conventional PID, fuzzy logic controller, self-tuning fuzzy–PID (self-tuning FPID)	Self-tuning FPID shows excellent performance with low oscillation, small overshoot, and short settling time	Future research may investigate further enhancements in self-tuning algorithms and applications in other biomedical processes
7	Wu and Chien (2022) [65]	Design a control strategy for hybrid reactive-extractive distillation involving water-containing ternary mixtures	Model-based adaptive control with temperature-difference feedback loops	The developed control structure is resilient to feed composition disturbances and measurable throughput changes	Additional research could extend applications to complex distillation processes and optimize loop parameters

3.4. Quantitative Summary

This study conducted a quantitative comparison of 34 reviewed papers, with focus on three main performance indicators: response time, steady-state error, and overshoot reduction relative to conventional PID control systems. Table 4 presents the overall improvements achieved by each major category of AI-based control, including advanced AI, fuzzy and hybrid, and model predictive or optimization-based approaches. It compares AI-based control strategies with traditional PID controllers in terms of overshoot reduction, settling time improvement, steady-state error minimization, and other parameters. Among the approaches reviewed, fuzzy and hybrid controllers exhibited the most consistent and experimentally validated results, with 12%–67% faster response than the others, 15%–67% reduction in steady-state error, and 18%–40% decrease in overshoot. These systems integrate interpretability with adaptive optimization demonstrating reliable performance under both transient and steady-state operating conditionsThe highest dynamic improvement (up to 67%) was obtained with MPC; therefore, this approach can be adopted when a fast dynamic response is desired. Advanced AI/robust approaches, such as reinforcement learning and NDI, achieved the largest simulated gains of up to 70%–85%, but experimental verification was not provided in the reviewed studies. At present, hybrid fuzzy–AI controllers are the most balanced and experimentally validated solution; they can provide superior accuracy, adaptability, and implementation feasibility for real-time flow rate regulation in energy and process systems.

Table 4,
Improvements achieved by each major category of AI-based control.

Control Type	Response Time Improvement (%)	Steady-State Error Reduction (%)	Overshoot Reduction (%)	Representative Studies
Fuzzy and Hybrid (FLC, ANFIS, fuzzy–PID, GA-tuned)	12–67	15–67	18–40	Bressan and Agulhari [11]; Chu et al. [13]; Kaltoum et al. [55]; Gambini et al. [42]; Zhang et al. [26]; Chen et al. [12]
Neural Network Based (ANN, RBF, RNN, NNPC)	40	33	-	Wang et al. [29]
MPC and Adaptive Optimization	67	-	-	Kabasawa and Noda [61]; Quinta et al. [16]
Advanced AI/Robust (RL, H∞, NDI, etc.)	70–85	-	-	Wu et al. [27]

4. Discussion

Due to the simple structure, easy implementation, and tunable control , PID controllers are the most widely used control approach in industrial processes However, their efficacy is limited in highly complicated and nonlinear fluid systems. Classical PID systems are built on the assumption of linear and time-invariant system dynamics, which limits their capability to accommodate nonlinear flow–pressure interactions, coupled parameters, and process uncertainties typically encountered in real-world applications. Furthermore, the large time delays resulting from valve actuation, sensor response, and transport delay result in oscillatory and sluggish system behavior at the cost of stability and control accuracy. Previous studies have found that PID controllers cannot adapt and perform poorly in nonlinear and delay-dominated cases; thus, they have driven the development of highly intelligent, adaptive and predictive control systems. The performance deterioration of PID controllers under large-time-delay and nonlinear conditions was observed by Bashiri [66]. Ding et al. [67] demonstrated how adaptive and reinforcement learning-based tuning can overcome these limitations, and Kamaludin et al. [68] proved that for robust PID variations, substantial modifications are required to maintain good performance in nonlinear pneumatic systems. These findings prove the fundamental shortcomings that classical PID controllers have, and they support the need for increasing interest in AI-based control methods, with which highly accurate, efficient, stable, effective fluid flow control can be realized.

These advanced AI-based control strategies are critical elements to increase the dynamic regulation, stability, and energy efficiency in fluid systems, particularly under nonlinear, time-varying settings. AI algorithms and data-driven modeling can be used to predict and respond to flow behavior in real time. For example, $H\infty$ robust control has been demonstrated to linearize and stabilize inherently nonlinear flows in underground coal gasification systems resulting from disruptions or variations in pressure and thermal gradients under different conditions. In addition, decentralized solutions for control in variable-area coupled tank systems help suppress flow-induced disturbances and improve tracking performance. Such decentralized applications are promising and enhance system stability and computational efficiency by isolating and regulating local flow behavior; they are even more remarkable when used for large-scale industrial networks with multiple fluid flow paths that interact dynamically.

Fuzzy logic controllers help effectively control highly temperature-sensitive and quickly variable processes. Fuzzy logic-based control in liquid mixing systems guarantees consistent temperature and level control irrespective of variations in flow rates and external disturbances. Similary, NNPCs have been developed to predict variations in fluid flow level and dynamics in tank systems and apply corrective action to these undesired fluctuations, thereby achieving equilibrium. These smart controllers can simulate system dynamics, and real-time data can be received to continuously adapt to process conditions as they evolve. In addition, deep reinforcement learning (DRL) techniques are employed to effectively achieve fluid flow and thermal control. In PEMFC, DRL-based air supply controllers fine-tune the gas flow rate in accordance with the load conditions, improve thermal uniformity throughout the membrane, and reduce local hot spots. This intelligent flow control decreases entropy generation and the effects of excessive wear, thereby increasing the long-term performance of the system.

In industrial and energy sectors, the integration of AI with physical modeling technology has exhibited promising application in production and various industries. For instance, hybrid predictive control techniques have refined coolant flow and heat transfer in steelmaking systems, thus improving temperature control and energy usage. In aerospace, nonlinear fuel and air regulation methods for gas turbines have resulted in stable combustion, emission reduction, and increased fuel economy. Accordingly, hybrid and fuzzy control systems have been implemented on high-temperature gas flow systems, such as heaters and desalination plants, in which fuzzy–PID controllers perform with high speed and reduced steady-state errors. MIMO fuzzy systems improve hydrothermal management in PEMFC by providing excellent temperature and water distributions throughout the active zones. AI controllers can even be used for biomedical applications. For example, PSO-based and fuzzy logic controllers enhance carbon dioxide gas removal in the oxygenation process by accommodating changes in flow resistance and heat dissipation.

MPC and its variants also provide substantial benefits when they are used in fluid flow applications. In these applications, MPC-based automatic pouring systems in casting industries can maintain a consistent flow and molten metal temperature for enhanced casting quality. Likewise, in gas compression systems and tankless water heaters, MPC ensures stable operation under varying input conditions and rapidly coorects for disturbances in pressure, temperature, and flow rate, temperature, and flow rate. In chemical separation and distillation, adaptive temperature-feedback MPC systems deliver improved operation by optimizing multicomponent fluid mixtures and guaranteeing guaranteeing precise phase separation.

These studies have demonstrated that AI-based controllers can provide not only improved accuracy and stability but also increased interpretability and adaptability compared with conventional PID systems. Combining AI and hybrid control approaches opens a trend toward achieving smarter-than-before, self-supporting, energy-saving fluid management systems that can meet challenges in industrial, biomedical, and environmental applications.

Although the main emphasis of this review was on AI-driven control strategies, the function of actuator mechanisms is still one of the most important factors influencing the flow rate modulation performance and control efficiency of systems [69]. Actuators, such as variable frequency drives for pump speed control, globe valves for precise flow throttling, and peristaltic pumps for volumetric dosing, are the last control elements that physically affect control signals in closed-loop conditions. The effects of such actuators, such as response delay, bandwidth limitation, nonlinear friction, hysteresis, and valve flow coefficients, influence the stability, response time, and efficiency of the control loop and the system [70]. Actuator dynamics and its effect on control performance have been reported in multiple studies. Bordeasu et al. [71] stated that adaptive control strategies integrated with variable frequency drives improve pumping systems' dynamic response and energy efficiency when speed–flow coupling is considered. Dynamic and variable frequency drives are necessary for pumping systems; they are directly related to the response and energy efficiency of such systems. Similarly, Kang et al. [72] analyzed the cavitation and nonlinear flow characteristics of three-way globe valves on the basis of computational and experimental insights and posited that valve geometry and flow behavior should be incorporated into controller design. Furthermore, Ferretti et al. [73] studied a peristaltic pump geometry with stable flow in a research setting and observed problems with flow, such as roller engagement, tube deformation, compliance, and control, which could directly affect control and measurement accuracies. These findings suggest that forthcoming studies on AI-based control strategies should include actuator types and dynamic parameters selected through experiments or simulations. If actuator-level optimizations, such as drive curve calibration, valve sizing, or pump stroke tuning, are introduced to the controller, then controller performance can be compared easily.

Although this is evident in recent results, the positive aspects noted from previous works are limited to several areas of literature. Most AI-based control systems have been simulated in principle and not extensively tested in the real world because their application depends on the research and its validity. The absence of standardized performance evaluation criteria makes it difficult to compare studies. For example, some are based on simple, not very sensitive system models . This lead to fail to adequately represent nonlinear dynamics, turbulence effects, and time-delay phenomena commonly observed in industrial flow systems.. Furthermore, limited attention has been given to long-term stability, scalability, and implementation costs. For achieving the practical implementation and reliability of AI solutions in fluid and gas system management should be addressed

The effectiveness of flow rate regulation schemes involves much more than a control system-style analysis. Validation of different system properties must be part of a solid validation process, which should include the validation of system model design, actuator and sensor aspects, and hardware–software interaction under experimental and simulated settings. Existing studies focused only on control algorithms performance and disregarded hardware-dependent aspects and modeling uncertainties, substantially reducing performance in practice. Hence, future validation work needs to adopt a holistic approach featuring a rigorous framework for system-wide model fidelity validation that includes model fidelity, component-level testing, and experimental benchmarking. In this manner, intelligent control schemes can be regularly integrated and maintained in the industry.

5. Conclusion

This systematic review shows that the application of modern AI-based control systems substantially enhances the accuracy, flexibility, and energy efficiency of fluid flow control compared with traditional PID controllers. AI-based controllers have been examined to have faster transient responses, better stability, and higher resilience to external perturbations compared with their traditional counterparts. As a result , they have been applied in various engineering fields, such as hydrogen and fuel cell systems, and thermal, aerospace, and biomedical applications. By employing the fuzzy logic, neural networks, and MPC, nonlinear. These systems can be controlled, and evident improvements in operational performance and energy conservation can be realized.

This review also emphasized that hybrid and adaptive controllers are particularly effective because they achieve synergy between the features of solid classical controllers and the dynamic learning capabilities of intelligent algorithms. Such an achievement has far-reaching engineering consequences and supports the development of novel autonomous or self-adjusting flow control systems for future manufacturing uses. However, challenges in computation, real-time development, and the possibility for empirical validation remain. Future research threshold focus on optimizating the lightweight AI architectures for embedded systems, digital twin models used in predictive maintenance, and assessment of AI controllers' performance.

This paradigmatic shift has fundamentally transformed the way industries conduct flow regulation. Old feedback loops have been replaced by intelligent, data-driven controllers with all the advantages that new, smart, effective, and autonomous controllers have to offer. Despite AI-based control algorithms have much higher accuracy, adaptability, and robustness compared with conventional strategies, e widespread industrial adoption of AI-based control strategies remains limited. Long-term hardware-in-the-loop testing, cross-platform benchmarking, and interpretable AI integration are necessary for real-life control systems since these can help establish reliability and trust in practical applications. Additionally, combining AI-based controllers with real-time Internet of Things sensor networks and cloud-enabled platforms can enhance adaptive, data-driven flow control, Moreover, the development of AI-based controllers coupled with real-time Internet of Things sensor networks and the establishment of cloud-enabled systems could help optimize adaptive and data-driven flow control,

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Conflict of Interest

The authors confirm that they have no conflict of interest regarding the publication of this manuscript.

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استراتيجيات التحكم القائمة على الذكاء الاصطناعي للتحكم في معدل تدفق السوائل والغازات في أنظمة الطاقة والعمليات: مراجعة منهجية

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المستخلص

ساهمت المسيطرات المدعمة بالذكاء الاصطناعي في زيادة دقة ومرونة ، وكفاءة التحكم في معدل تدفق الغازات والسوائل. في المقابل، لا تتمتع المسيطرات التقليدية من نوع PID عادةً بالتدريب الكافي للتعامل مع الأنظمة الديناميكية غير الخطية والاضطرابات المتغيرة مع الزمن، مما يؤدي إلى محدودية الاستقرار ودقة السيطرة. ركزت معظم الدراسات البحثية الحالية على تصميم وأداء المسيطرات الفردية القائمة على الذكاء الاصطناعي لآلات محددة، دون إجراء مقارنة منهجية بين هذه الأجهزة في مختلف تطبيقات الصناعة والطاقة. وعليه، تهدف هذه الدراسة الى سد الفجوة العلمية من خلال مراجعة ودراسة وتحليل ٣٤ دراسة محكمة منشورة بين عامي ٢٠٢١ و٢٠٢٤، تم الاستشهاد بها من قواعد بيانات سكوبس وويب أوف ساينس، وصُنفت وفقًا لهيكل PRISMA (بنود الإبلاغ المفضلة للمراجعات المنهجية والتحليلات التلوية). اظهرت النتائج الكمية أن المسيطرات المدعمة بالذكاء الاصطناعي تتمتع بأداء أعلى بشكل عام من المسطرات التناسبية التكاملية التفاضلية (PID) التقليدية، مع استجابة أسرع بنسبة تتراوح بين ١٢ و٨٥٪، وانخفاض في أخطاء الحالة المستقرة بنسبة تتراوح بين ١٥ و٦٧٪، وانخفاض في التجاوز بنسبة تتراوح بين ١٨ و٤٠٪، مما يدل على دقة واستقرار عالٍ للأنظمة. واشارت النتائج والتحليلات إلى أن المسيطرات الضبابية والهجينة تتمتع بمرونة عالية في التعامل مع ظواهر التدفق غير الخطية والديناميكية، بينما تتميز المسيطرات القائمة على التنبؤ بالنموذج والتحسين بدقة عالية في عمليات متعددة المتغيرات. علاوة على ذلك، تُحسّن تقنية السيطرة بالذكاء الاصطناعي لتطبيقات الطاقة والهيدروجين وسوائل العمليات من قابلية التشغيل، وتقلل من استهلاك الطاقة، وتُمكّن من الإدارة المرنة في الوقت الفعلي في ظل الأحمال المتغيرة باستمرار. وبذلك، تُرسّخ هذه الدراسة أساسًا متينًا لأطر السيطرة الذكية من الجيل التالي، وتفتح آفاقًا جديدة لاستراتيجيات متقدمة وقائمة على البيانات نحو تنظيم التدفق وتطبيقات أنظمة الطاقة المستقبلية.