Review

Not peer-reviewed version

Application of Artificial Intelligence in Control Systems: Trends, Challenges, and Opportunities

Enrique Fernández Mareco * and Diego P. Pinto-Roa

Posted Date: 10 October 2025

doi: 10.20944/preprints202510.0761.v1

Keywords: intelligent controllers; machine learning; metaheuristics

Review

Application of Artificial Intelligence in Control Systems: Trends, Challenges, and Opportunities

Enrique Fernández Mareco * and Diego P. Pinto-Roa

Polytechnic Faculty, National University of Asunción

* Correspondence: efernandezmareco@pol.una.com.py

Abstract

Context of the problem. **Artificial Intelligence (AI) has changed the way industries design, build, and enhance control systems.** AI uses machine learning and evolutionary algorithms to improve control systems. This technology helps them adapt to critical situations. It also helps them manage noise in input signals and adapt to changing environments. *Objectives of the study.* Given the large number of scientific papers published in this field, it is necessary to examine and analyze the newest AI techniques applied to control systems, determining recent advances, the advantages of these approaches over traditional methods, and the remaining challenges. *Method or Approach to the Study.* This paper looks at how AI is used in control systems. It does this by checking existing literature and searching key databases that connect AI and control systems. *Main results*. The systematic mapping resulted in a detailed review of 184 scientific articles published in the last 15 years. The study showed three key trends: (a) Hybrid control models mix machine learning with traditional methods, (b) Metaheuristic algorithms optimize architectures and parameters, and (c) AI techniques enable adaptive control models. *Conclusions or implications*. This study highlights current trends and benefits of smart controllers, while also identifying gaps in the literature and proposing future research directions.

Keywords: intelligent controllers; machine learning; metaheuristics

---

1. Introduction

Automatic control theory and artificial intelligence (AI) have developed side by side since the 1950s. They began with a focus on information science and later grew into control theory. In the 1980s, AI gained important uses in business and industry. It grew at a consistent pace until the end of the twentieth century, with many studies on intelligent controllers [1]. Control theory evolved into modern control as processes needed more complex control. It now combines AI techniques with both classical and contemporary methods [2].

The growing need for advanced solutions highlights the demand for intelligence control techniques. It shows how intelligent controllers manage complex processes. Traditional math models often struggle in these situations. Uncertainties in real systems usually show nonlinear dynamics and changing parameters. This has led to updates in AI theory and its use in controllers. AI and control theory work together. AI helps improve controllers, and they also give each other feedback. This boosts both fields. This article reviews the latest in AI controllers by analyzing 186 scientific papers

The authors organized this paper to provide a straightforward answer to key questions. It presents a clear synthesis of answers from the latest scientific literature. This study seeks to improve our understanding of intelligent controllers powered by artificial intelligence through analysis.

Justification of the review:

A systematic review of AI in control systems helps us to understand technology today. It shows the impact and explores future opportunities. Researchers can identify strengths, weaknesses, opportunities, and threats. This helps guide the evolution of these systems. It leads to better safety, greater effectiveness, and a systematic approach. It also helps build a strong framework for future

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 October 2025 doi:10.20944/preprints202510.0761.v1

research in this new field. It helps us to evaluate the latest applications. The lector can see which AI methods are the most successful. It shows the current limits and challenges of AI in control systems. This helps identify ways in which AI can increase efficiency, accuracy, and robustness. Control systems can adapt to new conditions and still perform well.

The systematic review sparks new ideas and methods. Combining various AI methods with traditional control strategies helps us create new architectures. This allows us to tackle challenges that seemed impossible before.

Article Structure:

Here is the framework of the article: Section 2 explains the method, covering data collection and analysis. Section 3 shows a systematic mapping. It shows important relationships and patterns. Section 4 concludes with findings, trends, gaps, and contributions, and provides recommendations. This section also lists the sources used in the references.

2. Methodology

a. Design of the systematic mapping:

This study has two main steps for the systematic review: (1) establishing the review protocol and (2) conducting the evaluation process.

A review protocol defines a clear strategy for conducting a literature review. This article uses a systematic review process. It uses a simple method to analyze and combine the existing literature on a specific topic.

The process includes:

- Defining clear criteria for choosing relevant studies.
- Do thorough search in academic databases.
- Checking the quality of the chosen items.
- Combining the findings to draw conclusions or identify research gaps.

The aim is to provide a comprehensive and unbiased overview of the current state of knowledge on the subject. To start the review, the authors of this study created a search equation applied to IEEE Xplore, ACM Digital Library, ScienceDirect, Elsevier, Springer, and Google Scholar. This helped them access a wide variety of relevant scientific publications.

This review searches for the chosen bibliographic databases for relevant articles. It includes those published in journals and conference proceedings. They constructed search expressions such as: ("Design Intelligent Controllers*") OR ("Control Systems Controllers*" AND "Intelligent*" AND ("Fuzzy" OR "Genetic Algorithms*" OR "PSO" OR "Machine Learning*" OR "Neural Networks*" OR "Hybrid Algorithms*")) OR ("Engineer applications*" AND "intelligent controllers*" AND ("Strategies*" OR "Methods*" OR "Process*")).

This study used the preliminary search equation to find 465 records. Table 1 summarizes these records and includes them in the evaluation process.

Table 1. Number of Research Articles Identified per Database. (Source: Own elaboration based on systematic review).

Database	Search results
IEEE Xplore	159
Springer	29
Elsevier / Science Direct	243
Digital Library	3
Google Scholar	12
AJC	2
JART	2
WILEY	9
JCSUT	1
JCSSI	1

After gathering many articles, the review team filtered and selected them according to specific criteria. They checked each article's relevance and quality, discarding those that fell short. Only papers that provided helpful and relevant information for the research questions made the cut.

The inclusion, exclusion, and selection criteria used were:

Inclusion Criteria (CI):

CI-1: Relevant terms appear in the title of the document or abstract.

CI-2: The publication of the article is dated from 2000 to 2025.

CI-3: The abstract of the primary study refers to the problem covered by the corresponding research question.

CI-4: The primary study has an implementation in control engineering.

CI-5: The primary study addresses techniques and strategies for implementing an intelligent controller.

CI-6: Research articles consisting of an evaluation of the research presented (survey, experiment, experience report, and case study).

Exclusion Criteria (EC):

EC-1: Documents published before 2000.

EC-2: Documents presenting a general approach to control systems.

CE-3: The primary study of the candidate is not an article, survey, art study, or review.

CE-4: Documents that present a general approach in applied engineering.

CE-5: The candidate did not write the primary study in English.

CE-6: The primary study is not related to the problem of the corresponding research question.

Selection criteria (SC).

CS-1: Apply inclusion and exclusion criteria to abstracts of articles, surveys, art studies, and reviews.

CS-2: We read the conclusions of the remaining papers to identify the necessary properties that were not evident in the abstracts.

CS-3: After you have obtained a refined list, we will read all of them. To do this, we used the inclusion and exclusion criteria for its content.

CS-4: Documents presenting an overview of intelligent controllers.

CS-5: Research articles that have discussed problems, techniques, and methods of implementing intelligent controllers.

CS-6: Research articles that have discussed the limitations and success factors of intelligence controller deployment processes.

b. Evaluation of the method:

Once the review protocol was defined, this study went to the evaluation phase of systematic analysis. We adopted an evidence-based approach, reporting the number of records identified, examined, verified for eligibility, and ultimately included in the review. The modified search query retrieved a total of 465 records. The authors analyzed each article's abstract in detail to assess its relevance. They selected articles that discussed control structures, algorithms, optimization techniques, and key parameters for full-text eligibility review, resulting in a final set of 186 articles (see Figure 1).

The authors of this work established and defined the research questions that guided the entire process. These questions aim to address specific aspects related to the application of artificial intelligence in control systems, such as:

Q1: What are the sources that publish the most about smart controllers?

Q2: What are the types of engineering contributions and applications to intelligent controllers?

Q3: What are the types and research approaches of intelligent controller studies?

Q4: What are the current research trends in intelligent controllers?

Q5: What control structures and techniques specify an intelligent controller?

 doi:10.20944/preprints202510.0761.v1

Q6: What are the most reported computational tools or algorithms in the literature for the design of intelligent controllers?

Q7: What are the open challenges and research opportunities?

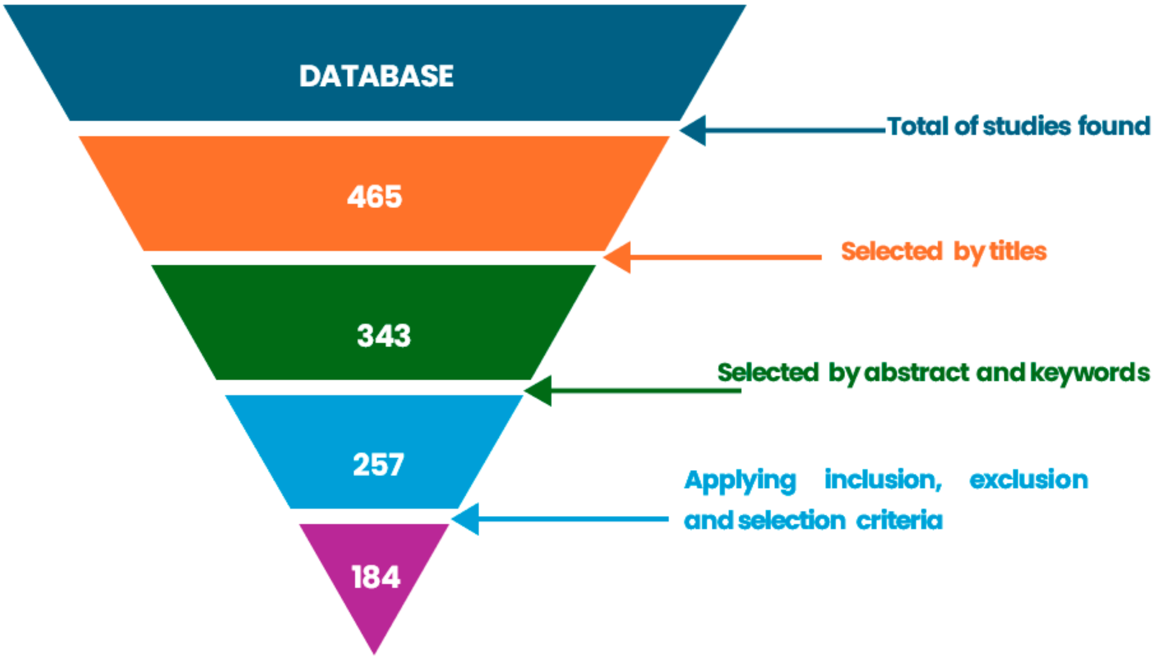

Figure 1. Evaluation of research articles. (Source: Own elaboration based on systematic review).

c. Data extraction:

Data extraction from chosen studies for AI control systems followed a systematic process. This ensured an accurate and complete collection of relevant information. The steps for extracting data from the studies are clear and follow systematic review methods.

We defined the inclusion, exclusion, and selection criteria at the start of the relevant studies. We examined every study to discover the control structure, control techniques, optimization methods, adaptation methods, and algorithms used. We grouped the studies by their categories, based on what they contributed. From each selected article, we extracted key information, including:

- General Information of the Study: Year of publication, authors, title, source of publication.
- The sections —abstract, introduction, and methodology—were reviewed in detail. The abstract sought an overview of the primary technique or method used, while the introduction clarified the objectives and specific applications of the control system.
- In the Methods section, we outline the specific algorithms and procedures utilized in each study, which streamlined the accurate sorting of the articles into those targeting optimization and control system structure
- From the results and discussion, we extracted information on the performance of each technique and the justification for its application in the study.

Specific algorithms for optimization, control, and adaptation were documented, along with their distinctive features, in each article. This document allowed us to pool the studies using similar algorithms.

This study examined the structure of the control system to see how each technique works in specific contexts. This helped it sort the articles into categories such as:

- Neural networks
- Evolutionary algorithms
- Machine learning
- Predictive control

- Metaheuristic optimisation
- Fuzzy logic
- Hybrids
- And more.

We label each item according to the structure of the control system used and the type of optimization or technique.

We compared the extracted data to identify key patterns and differences in the use of control techniques and structures between studies.

To ensure consistency in classification and data extraction, we cross-reviewed the articles. This task involved verifying that we correctly classified items with similar characteristics into the same categories.

Additionally, we used tables and matrices to organize and visualize the data. This structure allowed for efficient comparison between studies and ensured the extracted data was complete and representative of each article's content.

3. Results and Discussions

From identifying sources of publications on smart controllers to assessing research trends and methodological approaches used in this field, this comprehensive analysis provides a detailed view of the current landscape. We analyze the most reported computational tools and algorithms in the literature for the design of these controllers.

3.1. Publication Sources

The sources of intelligent controller publications reveal a marked predominance of publishers, Elsevier being the most prominent, representing 75% of the total of 186 articles reviewed. IEEE and Springer share a similar percentage, each contributing 12.1%. Wiley contributes 8%.

We found that the journals published 82.3% of the reviewed articles. Specialized intelligent controller conferences presented the other 17.7%. These figures highlight publishers' significant role in disseminating scientific articles in this domain. Figure 2 summarizes these values.

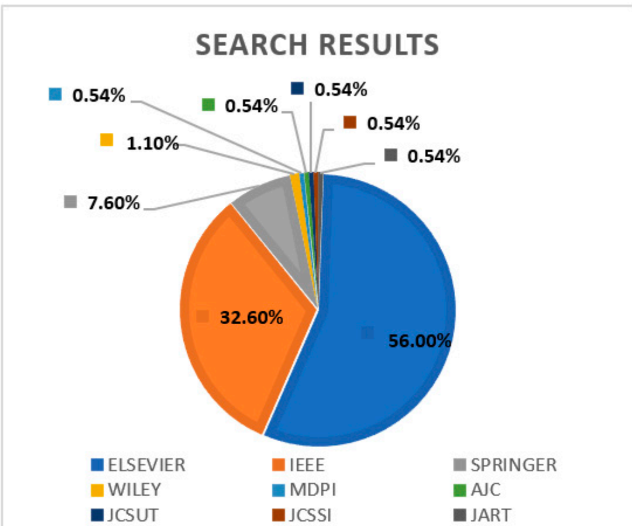

Figure 2. Search results for publications referring to intelligent controllers. (Source: Own elaboration based on systematic review).

3.2. Engineering Contributions and Applications in Smart Controllers

The review of research types has enabled us to identify and reduce three primary areas of contribution in the field of engineering. Firstly, the contribution related to *control model* strategies

doi:10.20944/preprints202510.0761.v1

stands out, representing 49.19% of the total, which encompasses the development and improvement of new intelligent algorithms for controllers, whether intelligent or conventional, as well as the introduction of new control structures with intelligent algorithms. The category of *optimization models* constitutes 27.41%, distinguishing itself through the presentation of new intelligent optimization models and the integration of artificial intelligence techniques with other conventional or intelligent ones.

Finally, the contribution of *adaptability*, with 23.28%, focuses on developing intelligent controllers that exhibit adaptability in their structure to provide control with high-speed response, robustness, and other qualities. These results provide a comprehensive overview of the various engineering contributions and applications in the field of intelligent controllers. Figure 3 presents a summary of the total number of articles according to the contribution made to intelligent controllers.

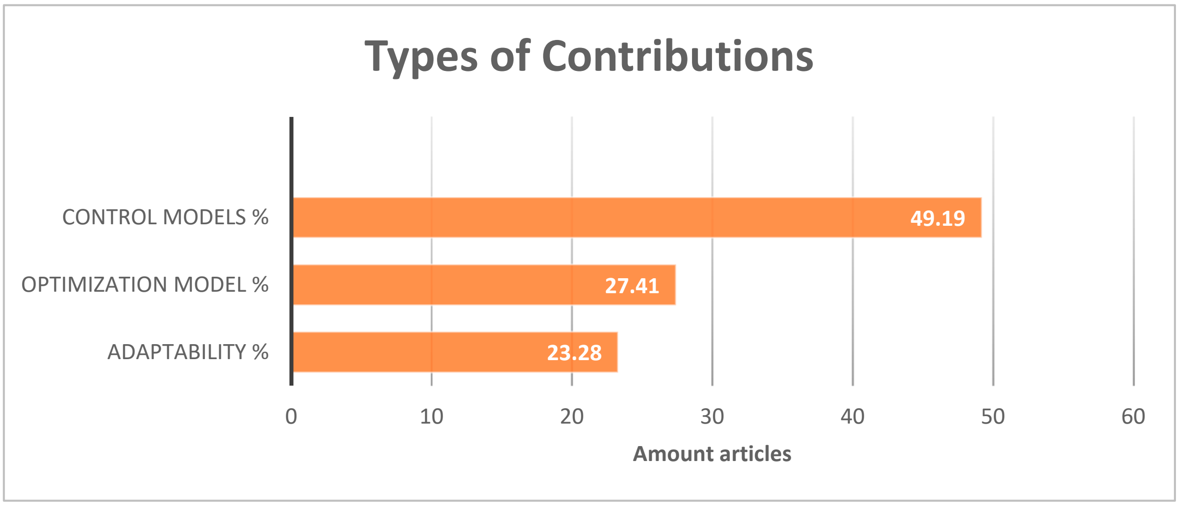

Figure 3. Types of Engineering Contributions to Intelligence Controllers. (Source: Own elaboration based on systematic review).

3.3. Structures and Techniques in Intelligent Controllers

Intelligent controllers use diverse control structures and techniques to optimize efficiency and adaptability across various systems. Artificial neural networks are among the most common structures; they excel at modelling nonlinear behaviors and learning complex patterns. Fuzzy logic and its ability to handle uncertainty offer a crucial option in dynamic environments.

Many specific techniques use meta-heuristics such as particle swarm optimization (PSO) and genetic algorithms (GA) to fine-tune controller parameters for better performance. Predictive Control is particularly good at anticipating and managing changes in a system's dynamics. Multilayer neural networks (MNAs) have adaptable structures that can model complex systems and learn from data. The Adaptive Fuzzy Tracking Algorithm-based Control and Fuzzy MIMO Control prove how fuzzy logic can adapt to many inputs and outputs in complex systems. In e-learning, dynamic parameter adjustment and grammatical evolution are effective strategies. These techniques show how control engineering is moving towards more adaptable solutions, combining fundamental principles with AI strategies to tackle modern system complexities.

3.4. Most Reported Computational Tools and Algorithms

The results of this study offer information on preferences and trends in algorithms and control structures. This comes from an analysis of scientific articles published from 2000 to early 2025. The most common classifications found are:

- Artificial Neural Networks: 9.77%
- Evolutionary or Optimization Algorithms: 15%

 doi:10.20944/preprints202510.0761.v1

- Fuzzy Logic: 19.46%
- Hybrid Methods: 26.6%
- Iterative Learning Control: 4.1%
- Internal Model Control: 3.1%
- Machine Learning: 1.85%
- Metaheuristic Optimization: 11.4%
- Model Predictive Control: 6.02%
- Others: 2.96%

For a better understanding, we provide a brief description of each algorithm mentioned in next subsection.

3.4.1. Artificial Neural Networks (ANNs) replicate the human brain, consisting of layered neurons that process data and refine weights to perform complex tasks. The layers consist of an input layer receiving the data, hidden layers that transform it, and an output layer that produces the result. ANNs employ backpropagation to eliminate errors and increase accuracy in applications such as image recognition and language processing. [129–131].

3.4.2. *Evolutionary Algorithms* (EAs) are methods inspired by biological evolution. They find optimal solutions using selection, crossover, mutation, and survival of the fittest. EAs are great for solving complex problems in large, nonlinear search spaces. Key components of EAs include:

- A population of possible solutions
- Selection processes to identify suitable individuals
- Crossover to create new solutions
- Mutation to maintain diversity
- Survival to maintain the strongest individuals

There are several types of EA. These include genetic algorithms, evolutionary programming, evolutionary strategies, and genetic programming. Researchers use these algorithms for optimization, design, artificial intelligence, and solving complex problems [132–134].

3.4.3. Fuzzy Logic (FL) is based on classical logic dealing with uncertainty and imprecision. Instead of just true or false, it uses truth values ranging from 0 to 1. This approach helps to model unclear situations, such as "high" or "hot." The key components of Fuzzy Logic include:

- Fuzzy sets: These have degrees of membership.
- Membership functions: They assign degrees of membership to items.
- Fuzzy rules: These guide decisions in an "if-then" style.
- Fuzzy inference: This process combines the rules.
- Defuzzification: Converts fuzzy results into clear values.

Solutions apply fuzzy logic in areas such as:

- Control systems
- Medical diagnosis
- Image processing
- Decision-making

This is especially useful when dealing with uncertainty [135–137].

3.4.4. Hybrid Methods (HMs) mix different approaches to tackle complex problems better. They use the strengths of each technique. HMs are flexible and can adapt to various issues. They overcome limitations while increasing accuracy, efficiency, and robustness.

Applications include hybrid optimization, hybrid neural networks that integrate FL, and fuzzy-genetic controllers that optimize control decisions. HMs are widely used in robotics, intelligent system design, control engineering, and optimization in economics and finance [138–140].

3.4.6. *Iterative Learning Control* (ILC) is an advanced control technique that improves performance in systems that perform repetitive tasks, adjusting control actions in each cycle to reduce errors based on previous attempts. T his a pproach i s h elpful i n a pplications t hat r equire h igh precision, such as in industrial automation, robotics, and manufacturing, where iterative learning

 doi:10.20944/preprints202510.0761.v1

optimizes the accuracy of the process. Through learning from past mistakes and iterative predictive control, ILC enables continuous improvements, making it ideal for high-precision systems, such as robots and devices such as 3D printers [141–143].

3.4.7. Internal Model Control (IMC) is a control technique that utilizes an internal model of the system to predict and compensate for disturbances in real-time, enabling early corrections to be applied and maintaining the accuracy of the results. IMC is exceptionally robust and effective in industrial environments with uncertainties, such as temperature and pressure control in chemical engineering and manufacturing processes. Its internal model allows for precise adjustments and rapid disturbance compensation, making it ideal for complex control systems in the process industry [144–146].

3.4.8. *Machine Learning* (ML) is a branch of AI that allows systems to learn and improve automatically from data, without the need for specific programming for each task. ML analyses patterns in the data to make predictions or decisions. Solutions applied ML in areas such as image recognition, language processing, fraud detection, and personalized recommendations. ML models are trained in large amounts of data to identify patterns, adjust parameters, and generalize new data. It encompasses various types, including supervised, unsupervised, and reinforcement learning, with applications in finance, healthcare, commerce, and autonomous vehicles [147–150].

3.4.9. Metaheuristic Optimization (MO) is a methodology that seeks approximate solutions to complex optimization problems, where traditional methods are ineffective due to high dimensionality, nonlinearity, or multiple local optima. MO explores the search space without depending on the specific characteristics of the problem. Natural processes inspire MOs approaches, such as biological evolution, flock behavior, or annealing in metallurgy. Used in engineering, logistics, finance, and bioinformatics, it alternates between exploring new solutions and refining current ones to optimize performance [151–154].

3.4.10. Model Predictive Control (MPC) is an advanced control technique that utilizes mathematical models to forecast the future behavior of a system and optimize control decisions in real-time. MPC calculates and applies optimal actions within a prediction horizon, continuously adapting through new measurements. These actions allow you to manage constraints and adjust decisions at every step, making them ideal for complex nonlinear systems with changing operating conditions. MPC is widely used in industrial processes, energy systems, autonomous vehicles, and finance, where adaptability and robustness are crucial to optimizing performance and minimizing costs [155–158].

3.5. Outcome of the Studies

Tables 2 to 4 present a classification of the 184 articles analyzed, specifying the type and focus of research that categorizes them into one of these three topics: the control model, the implementation of techniques for parameter optimization, and adaptive controllers. In addition, the classification is based on the type of contribution, exploring various contributions and engineering applications derived from advances in intelligent controllers, including contributions related to control, optimization, and adaptability models. In addition, the structures and control techniques used to specify and design intelligent controllers are analyzed, encompassing both classical and modern control structures, as well as the artificial intelligence techniques employed, such as neural networks, fuzzy logic, and evolutionary algorithms. Finally, the most widely used computational algorithms in the literature are those for designing and implementing controllers that enhance the efficiency and performance of intelligent controllers in various applications and scenarios.

3.5.1. Result of Contributions: Control Models

The integration of AI techniques into smart controllers represents a significant advance in the field of control systems. These new control models combine conventional methods with AI approaches to improve the adaptability, accuracy, and efficiency of control in complex and variable environments. This combination enables us to address challenges that range from variability in

 doi:10.20944/preprints202510.0761.v1

operating conditions to the presence of unforeseen disturbances, opening new opportunities to optimize and continuously improve system performance. These articles present a relevant contribution of control models in the following types:

3.5.1.1. Hybrid Controllers

This type of controller combines two or more control techniques or algorithms, typically to leverage the strengths of each and compensate for their weaknesses. Hybrid controllers are becoming increasingly popular in industrial, energy, and complex system applications, particularly in the context of AI, optimization, and classical control.

Advanced control and optimization approaches are evident in the articles, applied to dynamic, nonlinear, and complex systems. Several papers propose hybrid methods that combine techniques such as ANN and FL. At the same time, they apply EAs to improve model identification, controller design and tuning, and robustness against uncertainties and perturbations.

Several works address architectures that integrate ANNs and FL type-1, type-2 or fractional logic for control and compensation tasks in the presence of nonlinearities and uncertainties ([11,16,44,45,67,87,88,96,97,100,105]).

The application of genetic algorithms, differential evolution, evolutionary strategies, particle swarm optimization, harmony search, cuckoo search, and others for the optimization of strategies, design and rules in hybrid controllers is reported ([10,12,26,30,50,57,77,83,97,100,171,205]).).

Several studies have implemented model-based predictive control (MPC), often combined with ANNs or FL, to speed up calculations or improve tracking and robustness ([38,40,79,82,85,89,116]). The combination of classical control techniques (PI, PID, H∞, Deadbeat, SMC) with intelligent components (ANN, FL) allows for greater accuracy, adaptability, and robustness, even under changing conditions or with incomplete models ([14,21,25,41–43,46,57,63,112]).).

The revised approaches are applied and validated in real or simulated systems, such as power plants, turbines, robots, chemical processes, hybrid energy systems, irrigation control, and autonomous vehicles, showing improvements in performance, error reduction, robustness, and energy efficiency compared to traditional methods ([25,57,63,79,171,205]).

3.5.1.2. Fuzzy Logic Controllers

Fuzzy logic controllers (FLC) have proven to be highly effective in various applications. They are known for their ability to handle uncertainty in control systems and for their ease of adaptation to different operating conditions. These controllers use IF-THEN rules and fuzzy sets to adjust system output. They are beneficial in applications where operating conditions constantly change and require an adaptive response.

A Takagi–Sugeno-type incremental fuzzy state model improves stability and error rejection by integrating an FLC-LQR and an optimal observer [33]. In the automotive field, a comparison between PID and fuzzy logic controllers in vehicle stability shows that fuzzy logic is more robust, although PID is more straightforward to implement [36].

For the control of converters and rectifiers, a fuzzy neural type-2 controller (T2FNS) has been proposed, outperforming the traditional PI controller in speed, overshoot, and power quality [47]. Similarly, an FLC designed for a DC–DC converter achieves better response times and greater disturbance rejection compared to conventional PI controllers [17].

In water treatment systems, a Mamdani FLC has been employed for pH control, achieving system stability and reducing contaminants in scenarios where traditional PIDs fail [105]. For electric motors, a Mamdani FLC demonstrates better tracking performance and robustness against disturbances when compared to the PID [107].

In wind energy systems, an adaptive FLC is used to maximize power generation, delivering better dynamic performance than PI controllers [92]. In agricultural applications, an efficient FLC has been developed to regulate temperature and humidity in greenhouses, showing high efficiency and low error under real conditions [113]. Finally, for photovoltaic systems, an optimized FLC for MPPT achieves faster convergence and higher accuracy, while also reducing the number of rules and eliminating steady-state oscillations [121].

3.5.1.3. Predictive Controllers

Model-based predictive controllers (MPCs) predict system output based on an internal model and adjust control actions in real time. They are ideal for applications that require anticipation and continuous correction. A detailed review of the use of MPC in agriculture covers classical approaches as well as robust, nonlinear, distributed, and stochastic variants, reporting successful applications in irrigation, machinery, production, and environmental control in greenhouses [54]. It is worth noting that MPC surpasses traditional and AI-based methods by efficiently handling multivariable, time-delayed, and nonlinear systems. However, there are still challenges for its practical implementation in real agricultural environments.

A Robust Economic Predictive Control (reMPC) method integrates stochastic information on perturbations in time-invariant linear systems and employs a tube-based MPC formulation to ensure feasibility and robustness [34]. This approach makes use of known fault distributions to optimize performance and design suitable terminal costs, and has been validated in a CSTR reactor, demonstrating advantages over conventional robust MPCs.

3.5.1.4. Controllers with Iterative Learning

Applications that require precision in repetitive tasks utilize Iterative Learning Controllers (ILCs). These controllers adjust the control signal based on the errors observed in previous cycles, progressively reducing the error in each repetition. A comparison of three Norm-Optimal ILC schemes in repetitive systems—standard quadratic ILC (QILC), ILC with integrated estimation (E-QILC), and ILC with Kalman filter (K-ILC) in the iteration domain—shows that although the approaches are equivalent under certain conditions, the K-ILC method stands out by combining fast convergence with high robustness against noise [24]. Simulations on a mass-spring-shock absorber system validate its effectiveness.

A robust ILC controller incorporates performance weighting functions to ensure convergence even in the presence of plant uncertainty [73]. This method establishes clear convergence conditions and design criteria to improve tracking, validated through simulations using a mass-spring-shock system.

3.5.1.5. Neural Controllers

Artificial neural network-based controllers (ANNCs) can learn and adapt to changing conditions by adjusting their internal weights. These controllers help handle nonlinear and complex systems. A review of the impact of machine learning on control systems shows that data-driven models can replace or complement classical components of the control loop [89]. A case study demonstrates that a deep neural network enhances the performance of a surface-based autonomous vehicle, improving resilience against modeling and noise errors and outperforming the traditional linearizing controller.

A proposed robust predictive control strategy utilizes ANNC in two stages: one for modeling the plant and the other for residual uncertainty, achieving stability and improved robustness in a pneumatically actuated servomechanism validated experimentally [5]. Another approach introduces the learning feedback linearization (LFL) method, where a single NARMA-type MLP neural network learns to linearize the input of nonlinear systems, enabling subsequent control using a classical PI controller [28]. Simulations validate this method successfully.

A different controller is based on a fuzzy cerebellar model modified with a functional link network (FLMFC), combined with a sliding mode controller, and is used to synchronize chaotic systems and control an inverted pendulum, demonstrating high robustness to perturbations in simulations [8].

In the area of electric motors, an ANNC for a three-phase induction motor shows improved speed tracking and response to disturbances compared to a fuzzy controller [106]. For electric vehicle charging stations, an intelligent adaptive control system based on an ANN-PMC neural controller improves energy management, reducing overshoot and DC bus settling time [121].

Finally, two intelligent control strategies based on reinforcement learning with deep neural networks (RL-DLNN) have been applied to chiller-type HVAC systems, demonstrating superior adaptation, stability, and tracking compared to PID and MPC controllers, particularly in highly nonlinear and disturbed MIMO systems [216].

Table 2 presents the articles that contributed to control models in control systems-based AI.

In summary, Figure 4 presents a classification of the groups of control models that contribute to the application of AI in control systems.

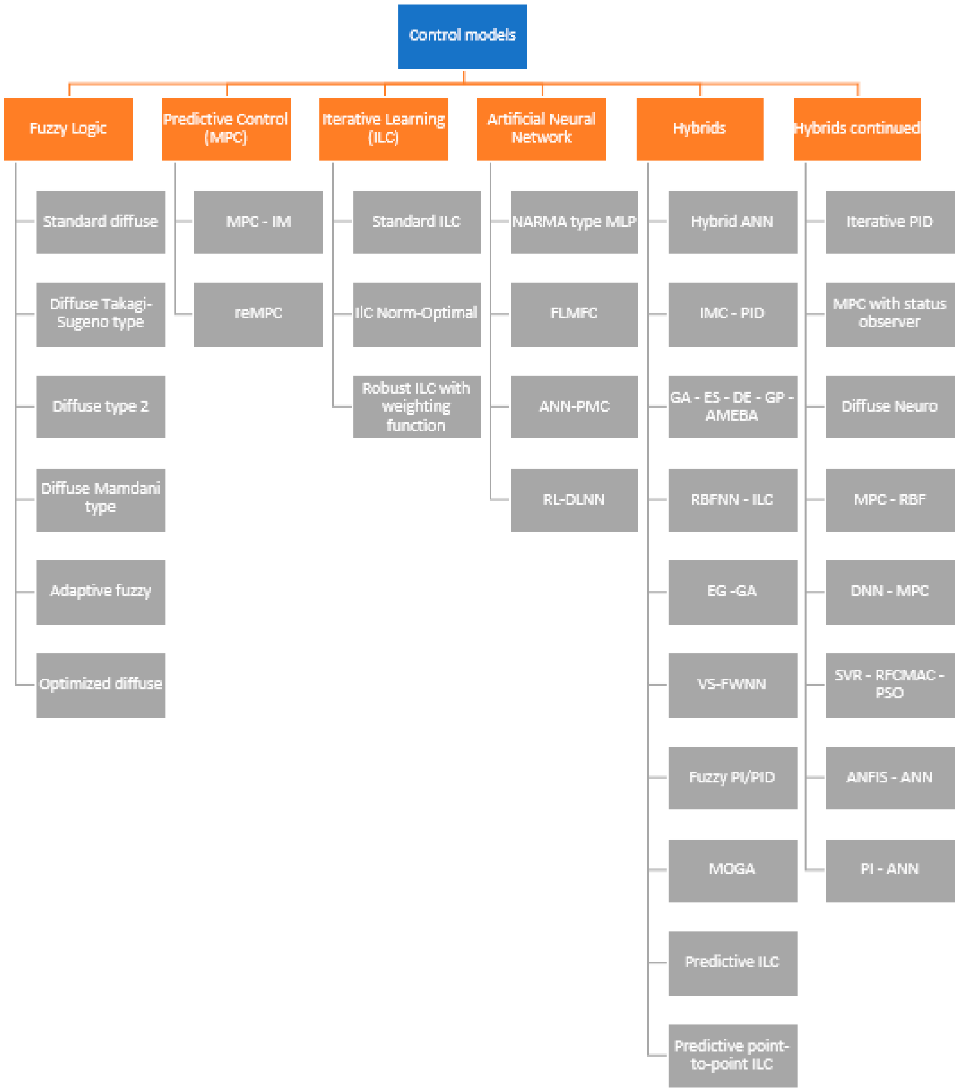

Figure 4. Control Model Contribution Type Groups. (Source: elaboration based on systematic review).

Table 2. Result of the classification of the analyzed articles according to the contribution of control models. (Source: Own elaboration based on systematic review).

ID	Year	Control structures	Set strategies	Algorithms	Ref.

1	2014	Neural Model and Controller, ANN	Supervised and unsupervised	Kohonen and the Gradient Descent Method	[45]
2	2016	Internal mode control PID, IMC-PID	Set-point Change Test y FOPDT	Least squares method.	[25]
3	2015	Fuzzy Logic Controller, FLC	Linear square diffuse base regulator (FLC-LQR)	FLC Tagaki-Sugeno Incremental State Model (T-S)	[33]
4	2016	PID, FLC, PID–FLC, Control with Thresholds	PID incremental, FLC Mandami	Fuzzy logic	[36]
5	2018	Model-Based Predictive Control, MPC	Predictive Control	Predictive algorithm	[54]
6	2016	Predictive control based on a robust economic model, REMPC	Predictive control using stochastic information	Predictive algorithm	[34]
7	2014	Optimal ILC based on standards, Norm-optimal ILC	Quadratic ILC, Estimation-based QILC, Kalman-based ILC	Optimal iterative learning	[24]
8	2015	PI	Identification of type grey box and black box	Parametric and Structural Evolutionary Algorithms	[26]
9	2006	Widespread IP	IL and ANN	LMI and RBFNN	[35]
10	2017	Red neuronal feedforward	ANN	GE Grammatical Evolution and Genetic Algorithm	[50]
11	2018	Fuzzy Wave Neural Networks, VS-FWNN	ANN	Gradient descent with adaptive rates	[67]
12	2002	Programmed Gain Control and Fuzzy PI	FL	MOGA	[77]
13	2017	PID and PI Cascading	Cascade control	GA	[57]
14	2001	H infinity	Designing a specified structured	GA	[30]
15	2004	H2	Feedback control of states and outputs, and control with a fixed structure	Sequential Linear Programming Matrix Method, SLPMM	[15]

16	2018	MLC, NN	CNN	RBF	[89]
17	2016	Predictive ILC, PILC	IL	Quadratic Cost Function	[39]
18	2018	Point-to-Point Iterative Learning of Predictive Control, PTP ILMPC	IL and MPC	Iterative Learning Observer, ILO, and Quadratic Programming, QP	[40]
19	2011	Iterative PID Learning Control	PID - ILC	ILC	[21]
20	2014	Robust ILC	Feedback + ILC	ILC	[73]
21	2017	MPC	MPC	SCESO y QP	[38]
22	2015	NFSS-MPC	Predictive Control	Gradient descent with backpropagation	[79]
23	2018	MPC	INNEM (Neural Inverse Model)	RBFNN	[82]
24	2018	DNN	LSTM, ANN, and LSTMSNN	NNB	[85]
25	2018	RMPC	MPC - ANN	NNF y MEM	[5]
26	2008	RFCMAC	CMAC	SVR - PSO	[80]
27	2016	Diffuse PID	PID with fuzzy logic with Mamdani structure	Euler-Lagrange y FL	[87]
28	2015	VOFFLC	Fuzzy variable-order fractional PID with Mamdani structure	Nelder–Mead	[88]
29	2004	PD-ELC	PD	ELC	[9]
30	2008	FC7, ANFIS, ANN	FC7, ANFIS with Sugeno structure, ANN	FL, Gradient Down and Least Squares, backpropagation	[91]

31	2018	ANN	PI - ANN	Levenberg-Marquardt	[96]
32	2016	ANN	NARMA and PI	LFL	[28]
33	2014	IT2F-PID	PID, IT2-FLS	Karnik–Mendel (KM) and the average of the extremes	[11]
34	2018	FPID y FO-FPID	FOPID and Fuzzy Logic	PSO and DE	[83]
35	2019	Deadbeat Fuzzy Logic Controller	Fuzzy logic	Fuzzy logic	[42]
36	2017	FLMFC	FLC	PI Learning Algorithm	[8]
37	2019	Fuzzy-based sliding mode (FSMC)	SMC	Hybrid Imperialist Competitive Algorithm (HICA)	[10]
38	2019	FNNC	FLC and ANNC	Multi-Objective Particle Swarm Optimization (MOPSO)	[41]
39	2019	Self-constructing fuzzy neural network controller (SCFNN)	FLC and ANNC	Adaptive Learning Rate (ALR) and Lyapunov Stability.	[46]
40	2017	Fuzzy logic smart controller (FLSC)	FLC and MIMO	Fuzzy logic	[63]
41	2016	Predictive Fuzzy Controller	FLC and ANNC	MLP, ART-2, and PNN	[14]
42	2019	FLC-MPPT	FLC	Fuzzy Logic Mamdani	[43]
43	2017	T2FNS (Type-2 Fuzzy Neural System)	FLC and ANNC	Gradient Descent	[47]
44	2017	scaling factor-based fuzzy logic controller (SF-FLC)	FLC	Algorithm QOHS (Quasi-Oppositional Harmony Search)	[12]
45	2014	ANFIS (Adaptive Neuro-Fuzzy Inference System)	FLC and Adaptive ANNC	Least Squares Estimation (LSE) and Backpropagation	[44]

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 October 2025 doi:10.20944/preprints202510.0761.v1

46	2014	FLC	FLC	Fuzzy logic, like Mamdani	[17]
47	2015	Online ANFIS supervised by Fuzzy PID	PID, FLC, and Adaptive ANNC	Fuzzy ART, Backpropagation, and Recursive Least Squares (RLS)	[16]
48	2017	Type-2 Fuzzy PID Interval Controller IT2FPIDC	FL and PID Cascading	Cuckoo Search (CS)	[97]
49	2011	FLC	Fuzzy logic	Fuzzy logic, like Mamdani	[105]
50	2017	Neuro–Fuzzy (NFC)	FL and NN	Fuzzy logic and adaptive learning	[20]
51	2017	NNC Neural Network Controller	NNC	Levenberg–Marquardt (LM)	[106]
52	2017	Fuzzy Logic Controller, FLC	Fuzzy logic	Fuzzy logic	[107]
53	2015	Hybrid diffuse-diffuse controller, HFFC	Fuzzy logic	Fuzzy logic	[22]
54	2013	Fuzzy Logic Controller, FLC	Fuzzy logic	Adaptive algorithm	[92]
55	2017	Controller Fuzzy-PID	FL y PID	Enhanced Gravitational Search (GSA-CW)	[86]
56	2013	Fuzzy Self-organizing with gray prediction, GPSOFC	Fuzzy logic	Grey Model (GM)	[94]
57	2013	Fuzzy with Linear Interpolation, LI-D-FC	Fuzzy logic	Fuzzy logic	[112]
58	2018	Fuzzy Logic Controller, FLC	Fuzzy logic	Fuzzy logic, like Mamdani	[113]
59	2015	Predictive-based neural networks, NNPC + Fuzzy P Controller	NN and FL	Levenberg–Marquardt (LM) and fuzzy logic Takagi–Sugeno type P	[116]
60	2019	Fuzzy Logic Controller, FLC	Fuzzy logic	Fuzzy Mamdani-like logic based on a new β (beta) parameter	[121]

61	2017	Range-2 Fuzzy PID (IT2FPID)	PID and Fuzzy Logic	Genetic Algorithms	[100]
62	2024	ANN-PMC	ANN	Levenberg-Marquardt Activation Function (LMAF) and interaction adaptive	[159]
63	2023	2-level FNN fuzzy neural network controller	Fuzzy logic and neural networks	Improved GA	[171]
64	2021	Neuro-Diffuse Adaptive Inference System, ANFIS	Fuzzy logic and ANN	Mayfly optimization algorithm, MOA	[205]
65	2025	Deep neural network reinforcement learning, RL-DLNN	TD3 Agent	Deep Learning Neural Network, DLNN	[216]

3.5.2. Result of Contributions: Optimization of Parameters

New AI optimization methods have led to significant improvements in performance, adaptability, and efficiency in the design and implementation of intelligent controllers for control systems.

Below are the articles that contribute to optimization models:

3.5.2.1. Artificial Neural Networks

Researchers utilize artificial neural networks (ANNs) to enhance optimization and learning in controllers, while machine learning facilitates parameter tuning and improves the accuracy of control models in complex systems. ANNs effectively handle nonlinear systems, thereby increasing the accuracy and robustness of controllers and other complex systems. They enable the handling of nonlinear systems, thereby improving the accuracy and robustness of controllers and other complex systems. ANNs are applied in the design of PID controllers, providing an advanced approach to enhance the system response [48].

On the other hand, support vector machines (SVMs) are used for excitation control, improving system stability through supervised learning [7]. Supervised learning neural networks are used for the learning and verification of feedback control systems [49]. Machine learning and predictive control techniques are applied to design an adaptive PID controller [72].

3.5.2.2. Evolutionary Algorithms

Research uses evolutionary algorithms, such as genetic algorithms (GAs), to optimize control parameters, particularly in systems with uncertainty or nonlinearities. These algorithms search for optimal solutions by simulating natural evolutionary processes.

GAs can refine the rule base of a Mamdani FLC [51], improve the performance of a modified PID controller [13], and enhance the adaptability of a self-adjusting PID controller [56].

Multi-objective GAs are crucial to improve controller performance across several competing criteria [78]—for example, a fractional-order PID controller for multivariable systems [58]. In addition, GAs can optimize control structures focusing on structural adaptation [81].

For vibration suppression, GA has been used to fine-tune fuzzy controllers [61]. A hybrid controller based on the Hydra structure has been developed and optimized using a GA-based strategy [52]. Additionally, the Taxi-Cab Evolutionary Algorithm has been used for multi-objective optimization in control systems [29].

3.5.2.3. Metaheuristic Optimization

Metaheuristic algorithms, such as Particle Swarm Optimization (PSO), can be applied to adjust controller parameters in complex systems. These methods are effective in exploring large search spaces to identify optimal solutions.

PSO has been used to tune a PID controller [62], to design a Fuzzy PID controller for a Quasi-Z Source converter [64], to optimize a Fuzzy-PDC controller [65], and to improve fuzzy controllers in distillation processes [99].

Grey wolf optimization optimizes a Fuzzy PID controller for frequency regulation in power systems [71]. The gravitational search algorithm improves the dynamic response of a PID controller [59], while the cuckoo optimization algorithm could manage the energy in a fuzzy controller [68].

Differential evolution algorithms (DEAs) design a fuzzy controller for wireless sensor networks [93]. At the same time, the Firefly Algorithm develops an optimized Fuzzy PID driver [23], and the bee colony algorithm (BCA) is a good method to design a fuzzy controller [75].

3.5.2.4. Fuzzy Controllers

Articles in this category focus on the design of fuzzy controllers, which use fuzzy logic to manage uncertainty and variability in complex systems.

A Fuzzy PID controller can improve continuous industrial processes [74] as a multivariable controller [66] and control underactuated manipulators [70]. The authors of [53] proposed a low-cost servo system based on a fuzzy controller, while [60] proposed a BLDC motor control based on a Fuzzy PID controller.

3.5.2.5. Hybrid Techniques

Studies in this category combine two or more techniques, such as fuzzy logic and metaheuristic optimization, to take advantage of the strengths of each. This combination improves the performance and adaptability of controllers.

Fuzzy control and optimization techniques have been integrated for frequency regulation in electrical networks [69]. Researchers have implemented a hybrid approach GWO-SCA in a Type II fuzzy controller for frequency control in multi-area systems [95]. A combination of harmony search and cuckoo optimization has been applied in a Fuzzy PID driver [98]. A hybrid PSO-GSA strategy has also been employed in a fuzzy sliding-mode controller for wind power systems [84].

3.5.2.6. Predictive Control

In this category, techniques focus on the use of predictive control, which allows us to anticipate changes in the system and adjust the controller based on predictions, improving performance in systems with high variability. Support vector machines (SVMs) are used in a nonlinear predictive controller to anticipate and correct system behavior in multiple steps forward [19].

3.5.2.7. Other Techniques

This category encompasses articles that employ unique or uncommon approaches and that do not fall within the above categories. These studies explore alternative optimization and control techniques. The researchers developed an optimized PID controller using multi-objective techniques, offering a method to manage multiple performance criteria in a control system [55].

Table 3 presents the articles that have contributed to the optimization of artificial intelligence in control systems.

Table 3. Result of the article classification according to the optimization contribution. (Source: Own elaboration based on systematic review).

 doi:10.20944/preprints202510.0761.v1

ID	Year	Control structures	Optimization Techniques	Algorithms	Ref.
1	2005	Fuzzy Controller	FLC Mamdani	Genetic Algorithm	[51]
2	2017	PID	GA Online Learning	Genetic Algorithm	[13]
3	2013	PID	Discrete FRIT method	Neuronal Network	[48]
4	2008	PID	PSO-tuned PID controller	PSO	[62]
5	2018	PID	FLC	Adaptive Fit	[74]
6	2006	Hydra Control Structure	Geno Hydra Hybrid	Genetic algorithm	[52]
7	2015	PID	PID using a gravitational search algorithm	Gravitational search algorithm	[59]
8	2018	Neural Networks	Control with advancing neural networks	Feedback Laws	[49]
9	2016	Fuzzy Controller	Adjustment of dynamic parameter	Adaptive bee colony algorithm	[75]
10	2016	PID	Optimized PID with PSO	Objective Function	[55]
11	2018	PID	Optimized PID with APFC	EO	[72]
12	2009	PID	PID with GA base rules	GA	[56]
13	2012	MOEA	MOEA-CCG	CCG	[78]
14	2014	FOPID		GA	[58]

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 October 2025 doi:10.20944/preprints202510.0761.v1

15	2005	NMPC	Numerical Methods SVM	SVM	[19]
16	2013	F-PID	F-PID	Fuzzy Predictor	[66]
17	2008	Approximate Model	Numerical Method	SVM	[7]
18	2015	PID-based structures	Optimized Classic Control	Evolutionary Algorithm	[81]
19	2013	SEA Method	Numerical method	Taxi-Cab	[29]
20	2019	Sliding Mode with Switching Surface (FSMC)-based control	PSO-GSA Optimization	PSO-GSA	[84]
21	2014	Fuzzy logic controller.	Search Algorithm Optimization	Cuckoo Search Algorithm	[68]
22	2016	Fuzzy Logic Controller.	Vehicle-to-Grid (V2G)	Membership Features and Fuzzy Rules	[69]
23	2017	MTEJ Controller	Fuzzily Tuning with an Additional Integrator	Fuzzy Coefficient Adjustment	[70]
24	2013	Fuzzy Logic Controller	Optimization by an Evolutionary Algorithm	Adjustment Approach Based on Evolutionary Algorithms	[53]
25	2017	PID	Tuned by Neural Networks	Neuronal Network	[60]
26	2018	PID Controller	Fuzzy logic	Improved Grey Wolf Optimization Algorithm	[71]
27	2012	PID Controller	Fuzzy logic	PSO Algorithm	[99]
28	2018	PID and Fuzzy Logic	Hybrid Algorithm	Hybrid optimization algorithm	[98]

 doi:10.20944/preprints202510.0761.v1

29	2016	Fuzzy Logic Controller	Evolutionary Algorithm	Differential evolution	[93]
30	2015	Fuzzy Logic Controller	Optimized by the Search Algorithm	PSO Algorithm	[64]
31	2019	Automatic Generation Control with Fuzzy Logic	Hybrid Algorithm	GWO-SCA hyper algorithm	[95]
32	2016	Fuzzy Logic Controllers	Fuzzy Rule Tuning	Genetic Algorithms	[61]
33	2018	Fuzzy Takagi Sugeno Control	Distributed Parallel Compensation Technique	Particle Swarm Optimization (PSO)	[65]
34	2016	PID Controller	Fuzzy logic	Fireflies Algorithm	[23]
35	2019	PID	ACS (Automatic control systems)	MT (Tunable model)	[160]
36	2024	PID	AVR	ARO (Artificial Rabbit Optimization)	[161]
37	2024	NN, NN-PIDD, ELNN-PID	NN, PID	COOA (Coot Optimization Algorithm)	[162]
38	2025	PI	FPI (Feedback PI)	GA	[163]
39	2024	Fuzzy Controller	Fuzzy logic	GA	[164]
40	2021	Controller Fuzzy type 1	Fuzzy logic	GWO (Grey Wolf Optimization)	[165]
41	2025	FL-SMC (Fuzzy logic sliding mode controller)	Fuzzy logic	hGWO-CS	[166]
42	2022	TOSMC (Third order sliding mode control)	IFOC (indirect field-orientated control)	GWO (Grey Wolf Optimizer)	[167]

doi:10.20944/preprints202510.0761.v1

43	2024	PID	PID	PSO, I-GWO, and NOA (Nutcracker optimization algorithm)	[168]
44	2020	Fuzzy Logic	Takagi-Sugeno	AIGA (Advanced Intelligent Genetic Algorithms)	[169]
45	2023	PID	AVR	ZOA (Zebra Optimization Algorithm) - OOA (Osprey Optimization Algorithm)	[170]
46	2020	Fuzzy - PD	PID	ABC (Artificial Bee Colony)	[172]
47	2019	FPID (Fuzzy PID)	FPID (Fuzzy PID)	IACO (Improved Ant Colony Optimization)	[173]
48	2021	PID	PID	Deep Reinforcement Learning	[174]
49	2024	FOPID	PID	ACO (Ant Colony Optimization)	[175]
50	2022	PSMC (Predictive Sliding Mode Control)	PSMC (Predictive Sliding Mode Control)	GWO (Grey Wolf Optimization)	[176]
51	2023	Fuzzy PID	PID	A-WOA (Advanced whale optimization algorithm	[177]
52	2022	PID	PID Cascaded	CIO (Cohort intelligence optimization)	[178]
53	2020	PID	AGC	MDE (Modified Differential Evolution)	[179]
54	2022	FOPID (Fuzzy fraction order PID)	OPID	ACO (Ant Colony Optimization)	[180]
55	2021	PID	PID	PSO (Particle Swarm Optimization)	[181]
56	2021	LFC (Load Frequency Control) - PI	PI	FAO (Firefly Algorithm Optimized)	[182]

57	2020	PID	fuzzy PID	GA	[183]
58	2020	PID	AVR	GSA (Gravitational Search Algorithm)	[184]
59	2023	PID	PID	DEA (Differential evolution algorithm)	[185]
60	2023	PID	PID	BFOA (Bacterial foraging optimization algorithm)	[186]
61	2022	PI	PI	PSO, GA, ABC	[187]
62	2024	PID	PID	RL (Reinforcement Learning)	[188]
63	2022	PID	PID	BFOA (Bacterial foraging optimization algorithm)	[189]
64	2023	Fuzzy PID	FPID	SIA (Swarm intelligence algorithm)	[190]
65	2022	PID	PID	Fuzzy, ANN, GA	[191]
66	2023	LFC (Load Frequency Control)	LFC	ANFIS	[192]
67	2020	PID	PID - MPPT	CGSA (Chaotic gravitational search algorithm)	[193]
68	2022	PID	PID	NN (Neural Networks)	[194]
69	2020	FFOPI (Fuzzy Fractional Order PI)	AGC	SOS (Symbiotic Organism search)	[195]
70	2021	PID	PID	FOFMO (Fractional Order Fish Migration Optimization Algorithm)	[196]
71	2020	FPI	PI	GOA (Grasshopper optimization algorithm)	[197]

 doi:10.20944/preprints202510.0761.v1

72	2020	PID	AVR	LGA (Lion group genetic algorithm)	[198]
73	2020	FOPID	AVR	HPSGWO (hybrid particle swarm and grey wolf optimization)	[199]
74	2024	PID	PID	ICDBO (Improved Chebyshev Dung Beetle Optimizer)	[200]
75	2023	PI	PI	PSO (Particle Swarm Optimization)	[201]
76	2022	PID	PID	SOA (Seagull optimization algorithm)	[202]
77	2020	PI	PI	BFOA (Bacterial foraging optimization algorithm)	[203]
78	2022	PID	PID	MPA (Marine Predator Algorithm)	[204]
79	2021	P-PI	P-PI	SSA (Slap swarm algorithm)	[205]
80	2022	PI	PI	NSGA-II (Multi-Objective Evolutionary Optimization Algorithm)	[206]
81	2021	PI	PI	GA, SA, RL, TD3 (Twin Delayed Deep Deterministic Policy gradient algorithm)	[207]
82	2023	PID	PID	HAOAGTO (Arithmetic optimization algorithm and Artificial gorilla troop's optimization)	[208]
83	2023	FOPID	PID	NewBAT, CS (Cuckoo Search), FF (Firefly), GWO (Grey Wolf optimizer), WOA (Whale optimization algorithm)	[217]
84	2021	PID	PID	ABC, ACO, ALO, BA, BHO, CLONALG, CS, CSO, DA, DE, FFA, GA, GBS, GOA, HS, KH, MFO, PSO, SCA, SFL, WOA	[218]

Figure 5 also presents a classification of the groups of optimization strategies that contribute to the application of AI in control systems.

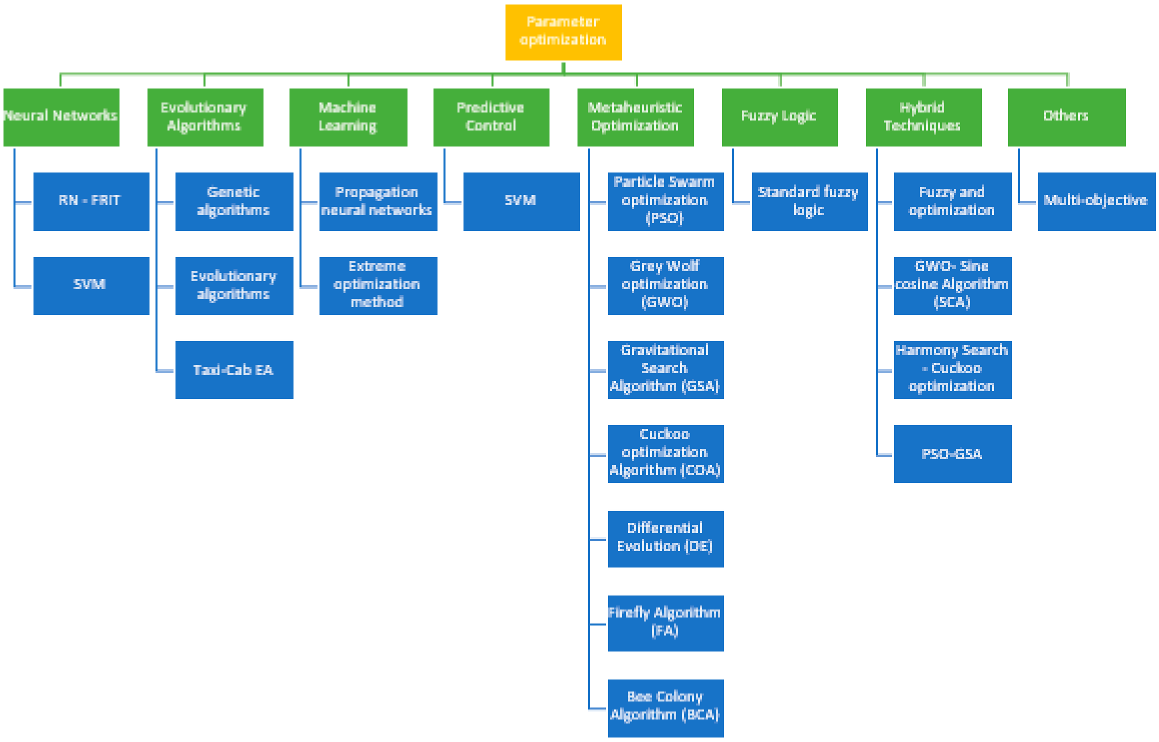

Figure 5. Optimization contribution groups. (Source: Own elaboration based on systematic review).

3.5.3. Result of Contributions: Adaptability

The development of adaptive control strategies has gained significant attention in recent decades due to the increasing complexity of dynamic systems, the presence of nonlinearities, time delays, parametric uncertainties, and external disturbances. In this context, several approaches have been proposed that combine classical control structures—such as PID controllers, fuzzy models, and neural networks—with modern techniques of adaptation, optimization, and machine learning.

The reviewed literature has been organized into different categories according to the predominant control technique, which allows a clear comparison of the strengths, limitations, and applications of each approach. The main categories are:

Adaptive PID-based controllers, where the classical PID structure is enhanced through optimization, fuzzy logic, or machine learning.

Adaptive Fuzzy-based controllers (Fuzzy / ANFIS / T-S), which employ fuzzy inference to support decision-making and online parameter tuning.

Adaptive Neural Network-based controllers, where neural models act as universal approximators to handle uncertain nonlinear dynamics.

Hybrid adaptive controllers, which synergistically combine fuzzy, neural, robust, or bio-inspired approaches.

Optimization and adaptive optimal controllers, where evolutionary algorithms, heuristics, and predictive methods are used to tune parameters of the classical or advanced controllers.

3.5.3.1. Adaptive PID-Based Controllers

An Adaptive Particle Swarm Optimization (APSO) to tune linear and nonlinear PID controllers, improving stability and convergence speed compared to classical methods [110].

An adaptive PID controller based on fuzzy predictors is introduced, where fuzzy modelling improves adjustment of online and tracking accuracy in nonlinear processes [111].

A MRAS (Model Reference Adaptive System) approach is applied to tune PID gains for launch vehicles, ensuring robust performance under parameter variations during flight [115].

A self-adaptive Genetic Algorithm (GA) is presented for PI/PID controllers, optimizing both gains and performance indices for faster and smoother responses [118].

A Fuzzy-PID controller implemented in a PLC is developed for oil pipeline flow regulation, automatically adjusting the PID parameters through fuzzy inference [122].

A Kalman filter-enhanced Fuzzy-PID controller is proposed for liquid level control in conical tanks, where fuzzy logic adjusts PID gains and Kalman filtering improves robustness against noise [124].

A hybrid OENN–OEANFIS system is designed to adapt PID parameters, combining endocrine-inspired neural networks with neuro-fuzzy inference for enhanced adaptability [104].

A Self-Adaptive Differential Evolution (SaDE) algorithm is applied for adjusting PID, dynamically adjusting the crossover and mutation rates to achieve optimal gains [215].

A deep learning-based intelligent PID controller (CNN–LSTM) is proposed for UAVs, where a neural network predicts parameter adjustments to improve stability and energy efficiency [212].

An AIEM-DDPG (Ambient Intelligence Exploration Multi-Delay Deep Deterministic Policy Gradient) is introduced to adapt the PI controller gains for PEM fuel cells, achieving improved stability and reduced overshoot [211].

A TD3 (Twin Delayed Deep Deterministic Policy Gradient)-based tuner is applied to the PI and Lead controllers, providing adaptive adjustment of parameters with improved robustness against uncertainties [214].

3.5.3.2. Adaptive Controllers Based on Fuzzy Logic (Fuzzy / ANFIS / T-S)

Control systems frequently adopt fuzzy logic-based adaptations due to their ability to handle uncertainty and variability under changing operating conditions. Fuzzy logic enables controllers to make precise adjustments without requiring an exact mathematical model of the system, making it well-suited for environments with complex or unpredictable dynamics.

An adaptive fuzzy controller for MPPT in photovoltaic systems, where the output scaling factor is adjusted online to efficiently track the maximum power point under varying irradiance and temperature [6].

An ANFIS controller applied to a PFC boost converter, trained online using data from a conventional fuzzy controller to improve voltage regulation and power factor [18].

An adaptive fuzzy PI controller for coupled tanks, where Mamdani rules and membership functions dynamically tune Kp and Ki gains to handle nonlinearities [31].

A fuzzy T–S adaptive controller with a state observer, designed for nonlinear systems with unknown dead zones, avoiding traditional backstepping complexity [32].

An ANFIS controller for autonomous mobile robots, trained with hybrid learning (least squares + backpropagation) to achieve trajectory tracking and target pursuit [76].

A self-learning fuzzy controller based on Autonomous Adaptive Control (AAC), which generates and updates fuzzy rules online from input–output data without external supervision [102].

An ANFIS optimized with Genetic Algorithms for greenhouse climate control, where GA tunes the membership functions and rules to minimize ISE and improve robustness [108].

A two-level adaptive fuzzy controller for DC motors, where the first level is a Mamdani fuzzy controller and the second is an inverse T–S model that updates the first in real time [123].

3.5.3.3. Adaptive Controllers Based on Bioinspired / Optimal Optimization

An adaptive fuzzy controller optimized with Adaptive Differential Evolution (FADE), applied to synthetic inertia in power systems, where DE dynamically tunes fuzzy membership functions to reduce the frequency nadir and improve stability [120].

An LQR controller optimized with Adaptive Cuckoo Search (ACS), applied to active suspension systems in vehicles, where ACS adjusts the weighting matrices Q and R to reduce vertical acceleration and improve ride comfort [213].

An Adaptive Model Predictive Control (MPC) scheme with set-membership identification, designed for linear systems with parametric uncertainty and disturbances, using tube-based predictions and convex optimization to guarantee constraint satisfaction [125].

3.5.3.4. Adaptive Controllers Based on Neural Networks

An Initial-Training-Free Online Extreme Learning Machine (ITF-OELM) is proposed for the adaptive control of nonlinear discrete-time systems with rapidly varying parameters, allowing online identification without prior training data [109].

A multilayer neural network (MLP) combined with integral sliding mode control is used as a direct adaptive controller to compensate for residual and approximation errors in systems with dead-zone nonlinearities [37].

An adaptive RBF neural network (RBFNN) is applied to nonlinear systems with unknown time delays, acting as a universal approximator with online weight adaptation laws derived from Lyapunov analysis [27].

An adaptive RBFNN integrated with second order sliding mode control estimates unknown dynamics and disturbances, ensuring robust trajectory tracking while eliminating chatter [101].

An RBFNN combined with backstepping and barrier Lyapunov functions (BLF) is developed for vibration suppression in flexible string systems with dead-zone nonlinearities and output constraints [114].

An adaptive RBFNN combined with sliding mode control and a neuro-inspired IAP mechanism (Incentive–Actuator–Preventor) is applied to robotic manipulators, enhancing robustness and trajectory tracking under switching constraints [103].

An observer of the Wavelet Neural Network (WNN) is integrated into an adaptive fuzzy sliding mode stabilizer for multimachine power systems, estimating uncertainties and improving low-frequency oscillation damping [119].

An adaptive neural network controller for DC–DC converters (based on [126]) uses online learning to compensate for model uncertainties and improve voltage regulation under dynamic load changes [126].

3.5.3.5. Adaptive Control based on Hybrid Techniques

A neuro-fuzzy backstepping adaptive controller applied to an induction motor with unified nonlinear friction and unknown model dynamics, where ANFIS is integrated into a robust backstepping design to ensure tracking accuracy [90].

A robust adaptive fuzzy–neural T-S controller for interconnected nonlinear systems, where a Takagi–Sugeno fuzzy model works with neural networks to approximate unknown interconnections, and a compensator handles approximation errors [117].

A hybrid adaptive–fuzzy navigation controller for mobile manipulators, combining adaptive control for dynamic parameter estimation with fuzzy logic (T-S rules) for obstacle avoidance and trajectory tracking in dynamic environments [128].

A robust adaptive controller based on Lyapunov/backstepping techniques (article [127]), designed to handle strong nonlinearities and uncertainties while ensuring global stability through adaptive update laws and robust compensation [127].

A fuzzy-PID hybridized with ant colony optimization (ACO) for UAV path planning, where fuzzy logic adjusts PID gains in real time, and improved ACO optimizes pheromone updating to generate shorter and smoother trajectories [210].

Table 4 presents a detailed table of the articles that contributed to the adaptability in artificial intelligence in control systems. Figure 6 also presents a classification of the adaptability groups that contribute to the application of AI in control systems.

Figure 6. Adaptability contribution type groups. (Source: Own elaboration based on systematic review).

Table 4. Result of the articles classification according to the contribution of adaptability. (Source: elaboration based on systematic review).

ID	Year	Control structures	Control Techniques	Algorithms	Ref.
1	2016	Neural networks	Multi-Model Adaptive Control (MMAC)	External online learning without initial training (ITFOELM)	[109]
2	2018	PID	PSO-tuned PID controller	PSO	[110]
3	2014	PID	FLC	Adaptive Fit	[111]
4	2013	Fuzzy logic based on back-stepping	Control based on an adaptive fuzzy tracking algorithm	Adaptive algorithm	[32]
5	2005	Multilayer Neural Networks with variable structure	Adaptive control with neural networks	Adaptive algorithm	[37]

6	2018	Neural networks	Control with an adaptive neural network	Adaptive algorithm applied to the Lyapunov barrier function	[114]
7	2004	PID	Estimating Profit Using a Reference System	Adaptive algorithm	[115]
8	2016	Neural networks	Robust Adaptive Control	Adaptive algorithm	[27]
9	2018	Neural networks	Radial Basis Function	Adaptive algorithm	[101]
10	2010	Neural networks	Fuzzy Neural Networks	Adaptive algorithm	[117]
11	2017	PID	GA adjusted PID	GA	[118]
12	2007	FLC	FLC-AAC	AAC	[102]
13	2017	MPC	Tuned MPC with adaptive algorithm	Adaptive Algorithm	[125]
14	2017	PID-Fuzzy	Adaptive fuzzy PID	PFC	[126]
15	2017	MPC	MPC-ANN	ANN	[127]
16	2016	FLC	Control by FLC-ANN	ANN	[90]
17	2018	RBF-NN	Control with hybrid functions	ILAP, SMC	[103]
18	2014	Hybrid Structure	Least Squares Optimization and Propagation Algorithm Back	ANFIS	[76]
19	2016	PID	PID	OENN-OEANFIS	[104]

20	2016	Hybrid, combining adaptive control with fuzzy logic	Adaptive Algorithm	fuzzy logic	[128]
21	2017	Adaptive Fuzzy Slider Mode Controller (AFSMC)	Adaptive Law	Lyapunov stability	[119]
22	2019	Adaptive Fuzzy Logic Controller (FADE)	Adaptive Law	Differential Evolution Algorithm (DEA)	[120]
23	2014	Adaptive Fuzzy Controller	Adaptive Adjustment of Fuzzy Rules	Fuzzy rules	[6]
24	2017	ANFIS (Adaptive Neuro-Fuzzy Inference System). HBCC (Hysteresis Band Current Control).	Adaptive Adjustment	ANFIS (Adaptive Neuro-Fuzzy Inference System)	[18]
25	2018	PID Controller	Fuzzy Logic Parameter Adjustment	Fuzzy Logic and PID Tuning	[122]
26	2018	Fuzzy logic	Adaptation Mechanism	Adaptive Algorithm	[123]
27	2017	Fuzzy Logic Controller	Adaptation Law	Kalman Algorithm	[124]
28	2014	PI Controller	Fuzzy logic	Fuzzy Rules	[31]
29	2018	(ANFIS)	Adaptive Law	Genetic Algorithms	[108]
30	2023	Fuzzy PID	PI	ACA (Ant Colony Algorithm)	[210]
31	2021	PI	PI	AIEM-DDPG (Ambient Intelligence Exploration Multidelay Deep Deterministic Policy Gradient)	[211]
32	2024	PID	ADAPTIVE PID	Deep Reinforcement Learning	[212]

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 October 2025 doi:10.20944/preprints202510.0761.v1

33	2020	LQR	LQR	ACS (Adaptive cuckoo search algorithm)	[213]
34	2022	Reinforcement Learning (RL) and Deep Neural Networks (DNN)	RL - DNN	Improved Twin Delayed Deep Deterministic Policy Gradient (TD3)	[214]
35	2020	PID	PID	SADE (Self-adaptive differential evolution)	[215]

3.5.4. Identification of Gaps and Controversies in the Models

Studies on advanced controllers have multiple limitations in their applicability and replicability in real environments, raising doubts about their practical effectiveness. One of the main shortcomings is the reliance on simulations for validation, rather than experimental testing in real-world environments, which limits the evaluation of their performance against factors such as noise, wear, and extreme variability. In addition, the lack of detail in parameter configuration, especially in fuzzy controllers, hinders the replication and adaptation of these methods in other systems, affecting consistency and accuracy under conditions of high uncertainty.

Most studies do not compare these approaches with other advanced methods, such as deep neural networks and modern optimization algorithms, making it difficult to fully assess their competitiveness. Additionally, the high computational complexity of some algorithms—particularly in hybrid implementations—poses a significant challenge for their deployment in embedded systems and critical applications. This issue becomes more severe due to the limited guidance available for parameter tuning and result interpretation, which further hinders their adoption in industrial settings.

In addition, many studies do not evaluate the robustness of controllers under harsh conditions or consider their scalability in large-scale applications. The lack of low-cost hardware testing and the complexity of design in fuzzy logic are additional barriers, as the industry often prefers more straightforward solutions. In conclusion, deficiencies in experimental validation, replicability, and scalability raise questions about the effectiveness of these advanced controllers in real industrial applications.

4. Conclusions

Main Findings

Studies on advanced control strategies report notable improvements in adaptability, accuracy, efficiency, and optimization. Controllers based on Type-2 fuzzy logic, neural networks, and hybrid configurations—such as fuzzy-PID systems or those combined with optimization algorithms such as PSO, GA, and GWO—enable adaptive responses to variability in complex systems. These approaches have proven effective in applications that include robotic manipulators, heat exchangers, greenhouses, and renewable energy systems, where they contribute to maintaining stability and precision in dynamic operating environments.

Optimization using evolutionary and metaheuristic algorithms (gravitational search, Cauchy mutation, PSO, GA) allows automatic and precise tuning of PID and fuzzy controller parameters. These techniques eliminate the need for continuous manual adjustments, facilitating rapid convergence to optimal configurations, especially in nonlinear systems and in applications with high uncertainty.

In terms of energy efficiency and resource management, adaptive and predictive controllers have proven to be effective in renewable energy systems, such as photovoltaics and wind turbines, maximizing generation under variations in irradiance and temperature. In applications such as greenhouses, optimized controllers help maintain stable conditions, minimizing water and energy usage, and optimizing resource utilization.

The validation of these controllers in simulations and controlled environments has shown improvements in stability, reduction of oscillations, and optimization of energy use in the systems studied. However, some studies still lack experimental testing under real-world conditions, it is challenging to evaluate their performance in industrial applications.

Fuzzy drivers, especially in hybrid configurations with optimization algorithms, achieve an optimal balance between stability and accuracy. These methods are highly effective in systems with variability and help improve robustness in power grids and systems with multiple energy sources. Hybrid approaches (such as GWO-SCA and PSO-GA) combine the strengths of different algorithms to overcome limitations and improve performance in exploration and exploitation.

Finally, the integration of optimization techniques with adaptive control (such as the use of genetic algorithms and the Kalman filter) allows for more precise real-time tuning, essential for embedded or real-time systems, such as DC motor control and flow in pipelines. Experimental validation in industrial applications, such as climate control and flow tracking, highlights the practical feasibility and potential for adoption of these advanced controllers in sectors that require high accuracy and adaptability.

Key Trends in Driver Development:

Recent research on advanced controllers has revealed a clear trend toward integrating multiple control techniques to enhance robustness and accuracy in complex, dynamic systems. The combination of fuzzy controllers, neural networks, and PID algorithms seeks to leverage the adaptability, learning capability, and predictability of each approach. These integrated strategies have demonstrated great effectiveness in applications characterized by significant uncertainty, such as robotics, renewable energy systems, and temperature regulation.

The optimization of parameters through evolutionary and metaheuristic algorithms (such as gravitational search, PSO, and Cauchy mutation) is a central technique in these developments, as it allows PID and fuzzy controllers to be adjusted quickly and accurately, optimizing efficiency and adaptability to changes in system conditions. Hybrid approaches, which combine two or more optimization algorithms, are increasingly used to enhance parameter tuning, leading to improved accuracy and stability.

The applications in sustainable energy stand out, with controllers designed to maximize energy capture in photovoltaic and wind systems under changing conditions. In agriculture, diffuse controllers enable the optimization of water and energy consumption in greenhouses, promoting sustainability.

The trend towards robust and adaptive controllers, especially those of the diffuse type II, is key in systems with high uncertainty. These controllers enable the handling of variability in applications that require high precision, such as power systems and robotics. Intelligent adaptive controllers, which integrate fuzzy logic and optimized neural networks, provide real-time responses and continuously adapt, representing a significant advancement for industrial applications where real-time stability and adaptability are crucial.

Simulations and comparisons with traditional methods demonstrate that advanced methods offer improved accuracy, stability, and energy efficiency compared to conventional control methods. In autonomous systems and sensors powered by ambient energy, optimization is crucial for efficiently managing energy, thus prolonging the useful life of IoT and monitoring devices in environments with low energy availability.

Ultimately, interest in nonlinear and high-uncertainty systems is driving the development of robust adaptive controllers, which can maintain stability and optimizing performance under adverse

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 October 2025 doi:10.20944/preprints202510.0761.v1

conditions. These systems are especially useful in applications such as industrial process control, mobile robotics, and power systems, where variability is frequent.

Identified Research Gaps:

Advanced controllers have identified several challenges and limitations that hinder their application in real-world conditions. One of the most critical shortcomings is the limited experimental validation in actual operating environments; most evaluations rely on simulations, which restrict insights into practical performance and raise concerns about their effectiveness in industrial scenarios. To confirm the benefits observed in the simulations, researchers must perform tests under real industrial conditions.

Another significant challenge is the lack of detail in the configuring and tuning of the parameters. Studies on fuzzy controllers and evolutionary algorithms often lack sufficient descriptions of the configuration of membership functions and fuzzy rules. Additionally, the configuration of parameters in optimization algorithms, such as population size and crossover rates, lacks clear guidelines, which limit replicability and adaptability across different environments.

Limited comparisons with other advanced control methods are another significant gap. Many studies only contrast their methods with conventional controllers, without considering advanced alternatives such as deep neural networks or predictive controllers. Comprehensive comparisons would help to comprehensively assess the advantages and limitations of each approach, highlighting its effectiveness in specific contexts.

Scalability and applicability are also issues that have a waiting list in more complex systems. Although controllers perform well in simulations, their performance in larger and more complicated systems, such as renewable energy plants and large-scale greenhouses, remains inadequately evaluated. Likewise, there is a lack of computational load assessment, a critical aspect for real-time applications and embedded systems.

Additionally, the complexity involved in designing fuzzy logic systems and configuring rule sets creates a barrier to their implementation in industrial applications, which require simplicity and ease of maintenance. Many studies overlook extreme test scenarios, instead focusing on standard operating conditions without assessing how controllers respond to significant disturbances or substantial load variations.

Finally, insufficient technical descriptions and configuration details affect the replicability of studies, especially in neuro-fuzzy and optimization methods. Detailed documentation of parameters and settings is crucial for facilitating the application of these approaches in new areas and ensuring their reproducibility.

Contribution of the study:

The reviewed studies consolidate a solid foundation in the field of advanced controllers, bringing significant advances in several key areas. Hybrid adaptive and predictive control techniques, which combine fuzzy logic, PID controllers, and neural networks, have enhanced adaptability and accuracy in systems characterized by high variability and nonlinearity, such as robotics and renewable energy systems. The introduction of fuzzy type-2 and predictive controllers based on neural networks expands the capabilities to handle uncertainties, setting a framework for future research into more robust and scalable controllers.

Real-time parameter optimization using evolutionary and metaheuristic algorithms (such as PSO, GA, and GWO) enables automatic and accurate tuning, thereby increasing efficiency and response speed in high-variability applications. These advances lay the groundwork for integrating machine learning techniques and creation of adaptive controllers that continuously adjust to changing conditions without human intervention.

In practical applications, researchers have developed optimized controllers that improve energy efficiency in photovoltaic and wind systems, as well as improve resource management in precision agriculture. These studies also emphasize the positive impact on sustainability by reducing water and energy consumption. Future research can extend these efforts to design controllers for other emerging areas, such as advanced agriculture and critical industrial sectors.

Strengthening the theoretical foundations for managing uncertainty through fuzzy logic and neural networks provides a solid basis for advancing adaptive control, promoting the use of artificial intelligence to enhance robustness and adaptability in complex systems. Despite significant progress, essential gaps persist in the experimental validation of these approaches under real-world conditions. Since most studies rely on simulations, conducting tests in actual operating environments remains critical to confirm the effectiveness of these controllers in industrial and commercial applications.

The computational complexity and processing load in real-time applications present an ongoing challenge. Several studies emphasize the need to optimize control algorithms for effective deployment in embedded and low-power systems. By integrating optimization techniques such as genetic algorithms and the Kalman filter, researchers enable controllers to rapidly adapt to environmental changes—an essential capability for industrial sectors that require dynamic responses in real-time.

In Finally, areas for improvement are identified in exhaustive comparisons with other advanced methods and in the robustness of controllers under extreme conditions, highlighting the need for studies that evaluate the comparative effectiveness of optimization approaches and develop controllers capable of operating reliably under significant disturbances. These contributions lay a foundation for future research in intelligent control applications, opening doors to new techniques and methods in sectors such as Industry 4.0 and advanced automation.

Future work:

Research on adaptive, predictive, and optimized controllers has identified several promising directions to improve their applicability, scalability, and robustness in real-world scenarios. A key priority is the experimental validation of these systems under actual operating conditions, as most existing studies rely primarily on simulations. Conducting tests on physical systems—such as renewable energy platforms, industrial robotics, and agricultural applications—would enable researchers to evaluate performance in realistic environments and accelerate the adoption of these controllers in industrial settings.

A detailed comparison with other advanced methods, such as deep neural networks and optimization algorithms, would allow us to determine the effectiveness of these approaches in various contexts and select the most appropriate techniques. In addition, exploring adaptive and evolutionary optimization algorithms for continuous tuning is crucial to enhancing the adaptability of controllers under varying conditions, particularly in applications such as renewable energy and advanced robotics.

The development of fuzzy type-2 controllers combined with machine learning is another key area to improve the handling of uncertainties in systems with high variability, such as industrial processes and collaborative robotics. It also highlights the need to study scalability in large-scale applications, such as power plants and large greenhouses, and to implement distributed control networks to improve the management of complex systems.

To facilitate replicability, this study recommends creating detailed guides and adjustable libraries for driver configuration, particularly for fuzzy logic and PID, as well as accessible libraries for testing in various applications. The application in new fields of control and resource optimization, such as smart cities and advanced manufacturing, highlights the potential of these controllers to improve energy efficiency and sustainability in multiple sectors.

Other areas of development include advanced simulation to evaluate controller performance in critical situations without the risks associated with physical testing, as well as research into low-computational-load controllers for real-time applications and IoT devices. Additionally, enhancing the interpretability and maintainability of controllers is crucial for use in industries where transparency and end-user understanding are paramount.

Researchers emphasize the importance of robustness and resilience under extreme conditions, as well as the use of automation in designing fuzzy logic and configuring rules and integrating prediction techniques to anticipate system changes. These strategies maximize the adaptability and responsiveness of controllers in applications such as advanced robotics and energy systems. Pursuing

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 October 2025 doi:10.20944/preprints202510.0761.v1

these research directions will lay the groundwork for significant advances in the adoption of optimized controllers in various industrial and technological sectors, thus expanding their impact in critical and emerging fields.

Abbreviations

ANN	Artificial Neural Network
ANNC	Artificial Neural Network Controller
ANFIS	Adaptive Neuro-Fuzzy Inference System
RL-DLNN	Reinforcement Learning - Deep Learning Neural Network
FL	Fuzzy Logic
FLC	Fuzzy Logic Controller
T-S	Takagi–Sugeno Fuzzy Model
IT2FLS	Interval Type-2 Fuzzy Logic System
FOPID	Fractional Order PID
PID	Proportional-Integral-Derivative Controller
PI	Proportional-Integral Controller
MPC	Model Predictive Control
reMPC	Robust Economic Model Predictive Control
IMC	Internal Model Control
ILC	Iterative Learning Control
QILC	Quadratic Iterative Learning Control
K-ILC	Kalman-based ILC
E-QILC	Estimation-based Quadratic ILC
LFL	Learning Feedback Linearization
RBFNN	Radial Basis Function Neural Network
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory Network
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
DE	Differential Evolution
ES	Evolutionary Strategy
GP	Genetic Programming
MOA	Mayfly Optimization Algorithm
HICA	Hybrid Imperialist Competitive Algorithm
GWO	Grey Wolf Optimizer
BFOA	Bacterial Foraging Optimization Algorithm
WOA	Whale Optimization Algorithm
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
FA	Firefly Algorithm
CS	Cuckoo Search
HPSGWO	Hybrid PSO-GWO
NSGA-II	Non-dominated Sorting Genetic Algorithm II
SMC	Sliding Mode Control
FSMC	Fuzzy Sliding Mode Control
FLMFC	Fuzzy Cerebellar Model with Functional Link Network
PMC	Predictive Model Controller
RFCMAC	Recurrent Fuzzy CMAC Network
NARMA	Nonlinear Auto-Regressive Moving Average model
LSE	Least Squares Estimation
RLS	Recursive Least Squares
LM	Levenberg–Marquardt Algorithm
QP	Quadratic Programming

SVR	Support Vector Regression
SVM	Support Vector Machine
DLNN	Deep Learning Neural Network
TD3	Twin Delayed Deep Deterministic Policy Gradient
DDPG	Deep Deterministic Policy Gradient
SaDE	Self-Adaptive Differential Evolution
APSO	Adaptive Particle Swarm Optimization
AIGA	Advanced Intelligent Genetic Algorithm

References

1. S. N. Vassilyev, A. Y. Kelina, Y. I. Kudinov, & F. F. Pashchenko, “Intelligent control systems,” Procedia Computer Science, vol. 103, pp. 623-628, 2017.
2. T. RayChauduri, L.G.C. Hamey, R.D. Bell, "From conventional control to autonomous intelligent methods," IEEE Control Systems, vol. x, no. x, pp. 78-84, Abbrev. 1996.
3. M. Santos, "Un enfoque aplicado del control inteligente," Revista Iberoamericana de Automática e Informática Industrial RIAI, vol. 8, no. 4, pp. 283-296, 2011.
4. D. CARRIZO, C. MOLLER, “Estructuras metodológicas de revisiones sistemáticas de literatura en Ingeniería de Software: un estudio de mapeo sistemático”. Ingeniare. Revista chilena de ingeniería, vol. 26, pp. 45-54, 2018.
5. Krzysztof PATAN, "Two stage neural network modelling for robust model predictive control," ISA transactions, vol. 72, pp. 56-65, 2018.
6. Ouahib GUENOUNOU, Boutaib DAHHOU, Ferhat CHABOUR, "Adaptive fuzzy controller based MPPT for photovoltaic systems," Energy Conversion and Management, vol. 78, pp. 843-850, 2014.
7. Xiaofang YUAN, Yaonan WANG, Shutao LI, "A novel excitation controller using support vector machines and approximate models," Journal of Control Theory and Applications, vol. 6, pp. 239-245, 2008.
8. Tuan-Tu HUYNH, et al., "A modified function-link fuzzy cerebellar model articulation controller using a PI-type learning algorithm for nonlinear system synchronization and control," Chaos, Solitons & Fractals, vol. 118, pp. 65-82, 2019.
9. P. R. OUYANG, W. J. ZHANG, M. M. GUPTA, "A robust PD-type evolutionary learning control for nonlinear time-varying systems," in Proceedings of the 2004 IEEE International Symposium on Intelligent Control, IEEE, 2004, pp. 90-95.
10. Zhihuan CHEN, et al., "Parameter estimation of fuzzy sliding mode controller for hydraulic turbine regulating system based on HICA algorithm," Renewable energy, vol. 133, pp. 551-565, 2019.
11. Mohammad EL-BARDINI, Ahmad M. EL-NAGAR, "Interval type-2 fuzzy PID controller for uncertain nonlinear inverted pendulum system," ISA transactions, vol. 53, no. 3, pp. 732-743, 2014.
12. Tarkeshwar MAHTO, V. MUKHERJEE, "A novel scaling factor based fuzzy logic controller for frequency control of an isolated hybrid power system," Energy, vol. 130, pp. 339-350, 2017.
13. Hwang Hun JEONG, "A study for learning method of modified PID controller with on-line hybrid genetic algorithm," in AETA 2017-Recent Advances in Electrical Engineering and Related Sciences: Theory and Application, Springer International Publishing, 2018, pp. 488-497.
14. Andrzej BIELECKI, Marzena BIELECKA, Sebastian ERNST, "Proposal of an intelligent, predictive fuzzy controller for off-grid devices," IFAC-PapersOnLine, vol. 49, no. 25, pp. 523-528, 2016.
15. Lilei LU, Lihua XIE, Wenjian CAI, "H2 controller design for networked control systems," Asian Journal of Control, vol. 6, no. 1, pp. 88-96, 2004.
16. K. PREMKUMAR, B. V. MANIKANDAN, "Fuzzy PID supervised online ANFIS based speed controller for brushless DC motor," Neurocomputing, vol. 157, pp. 76-90, 2015.
17. A. Gnana SARAVANAN, M. RAJARAM, "Fuzzy controller for dynamic performance improvement of a half-bridge isolated DC–DC converter," Neurocomputing, vol. 140, pp. 283-290, 2014.
18. Abderrahmen Benyaminaa, Samir Moulahouma, Ilhami Colak b,Ramazan Bayindir. (2017). *Design and real time implementation of adaptive neural-fuzzy inference system controller based unity single phase power factor converter*.

19. Wei-min ZHONG, Dao-ying PI, You-xian SUN, "Support vector machine based nonlinear model multi-step-ahead optimizing predictive control," Journal of Central South University of Technology, vol. 12, no. 5, pp. 591-595, 2005.
20. H. SATHISHKUMAR, S. S. PARTHASARATHY, "A novel neuro-fuzzy controller for vector-controlled induction motor drive," Energy Procedia, vol. 138, pp. 698-703, 2017.
21. R. MARINO, et al., "Generalized PID learning control," in IFAC Proceedings Volumes, 2011, vol. 44, no. 1, pp. 3629-3634.
22. Muawia A. MAGZOUB, Nordin B. SAAD, Rosdiazli B. IBRAHIM, "Efficiency improvement of induction motor variable speed drive using a hybrid fuzzy-fuzzy controller," Energy Procedia, vol. 75, pp. 1529-1535, 2015.
23. Pratap Chandra PRADHAN, Rabindra Kumar SAHU, Sidhartha PANDA, "Firefly algorithm optimized fuzzy PID controller for AGC of multi-area multi-source power systems with UPFC and SMES," Engineering Science and Technology, an International Journal, vol. 19, no. 1, pp. 338-354, 2016.
24. Nicolas DEGEN, Angela P. SCHOELLIG, "Design of norm-optimal iterative learning controllers: The effect of an iteration-domain Kalman filter for disturbance estimation," in 53rd IEEE Conference on Decision and Control, IEEE, 2014, pp. 3590-3596.
25. Xiao-Feng LI, Gang CHEN, Ya-Gang WANG, "IMC-PID controller design for power control loop based on closed-loop identification in the frequency domain," IFAC-PapersOnLine, vol. 49, no. 4, pp. 79-84, 2016.
26. Marko CORN, Maja ATANASIJEVIĆ-KUNC, "Designing model and control system using evolutionary algorithms," IFAC-PapersOnLine, vol. 48, no. 1, pp. 526-531, 2015.
27. Hongwen MA, et al., "Neural-network-based distributed adaptive robust control for a class of nonlinear multiagent systems with time delays and external noises," IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 46, no. 6, pp. 750-758, 2015.
28. Savaş ŞAHIN, "Learning feedback linearization using artificial neural networks," Neural Processing Letters, vol. 44, pp. 625-637, 2016.
29. Hans JF MOEN, et al., "Many-objective optimization using taxi-cab surface evolutionary algorithm," in Evolutionary Multi-Criterion Optimization: 7th International Conference, EMO 2013, Sheffield, UK, March 19-22, 2013. Proceedings, Springer Berlin Heidelberg, 2013, pp. 128-142.
30. I. KITSIOS, T. PIMENIDES, P. GROUMPOS, "A genetic algorithm for designing H/sub/spl infin//structured specified controllers," in Proceedings of the 2001 IEEE International Conference on Control Applications (CCA'01)(Cat. No. 01CH37204), IEEE, 2001, pp. 1196-1201.
31. Soumya Ranjan MAHAPATRO, Bidyadhar SUBUDHI, Subhojit GHOSH, "Adaptive fuzzy PI controller design for coupled tank system: an experimental validation," IFAC Proceedings Volumes, vol. 47, no. 1, pp. 878-881, 2014.
32. Rui WANG, Fusheng YU, Jiayin WANG, "Adaptive fuzzy control for a class of uncertain nonlinear systems with unknown nonsymmetric dead-zone input," in Proceedings of the 32nd Chinese Control Conference, IEEE, 2013, pp. 513-518.
33. Al-Hadithi, B. M., Jiménez, A., & Perez-Oria, J. (2015). *New incremental Takagi–Sugeno state model for optimal control of multivariable nonlinear time delay systems.* Engineering Applications of Artificial Intelligence, 45, 259-268.
34. Florian A. BAYER, et al., "Robust economic model predictive control using stochastic information," Automatica, vol. 74, pp. 151-161, 2016.
35. Hong WANG, Puya AFSHAR, Hong YUE, "Ilc-based generalised pi control for output pdf of stochastic systems using lmi and rbf neural networks," in Proceedings of the 45th IEEE Conference on Decision and Control, IEEE, 2006, pp. 5048-5053.
36. Li, H. M., Wang, X. B., Song, S. B., & Li, H. (2016). *Vehicle control strategies analysis based on PID and fuzzy logic control.* Procedia engineering, 137, 234-243.
37. Tian-Ping ZHANG, et al., "Adaptive neural network control of nonlinear systems with unknown dead-zone model," in 2005 International Conference on Machine Learning and Cybernetics, IEEE, 2005, pp. 1351-1355.

38. Chenguang LIU, et al., "A state-compensation extended state observer for model predictive control," European Journal of Control, vol. 36, pp. 1-9, 2017.
39. Liuping WANG, Chris T. FREEMAN, Eric ROGERS, "Predictive iterative learning control with experimental validation," Control Engineering Practice, vol. 53, pp. 24-34, 2016.
40. Se-Kyu OH, Byung Jun PARK, Jong Min LEE, "Point-to-point iterative learning model predictive control," Automatica, vol. 89, pp. 135-143, 2018.
41. Hong-Gui HAN, et al., "Multiobjective design of fuzzy neural network controller for wastewater treatment process," Applied Soft Computing, vol. 67, pp. 467-478, 2018.
42. C. M. ROCHA-OSORIO, et al., "Deadbeat–fuzzy controller for the power control of a Doubly Fed Induction Generator based wind power system," ISA transactions, vol. 88, pp. 258-267, 2019.
43. Nurul Afiqah ZAINAL, Ahmad Razlan YUSOFF, Ajisman APEN, "Integrated cooling systems and maximum power point tracking of fuzzy logic controller for improving photovoltaic performances," Measurement, vol. 131, pp. 100-108, 2019.
44. K. PREMKUMAR, B. V. MANIKANDAN, "Adaptive Neuro-Fuzzy Inference System based speed controller for brushless DC motor," Neurocomputing, vol. 138, pp. 260-270, 2014.
45. Mounir Ben NASR, Mohamed CHTOUROU, "Neural network control of nonlinear dynamic systems using hybrid algorithm," Applied Soft Computing, vol. 24, pp. 423-431, 2014.
46. Ali Reza TAVAKOLI, Ali Reza SEIFI, Mohammad Mehdi AREFI, "Designing a self-constructing fuzzy neural network controller for damping power system oscillations," Fuzzy Sets and Systems, vol. 356, pp. 63-76, 2019.
47. Resul COTELI, et al., "Design and implementation of Type-2 fuzzy neural system controller for PWM rectifiers," International Journal of Hydrogen Energy, vol. 42, no. 32, pp. 20759-20771, 2017.
48. Ohnishi, Y., Kitagawa, H., Mori, S., Wakitani, S., & Yamamoto, T. (2013). *Design of Neural Networks Based FRIT PID Controllers and Its Applications*. IFAC Proceedings Volumes, 46(11), 355-359.
49. Souradeep DUTTA, et al., "Learning and verification of feedback control systems using feedforward neural networks," IFAC-PapersOnLine, vol. 51, no. 16, pp. 151-156, 2018.
50. D. E. KAZARYAN, A. V. SAVINKOV, "Grammatical evolution for neural network optimization in the control system synthesis problem," Procedia Computer Science, vol. 103, pp. 14-19, 2017.
51. Khaled BELARBI, et al., "Design of Mamdani fuzzy logic controllers with rule base minimisation using genetic algorithm," Engineering applications of artificial intelligence, vol. 18, no. 7, pp. 875-880, 2005.
52. Nitiwat SANORNOI, et al., "A Geno-Hydra Control System: Design and Tuning Hybrid Controller based on Hydra Control Structure by using Genetic Algorithms," in 2006 1ST IEEE Conference on Industrial Electronics and Applications, IEEE, 2006, pp. 1-6.
53. Radu-Emil PRECUP, et al., "Evolutionary optimization-based tuning of low-cost fuzzy controllers for servo systems," Knowledge-Based Systems, vol. 38, pp. 74-84, 2013.
54. Ying Ding, Liang Wang, Yongwei Li, Daoliang Li, (2018). *Model predictive control and its application in agriculture*.
55. Mouayad A. SAHIB, Bestoun S. AHMED, "A new multiobjective performance criterion used in PID tuning optimization algorithms," Journal of advanced research, vol. 7, no. 1, pp. 125-134, 2016.
56. Liu FAN, Er Meng JOO, "Design for auto-tuning PID controller based on genetic algorithms," in 2009 4th IEEE conference on industrial electronics and applications, IEEE, 2009, pp. 1924-1928.
57. N. A. PATIL, G. V. LAKHEKAR, "Design of PID controller for cascade control process using genetic algorithm," in 2017 International Conference on Intelligent Computing and Control Systems (ICICCS), IEEE, 2017, pp. 1089-1095.
58. Morteza MORADI, "A genetic-multivariable fractional order PID control to multi-input multi-output processes," Journal of Process Control, vol. 24, no. 4, pp. 336-343, 2014.
59. P.B. de Moura Oliveiraa*, E.J. Solteiro Piresa, Paulo Novaisb. (2015). *Design of Posicast PID control systems using a gravitational search algorithm*.
60. Jirapun PONGFAI, Wudhichai ASSAWINCHAICHOTE, "Optimal PID parametric auto-adjustment for BLDC motor control systems based on artificial intelligence," in 2017 International Electrical Engineering Congress (iEECON), IEEE, 2017, pp. 1-4.

61. G. TAIRIDIS, et al., "Fine tuning of a fuzzy controller for vibration suppression of smart plates using genetic algorithms," Advances in Engineering Software, vol. 101, pp. 123-135, 2016.
62. Akihiro OI, et al., "Development of PSO-based PID tuning method," in 2008 International Conference on Control, Automation and Systems, IEEE, 2008, pp. 1917-1920.
63. A. Derrouazin a, M. Aillerie b, N. Mekkakia-Maaza d, J.-P. Charles. (2017). *Multi input-output fuzzy logic smart controller for a residential hybrid solar-wind-storage energy System*.
64. Mani RANJANI, Palzha MURUGESAN, "Optimal fuzzy controller parameters using PSO for speed control of Quasi-Z Source DC/DC converter fed drive," Applied Soft Computing, vol. 27, pp. 332-356, 2015.
65. Dibyendu PAL, Amitava CHATTERJEE, Anjan RAKSHIT, "Robust-stable quadratic-optimal fuzzy-PDC controllers for systems with parametric uncertainties: A PSO based approach," Engineering Applications of Artificial Intelligence, vol. 70, pp. 38-51, 2018.
66. Aydogan SAVRAN, "A multivariable predictive fuzzy PID control system," Applied Soft Computing, vol. 13, no. 5, pp. 2658-2667, 2013.
67. Younes Solgi, Soheil Ganjefar. (2018). *Variable structure fuzzy wavelet neural network controller for complex nonlinear systems.* Applied Soft Computing, 2018, vol. 64, p. 674-685.
68. Sofiane BERRAZOUANE, Kamal MOHAMMEDI, "Parameter optimization via cuckoo optimization algorithm of fuzzy controller for energy management of a hybrid power system," Energy conversion and management, vol. 78, pp. 652-660, 2014.
69. Saber FALAHATI, Seyed Abbas TAHER, Mohammad SHAHIDEHPOUR, "Grid frequency control with electric vehicles by using of an optimized fuzzy controller," Applied Energy, vol. 178, pp. 918-928, 2016.
70. S. Reza NAGHIBI, Ali A. PIRMOHAMADI, S. Ali A. MOOSAVIAN, "Fuzzy MTEJ controller with integrator for control of underactuated manipulators," Robotics and Computer-Integrated Manufacturing, vol. 48, pp. 93-101, 2017.
71. B. P. SAHOO, S. PANDA, "Improved grey wolf optimization technique for fuzzy-aided PID controller design for power system frequency control," Sustainable Energy, Grids and Networks, vol. 16, pp. 278-299, 2018.
72. LU, Kangdi, et al. (2018). *Design of PID controller based on a self-adaptive state-space predictive functional control using extremal optimization method*. Journal of the Franklin Institute, 2018, vol. 355, no 5, p. 2197-2220.
73. Doh, T. Y., Ryoo, J. R., & Chang, D. E. (2014). *Robust iterative learning controller design using the performance weighting function of feedback control systems*. International Journal of Control, Automation and Systems, 12(1), 63-70.
74. Jhon Edisson RODRÍGUEZ-CASTELLANOS, Victor H. GRISALES-PALACIO, Jorge Eduardo COTE-BALLESTEROS, "A tuning proposal for direct fuzzy PID controllers oriented to industrial continuous processes," IFAC-PapersOnLine, vol. 51, no. 4, pp. 657-662, 2018.
75. Camilo CARAVEO, Fevrier VALDEZ, Oscar CASTILLO, "Optimization of fuzzy controller design using a new bee colony algorithm with fuzzy dynamic parameter adaptation," Applied Soft Computing, vol. 43, pp. 131-142, 2016.
76. Lakhmissi CHERROUN, Mohamed BOUMEHRAZ, "Path following behavior for an autonomous mobile robot using neuro-fuzzy controller," International Journal of System Assurance Engineering and Management, vol. 5, pp. 352-360, 2014.
77. R. STIRRUP, A. J. CHIPPERFIELD, "Hybrid control and evolutionary decision support within a sustainable environment," in Proceedings of the IEEE International Symposium on Intelligent Control, IEEE, 2002, pp. 526-531.
78. Hiroyuki SATO, et al., "Adaptive control of the number of crossed genes in many-objective evolutionary optimization," in Learning and Intelligent Optimization: 6th International Conference, LION 6, Paris, France, January 16-20, 2012, Revised Selected Papers, Springer Berlin Heidelberg, 2012, pp. 478-484.
79. Todorov, Y. V., Terziyska, M. N., & Petrov, M. G.(2015). *NEO-Fuzzy State-Space Predictive Control*. IFAC-Papers On Line, 48(24), 99-104.
80. Zne-Jung LEE, "A robust learning algorithm based on support vector regression and robust fuzzy cerebellar model articulation controller," Applied intelligence, vol. 29, no. 1, pp. 47-55, 2008.

81. Andrzej PRZYBYŁ, Jacek SZCZYPTA, Lipo WANG, "Optimization of controller structure using evolutionary algorithm," in Artificial Intelligence and Soft Computing: 14th International Conference, ICAISC 2015, Zakopane, Poland, June 14-18, 2015, Proceedings, Part II, Springer International Publishing, 2015, pp. 261-271.
82. Stogiannos, M., Alexandridis, A., & Sarimveis, H. (2018). *Model predictive control for systems with fast dynamics using inverse neural models*. ISA transactions, 72, 161-177.
83. Amirhossein ASGHARNIA, Reza SHAHNAZI, Ali JAMALI, "Performance and robustness of optimal fractional fuzzy PID controllers for pitch control of a wind turbine using chaotic optimization algorithms," ISA transactions, vol. 79, pp. 27-44, 2018.
84. N. BOUNAR, S. LABDAI, A. BOULKROUNE, "PSO–GSA based fuzzy sliding mode controller for DFIG-based wind turbine," ISA transactions, vol. 85, pp. 177-188, 2019.
85. Kumar, S. S. P., Tulsyan, A., Gopaluni, B., & Loewen, P. (2018) *A Deep Learning Architecture for Predictive Control*. IFAC-Papers On Line, 51(18), 512-517.
86. Chaoshun LI, et al., "Design of a fuzzy-PID controller for a nonlinear hydraulic turbine governing system by using a novel gravitational search algorithm based on Cauchy mutation and mass weighting," Applied Soft Computing, vol. 52, pp. 290-305, 2017.
87. Londhe, P. S., Singh, Y., Santhakumar, M., Patre, B. M., & Waghmare, L. M. (2016). *Robust nonlinear PID-like fuzzy logic control of a planar parallel (2PRP-PPR) manipulator*. ISA transactions, 63, 218-232.
88. Liu, L., Pan, F., & Xue, D. (2015). *Variable-order fuzzy fractional PID controller*. ISA transactions, 55, 227-233.
89. Signe MOE, Anne Marthine RUSTAD, Kristian G. HANSSEN, "Machine learning in control systems: An overview of the state of the art," in Artificial Intelligence XXXV: 38th SGAI International Conference on Artificial Intelligence, AI 2018, Cambridge, UK, December 11–13, 2018, Proceedings 38, Springer International Publishing, 2018, pp. 250-265.
90. Boulkroune, A., Issaouni, S., & Chekireb, H. (2016). *Adaptive Neuro-Fuzzy Controller of Induction Machine Drive with Nonlinear Friction*. In Nature-Inspired Computing for Control Systems (pp. 169-192). Springer, Cham.
91. Bradai, R., Shetat, B., & Ladygin, A. N. (2008). *Increase in the efficiency of the speed controller of an induction machine drive by means of artificial intelligence.* Russian Electrical Engineering, 79(12), 676-684.
92. Abdel Ghani AISSAOUI, et al., "Power control of wind turbine based on fuzzy controllers," Energy Procedia, vol. 42, pp. 163-172, 2013.
93. Michal PRAUZEK, et al., "Differential evolution of fuzzy controller for environmentally-powered wireless sensors," Applied Soft Computing, vol. 48, pp. 193-206, 2016.
94. Jeen LIN, Ruey-Jing LIAN, "Design of a grey-prediction self-organizing fuzzy controller for active suspension systems," Applied Soft Computing, vol. 13, no. 10, pp. 4162-4173, 2013.
95. Prakash Chandra SAHU, Ramesh Chandra PRUSTY, Sidhartha PANDA, "Approaching hybridized GWO-SCA based type-II fuzzy controller in AGC of diverse energy source multi area power system," Journal of King Saud University-Engineering Sciences, vol. 32, no. 3, pp. 186-197, 2020.
96. Sendoya-Losada, D. F., Vargas-Duque, D. C., & Ávila-Plazas, I. J. (2018). *Implementation of a neural control system based on PI control for a non-linear process*. In 2018 IEEE 1st Colombian Conference on Applications in Computational Intelligence (ColCACI) (pp. 1-6). IEEE.
97. Mukhtar Fatihu Hamzaa,b, Hwa Jen Yapa, Imtiaz Ahmed Choudhurya. (2017). *Cuckoo search algorithm based design of interval Type-2 Fuzzy PID Controller for Furuta pendulum System*.
98. Meysam GHEISARNEJAD, "An effective hybrid harmony search and cuckoo optimization algorithm based fuzzy PID controller for load frequency control," Applied Soft Computing, vol. 65, pp. 121-138, 2018.
99. Hassen T. Dorrah a, Ahmed M. El-Garhy b, Mohamed E. El-Shimy. (2012). *PSO based optimized fuzzy controllers for decoupled highly interacted distillation process*.
100. Anupam Kumar, Vijay Kumar. (2017). *Evolving an interval type-2 fuzzy PID controller for the redundant robotic manipulator*.
101. Nada M. MOAWAD, Wael M. ELAWADY, Amany M. SARHAN, "Development of an adaptive radial basis function neural network estimator-based continuous sliding mode control for uncertain nonlinear systems," ISA transactions, vol. 87, pp. 200-216, 2019.

102. M. V. KARAVAEV, A. A. ZHDANOV, "Construction of self-learning fuzzy controllers using autonomous adaptive control methodology," Journal of Computer and Systems Sciences International, vol. 46, pp. 255-261, 2007.
103. Sophie KLECKER, Bassem HICHRI, Peter PLAPPER, "Learning-while controlling RBF-NN for robot dynamics approximation in neuro-inspired control of switched nonlinear systems," in Artificial Neural Networks and Machine Learning–ICANN 2018: 27th International Conference on Artificial Neural Networks, Rhodes, Greece, October 4-7, 2018, Proceedings, Part III, Springer International Publishing, 2018, pp. 717-727.
104. Miroslav B. MILOVANOVIĆ, et al., "Adaptive PID control based on orthogonal endocrine neural networks," Neural Networks, vol. 84, pp. 80-90, 2016.
105. Zhou Jianguang, Zhang Liguang. (2011). *The Design and Application of Fuzzy Controller in a Novel Plasma Water Treatment System*.
106. H.Sathishkumara, S.S.Parthasarathyb. (2017*). A novel neural network intelligent controller for vector controlled induction motor drive*.
107. H.Sathishkumara, S.S.Parthasarathyb. (2017). *A novel fuzzy logic controller for vector controlled induction motor drive*.
108. S. MOHAMED, I. A. HAMEED, "A GA-based adaptive neuro-fuzzy controller for greenhouse climate control system," Alexandria Engineering Journal, vol. 57, no. 2, pp. 773-779, 2018.
109. Xiang Hui GAO, et al., "Adaptive control of rapidly time-varying discrete-time system using initial-training-free online extreme learning machine," Neurocomputing, vol. 194, pp. 117-125, 2016.
110. Sudarshan K. VALLURU, Madhusudan SINGH, "Performance investigations of APSO tuned linear and nonlinear PID controllers for a nonlinear dynamical system," Journal of Electrical Systems and Information Technology, vol. 5, no. 3, pp. 442-452, 2018.
111. Aydogan SAVRAN, Gokalp KAHRAMAN, "A fuzzy model based adaptive PID controller design for nonlinear and uncertain processes," ISA transactions, vol. 53, no. 2, pp. 280-288, 2014.
112. Yanhong BAI, Zhijuan ZHAO, Zhiyi SUN, Long QUAN. (2013). *A Linear Interpolation Fuzzy Controller for a Boiler Pressure Control System*.
113. Rim Ben Alia, Salwa Bouadilab, Abdelkader Mamia. (2018). *Development of a Fuzzy Logic Controller applied to an agricultural greenhouse experimentally validated*.
114. Zhijia ZHAO, et al., "Adaptive neural network control of a flexible string system with non-symmetric dead-zone and output constraint," Neurocomputing, vol. 283, pp. 1-8, 2018.
115. Yasser M. ABDALLAH, Waldemar C. LEITE FILHO, "An Adaptive Tuning Strategy of PID Attitude Control System," IFAC Proceedings Volumes, vol. 37, no. 6, pp. 1009-1014, 2004.
116. Anna Vasickaninova, Monika Bakosova. (2015). *Control of a heat exchanger using neural network predictive controller combined with auxiliary fuzzy controller*.
117. Yan-xin ZHANG, "Fuzzy neural network adaptive robust control of a class of nonlinear interconnected systems based on TS fuzzy model," in 2010 Chinese Control and Decision Conference, IEEE, 2010, pp. 2561-2564.
118. Monica PATRASCU, Andreea ION, "Self-Adaptation in Genetic Algorithms for Control Engineering: The Case of Time Delay Systems," in 2017 21st International Conference on Control Systems and Computer Science (CSCS), IEEE, 2017, pp. 19-25.
119. Mohsen FARAHANI, Soheil GANJEFAR, "Intelligent power system stabilizer design using adaptive fuzzy sliding mode controller," Neurocomputing, vol. 226, pp. 135-144, 2017.
120. Harold R. CHAMORRO, et al., "Synthetic inertia control based on fuzzy adaptive differential evolution," International Journal of Electrical Power & Energy Systems, vol. 105, pp. 803-813, 2019.
121. Xingshuo Li a, b, Huiqing Wen a, Yihua Hu b, Lin Jiang. (2019). *A novel beta parameter based fuzzy-logic controller for photovoltaic MPPT application*.
122. E. B. PRIYANKA, C. MAHESWARI, S. THANGAVEL, "Online monitoring and control of flow rate in oil pipelines transportation system by using PLC based Fuzzy-PID Controller," Flow Measurement and Instrumentation, vol. 62, pp. 144-151, 2018.

123. Ahmad M. ZAKI, et al., "Embedded two level direct adaptive fuzzy controller for DC motor speed control," Ain Shams Engineering Journal, vol. 9, no. 1, pp. 65-75, 2018.
124. G. M. TAMILSELVAN, P. AARTHY, "Online tuning of fuzzy logic controller using Kalman algorithm for conical tank system," Journal of Applied Research and Technology, vol. 15, no. 5, pp. 492-503, 2017.
125. Matthias LORENZEN, Frank ALLGÖWER, Mark CANNON, "Adaptive model predictive control with robust constraint satisfaction," IFAC-PapersOnLine, vol. 50, no. 1, pp. 3313-3318, 2017.
126. Yuzhong WANG, Qibing JIN, Ridong ZHANG, "Improved fuzzy PID controller design using predictive functional control structure," ISA transactions, vol. 71, pp. 354-363, 2017.
127. Bahareh VATANKHAH, Mohammad FARROKHI, "Nonlinear model-predictive control with disturbance rejection property using adaptive neural networks," Journal of the Franklin Institute, vol. 354, no. 13, pp. 5201-5220, 2017.
128. Amal KARRAY, et al., "Intelligent mobile manipulator navigation using hybrid adaptive-fuzzy controller," Computers & Electrical Engineering, vol. 56, pp. 773-783, 2016.
129. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.
130. Haykin, S. (2009). *Neural Networks and Learning Machines*. Prentice Hall.
131. Bishop, C. M. (2006). *Pattern Recognition and Machine Learning*. Springer.
132. Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimization, and Machine Learning*. Addison-Wesley.
133. Michalewicz, Z. (1996). *Genetic Algorithms + Data Structures = Evolution Programs*. Springer.
134. Eiben, A. E., & Smith, J. E. (2003). *Introduction to Evolutionary Computing*. Springer.
135. Zadeh, L. A. (1965). Fuzzy Sets. Information and Control.
136. Klir, G. J., & Yuan, B. (1995). *Fuzzy Sets and Fuzzy Logic: Theory and Applications*. Prentice Hall.
137. Ross, T. J. (2010). *Fuzzy Logic with Engineering Applications*. Wiley.
138. Talbi, E. G. (2009). *Metaheuristics: From Design to Implementation*. Wiley.
139. Fogel, D. B. (2006). *Evolutionary Computation: Toward a New Philosophy of Machine Intelligence*. Wiley-IEEE Press.
140. Zitzler, E., Deb, K., & Thiele, L. (2000). *Comparison of Multiobjective Evolutionary Algorithms: Empirical Results*. IEEE Transactions on Evolutionary Computation.
141. Moore, K.L., & Xu, J.X. (1997). *Iterative Learning Control for Deterministic Systems*. Springer.
142. Bristow, D.A., Tharayil, M., & Alleyne, A.G. (2006). *A Survey of Iterative Learning Control: A Learning-Based Method for High-Performance Tracking Control*. IEEE Control Systems Magazine.
143. Amann, N., Owens, D.H., & Rogers, E. (1996). *Iterative learning control using optimal feedback and feedforward actions.* International Journal of Control.
144. Morari, M., & Zafiriou, E. (1989). *Robust Process Control*. Prentice-Hall.
145. Seborg, D.E., Edgar, T.F., & Mellichamp, D.A. (2010). *Process Dynamics and Control*. Wiley.
146. Rivera, D.E., Morari, M., & Skogestad, S. (1986). *Internal Model Control: PID Controller Design.* Industrial & Engineering Chemistry Process Design and Development.
147. Mitchell, T.M. (1997). *Machine Learning*. McGraw-Hill.
148. Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction.* Springer.
149. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.
150. Murphy, K.P. (2012). *Machine Learning: A Probabilistic Perspective*. MIT Press.
151. Glover, F., & Kochenberger, G.A. (2003). *Handbook of Metaheuristics.* Springer.
152. Michalewicz, Z., & Fogel, D.B. (2004). *How to Solve It: Modern Heuristics.* Springer.
153. Dorigo, M., & Stützle, T. (2004). *Ant Colony Optimization*. MIT Press.
154. Talbi, E.G. (2009). *Metaheuristics: From Design to Implementation*. Wiley.
155. Qin, S.J., & Badgwell, T.A. (2003). "A survey of industrial model predictive control technology." Control Engineering Practice.
156. Camacho, E.F., & Bordons, C. (2004). *Model Predictive Control*. Springer.
157. Rawlings, J.B., & Mayne, D.Q. (2009). *Model Predictive Control: Theory and Design.* Nob Hill Publishing.
158. Maciejowski, J.M. (2002). *Predictive Control with Constraints.* Pearson Education.

159. Singh, A. P., Kumar, Y., Sawle, Y., Alotaibi, M. A., Malik, H., & Márquez, F. P. G. (2024). Development of artificial Intelligence-Based adaptive vehicle to grid and grid to vehicle controller for electric vehicle charging station. *Ain Shams Engineering Journal*, *15*(10), 102937.
160. Lisitsyn, A. N., & Zadorozhnaya, N. M. (2019). Adaptive wind turbine PID controller tuner algorithm with elements of artificial intelligence. *Procedia Computer Science*, *150*, 591-596.
161. Saravanan, G., Suresh, K. P., Pazhanimuthu, C., & Kumar, R. S. (2024). Artificial rabbits optimization algorithm based tuning of PID controller parameters for improving voltage profile in AVR system using IoT. *e-Prime-Advances in Electrical Engineering, Electronics and Energy*, *8*, 100523.
162. Mohamed, M. J., Oleiwi, B. K., Azar, A. T., & Hameed, I. A. (2024). Coot optimization algorithm-tuned neural network-enhanced PID controllers for robust trajectory tracking of three-link rigid robot manipulator. *Heliyon*, *10*(13).
163. Benbouhenni, H., Colak, I., Yessef, M., Elbarbary, Z. M. S., & Bizon, N. (2025). Feedback action and genetic algorithm-based proportional-integral controller to improve the performance of the direct power control of a variable-speed contra-rotating wind turbine generation system. *Energy Reports*, *13*, 2153-2173.
164. Rodríguez-Abreo, O., Rodríguez-Reséndiz, J., García-Cerezo, A., & García-Martínez, J. R. (2024). Fuzzy logic controller for UAV with gains optimized via genetic algorithm. *Heliyon*, *10*(4).
165. Bojan-Dragos, C. A., Precup, R. E., Preitl, S., Roman, R. C., Hedrea, E. L., & Szedlak-Stinean, A. I. (2021). GWO-based optimal tuning of type-1 and type-2 fuzzy controllers for electromagnetic actuated clutch systems. *IFAC-PapersOnLine*, *54*(4), 189-194.
166. Bouaddi, A., Rabeh, R., & Ferfra, M. (2025). Load Frequency Control in Autonomous Microgrids using Hybrid Algorithm GWO-CS based Fuzzy logic Sliding Mode Controller. *Results in Engineering*, 104412.
167. Terfia, E. S., Mendaci, S., Rezgui, S. E., Gasmi, H., & Kantas, W. (2024). Optimal third-order sliding mode controller for dual star induction motor based on grey wolf optimization algorithm. *Heliyon*, *10*(12).
168. Shekher, V., Sisodiya, A., Sinha, A. K., Harsh, H., & Soren, N. (2024). Optimal tuning of PID controller for V/f control of linear induction motor using artificial biological intelligence. *Franklin Open*, *9*, 100183.
169. Civelek, Z. (2020). Optimization of fuzzy logic (Takagi-Sugeno) blade pitch angle controller in wind turbines by genetic algorithm. *Engineering Science and Technology, an International Journal*, *23*(1), 1-9.
170. Pazhanimuthu, C., Saravanan, G., Suresh, K. P., & Kumar, R. S. (2023). Performance analysis of voltage profile improvement in AVR system using zebra optimization algorithms based on PID controller. *e-Prime-Advances in Electrical Engineering, Electronics and Energy*, *6*, 100380.
171. Gao, Y. (2023, September). Design of Automatic Control System for Garden Irrigation Based on Artificial Intelligence Algorithm. In *2023 International Conference on Power, Electrical Engineering, Electronics and Control (PEEEC)* (pp. 435-440). IEEE.
172. Arostegui, A., Benítez, D. S., & Caiza, L. (2020, October). A fuzzy-PD controller optimized by artificial bee colony algorithm applied to a small-scale pasteurization plant. In *2020 IEEE ANDESCON* (pp. 1-6). IEEE.
173. Chen, G., Li, Z., Zhang, Z., & Li, S. (2019). An improved ACO algorithm optimized fuzzy PID controller for load frequency control in multi area interconnected power systems. *Ieee Access*, *8*, 6429-6447.
174. Gheisarnejad, M., & Khooban, M. H. (2020). An intelligent non-integer PID controller-based deep reinforcement learning: Implementation and experimental results. *IEEE Transactions on Industrial Electronics*, *68*(4), 3609-3618.
175. Nair, A. A. (2024, April). Ant Colony Optimization-Tuned Fractional Order PID Controller for Speed Regulation In Hybrid Electric Vehicle. In *2024 International Conference on Recent Advances in Electrical, Electronics, Ubiquitous Communication, and Computational Intelligence (RAEEUCCI)* (pp. 1-5). IEEE.
176. Tian, C., Ni, S., Wang, Z., & Zhang, Y. (2022, July). Application of Grey Wolf Optimization Algorithm in Tuning Controller Parameters of Hypersonic Vehicle. In *2022 41st Chinese Control Conference (CCC)* (pp. 323-328). IEEE.
177. Mohapatra, A. K., Sahu, P. C., Mohapatra, S., Bhatta, S. K., & Debnath, M. K. (2023, June). Artificial Intelligence technique governed robust fuzzy controller for microgrid frequency control. In *2023 International Conference in Advances in Power, Signal, and Information Technology (APSIT)* (pp. 236-241). IEEE.
178. Murugesan, D., Shah, P., Jagatheesan, K., Sekhar, R., & Kulkarni, A. J. (2022, September). Cohort intelligence optimization based controller design of isolated and interconnected thermal power system for

automatic generation control. In *2022 Second International Conference on Computer Science, Engineering and Applications (ICCSEA)* (pp. 1-6). IEEE.
179. Pattnaik, R., Chandak, S., Rout, P. K., Routray, S. K., & Sahu, B. K. (2020, July). Design and analysis of automatic generation control of two area power system based on modified differential evolution algorithm. In *2020 International Conference on Computational Intelligence for Smart Power System and Sustainable Energy (CISPSSE)* (pp. 1-6). IEEE.
180. Ibrahim, E. K., Gitaffa, S. A., & Issa, A. H. (2022, December). Design of FOPID controller for DC motor speed control using intelligent swarm techniques. In *2022 4th International Conference on Current Research in Engineering and Science Applications (ICCRESA)* (pp. 40-46). IEEE.
181. Xu, J., & Bhattacharyya, S. P. (2021, November). Efficient Tuning of PID Controllers using Swarm-based Optimization Algorithms. In *2021 9th International Conference on Systems and Control (ICSC)* (pp. 572-579). IEEE.
182. Ranjitha, K., Sivakumar, P., Elavarasu, R., Monica, M., & Rajapandiyan, A. (2021, May). Firefly algorithm optimized load frequency controller for multi-source power system. In *2021 Emerging Trends in Industry 4.0 (ETI 4.0)* (pp. 1-6). IEEE.
183. Ahmadi, S., Talami, S. H., Sahnesaraie, M. A., Dini, F., Tahernejadjozam, B., & Ashgevari, Y. (2020, January). FUZZY aided PID controller is optimized by GA algorithm for Load Frequency Control of Multi-Source Power Systems. In *2020 IEEE 18th World Symposium on Applied Machine Intelligence and Informatics (SAMI)* (pp. 000207-000212). IEEE.
184. Ray, N. K., Mohapatra, S. K., & Dash, S. S. (2020, July). Gravitational Search Algorithm for Optimal Tunning of controller parameters in AVR system. In *2020 International Conference on Computational Intelligence for Smart Power System and Sustainable Energy (CISPSSE)* (pp. 1-6). IEEE.
185. Jia, W., Zhan, Y., Sun, J., Zhang, J., & Dai, Y. (2023, July). Grinding Constant Force Control based on PID Controller with Nonlinear Differential Link Optimized by Differential Evolution Algorithm. In *2023 42nd Chinese Control Conference (CCC)* (pp. 4298-4303). IEEE.
186. Rosnani, A. A. M., Hadi, M. S., Jamali, A., Darus, I. Z. M., Yatim, H. M., & Ab Talib, M. H. (2023, February). Hub Angle Control of Double Link Flexible Robotic Arm Manipulator Using PID Controller Tuned by Bacterial Foraging Optimization Algorithm. In *2023 13th International Conference on Power, Energy and Electrical Engineering (CPEEE)* (pp. 144-148). IEEE.
187. Guru, N., Prusty, A., Pani, S., Nanda, K., & Barisal, A. K. (2022, July). Intelligent control based level shifted PWM Multilevel Inverter. In *2022 International Conference on Intelligent Controller and Computing for Smart Power (ICICCSP)* (pp. 1-6). IEEE.
188. Zhai, Y., Zhao, Q., Han, Y., Wang, J., & Zeng, W. (2024, January). Intelligent PID Controller Based on Deep Reinforcement Learning. In *2024 8th International Conference on Robotics, Control and Automation (ICRCA)* (pp. 343-348). IEEE.
189. Abd Raof, A. I., Hadi, M. S., Jamali, A., Yatim, H. M., Ab Talib, M. H., & Darus, I. Z. M. (2022, September). Intelligent PID controller tuned by bacterial foraging optimization algorithm for vibration suppression of horizontal flexible structure. In *2022 IEEE 8th International Conference on Smart Instrumentation, Measurement and Applications (ICSIMA)* (pp. 237-241). IEEE.
190. Hua, S., Xu, M., Li, S., Han, K., Xu, Z., & Zhao, Z. (2023, October). Intelligent water and fertilizer control strategy of fuzzy PID optimized by swarm intelligence algorithm. In *2023 2nd International Conference on Artificial Intelligence and Intelligent Information Processing (AIIIP)* (pp. 262-267). IEEE.
191. Lanker, J. H., Bhushan, R., & Gupta, N. (2022, July). Load Frequency Control of Multi Area Power System Using Meta-heuristic/Artificial Intelligence Techniques. In *2022 International Conference on Intelligent Controller and Computing for Smart Power (ICICCSP)* (pp. 1-6). IEEE.
192. Saklani, M., Chhetri, A., Saini, D. K., Yadav, M., & Gupta, Y. C. (2023, June). Load frequency control of two area power systems using optimised ANFIS controller. In *2023 5th International Conference on Energy, Power and Environment: Towards Flexible Green Energy Technologies (ICEPE)* (pp. 1-6). IEEE.
193. Pattnayak, S. K., Choudhury, S., Nayak, N., Bagarty, D. P., & Biswabandhya, M. (2020, July). Maximum power tracking & harmonic reduction on grid PV system using chaotic gravitational search algorithm

based MPPT controller. In *2020 International Conference on Computational Intelligence for Smart Power System and Sustainable Energy (CISPSSE)* (pp. 1-6). IEEE.
194. Xu, P. (2022, October). Neural network based self-tuning PID controller. In *2022 2nd International Conference on Algorithms, High Performance Computing and Artificial Intelligence (AHPCAI)* (pp. 655-661). IEEE.
195. Sahoo, S., Jena, N. K., Naik, A. K., Sahu, B. K., & Debnath, M. K. (2020, July). Optimal design and implementation of fuzzy fractional order PID controller for AGC study. In *2020 International Conference on Computational Intelligence for Smart Power System and Sustainable Energy (CISPSSE)* (pp. 1-6). IEEE.
196. Guo, B., Zhuang, Z., Pan, J. S., & Chu, S. C. (2021). Optimal design and simulation for PID controller using fractional-order fish migration optimization algorithm. *IEEE Access*, *9*, 8808-8819.
197. Chen, D., & Li, J. (2020, November). Optimal Design of Speed Controller in PMSM Based on Grasshopper Optimization Algorithm. In *2020 IEEE 1st China International Youth Conference on Electrical Engineering (CIYCEE)* (pp. 1-7). IEEE.
198. Sun, J., Wu, L., & Yang, X. (2020, August). Optimal Fractional Order PID Controller Design for AVR System Based on Improved Genetic Algorithm. In *2020 IEEE International Conference on Advances in Electrical Engineering and Computer Applications (AEECA)* (pp. 351-355). IEEE.
199. Oladipo, S., Sun, Y., & Wang, Z. (2020, September). Optimization of FOPID controller with hybrid Particle Swarm and Grey Wolf optimization for AVR System. In *2020 12th International Conference on Computational Intelligence and Communication Networks (CICN)* (pp. 273-279). IEEE.
200. Ma, T., Ma, H., & Xue, J. (2024, July). Optimization of PID Parameter Tuning Based on Improved Dung Beetle Algorithm. In *2024 6th International Conference on Internet of Things, Automation and Artificial Intelligence (IoTAAI)* (pp. 515-520). IEEE.
201. Rojas-López, A. G., Villarreal-Cervantes, M. G., & Rodríguez-Molina, A. (2023, November). Optimum online controller tuning through de and pso algorithms: Comparative study with bldc motor and offline controller tuning strategy. In *2023 10th International Conference on Soft Computing & Machine Intelligence (ISCMI)* (pp. 215-221). IEEE.
202. You, M., Wu, Y., Wang, Y., Xie, X., & Xu, C. (2022, August). Parameter optimization of PID controller based on improved sine-SOA algorithm. In *2022 IEEE International Conference on Mechatronics and Automation (ICMA)* (pp. 12-17). IEEE.
203. Ronald, R. H., Alejandra, A. B., Jaime, R. C., & Antonio, T. B. J. (2020, November). PI tuning based on Bacterial Foraging Algorithm for flow control. In *2020 IX International Congress of Mechatronics Engineering and Automation (CIIMA)* (pp. 1-6). IEEE.
204. Ghith, E. S., & Tolba, F. A. A. (2022, May). Real-time implementation of an enhanced PID CONTROLLER based on marine predator algorithm (MPA) for micro-robotics system. In *2022 3rd International Conference on Artificial Intelligence, Robotics and Control (AIRC)* (pp. 40-45). IEEE.
205. Elsisi, M., Tran, M. Q., Mahmoud, K., Lehtonen, M., & Darwish, M. M. (2021). Robust design of ANFIS-based blade pitch controller for wind energy conversion systems against wind speed fluctuations. *IEEE Access*, *9*, 37894-37904.
206. Hussein, O. M., & Yasin, N. M. (2022, September). Salp Swarm Algorithm-based Position Control of a BLDC Motor. In *2022 4th International Conference on Advanced Science and Engineering (ICOASE)* (pp. 188-193). IEEE.
207. Dos Santos, G. F., Da Silva, W. G., & Júnior, G. D. C. (2022, November). Tuning of pi controllers for electric drives using evolutionary multi-objective optimization algorithm. In *2022 IEEE Latin American Conference on Computational Intelligence (LA-CCI)* (pp. 1-6). IEEE.
208. Nicola, M., & Nicola, C. I. (2021, October). Tuning of PI speed controller for PMSM control system using computational intelligence. In *2021 21st International Symposium on Power Electronics (Ee)* (pp. 1-6). IEEE.
209. Ghith, E. S., & Tolba, F. A. A. (2023). Tuning PID controllers based on hybrid arithmetic optimization algorithm and artificial gorilla troop optimization for micro-robotics systems. *IEEE access*, *11*, 27138-27154.
210. Yang, H., Zheng, J., Li, Y., & Zhang, Z. (2023, July). UAV oute Planning Based on Fuzzy PID Control Ant Colony Algorithm. In *2023 42nd Chinese Control Conference (CCC)* (pp. 4726-4731). IEEE.
211. Li, J., Yu, T., & Yang, B. (2021). Adaptive controller of PEMFC output voltage based on ambient intelligence large-scale deep reinforcement learning. *IEEE Access*, *9*, 6063-6075.

212. Zhao, F., Wang, S., Li, S., Zhao, L., Zhang, H., Wang, Y., & Jin, M. (2024, July). Adaptive Flight Control Based on Artificial Intelligence Algorithms. In *2024 20th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD)* (pp. 1-5). IEEE.
213. Chi, X., & Chi, R. (2020, December). Optimal design of linear quadratic regulator controller based on adaptive cuckoo search algorithm. In *2020 7th International Conference on Information Science and Control Engineering (ICISCE)* (pp. 1981-1986). IEEE.
214. Detroja, K. P. (2022, December). Parameterized Adaptive Controller Design using Reinforcement Learning and Deep Neural Networks. In *2022 Eighth Indian Control Conference (ICC)* (pp. 121-126). IEEE.
215. Emami, H., Sharifi, A. A., & Azarnia, G. (2020, August). Tuning PID Controller using Self-Adaptive Differential Evolution Algorithm. In *2020 28th Iranian Conference on Electrical Engineering (ICEE)* (pp. 1-5). IEEE.
216. Tudoroiu, R. E., Zaheeruddin, M., Curiac, D. I., Radu, M. S., & Tudoroiu, N. (2025). Investigations into the Design and Implementation of Reinforcement Learning Using Deep Learning Neural Networks. *Algorithms*, *18*(3), 170.
217. Güven, A. F., & Mengi, O. Ö. (2024). Nature-ınspired algorithms for optimizing fractional order PID controllers in time-delayed systems. *Optimal Control Applications and Methods*, *45*(3), 1251-1279.
218. Fernando, L., DM, L., Garc, F. S., Hern, N., & Nuria, G. (2021). Speed Proportional Integrative Derivative Controller: Optimization Functions in Metaheuristic Algorithms.