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Comparative Study of AI Algorithms for Mechatronic System Optimization

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Abstract
Artificial intelligence (AI) is increasingly applied in mechatronic system optimization to improve efficiency, adaptability, and performance. This paper compares important AI methods—like neural networks, genetic algorithms, reinforcement learning, fuzzy logic, and hybrid approaches—showing their advantages and disadvantages regarding accuracy, computing power needed, how easy they are to understand, and how well they can be integrated. Neural networks provide strong modeling capabilities for nonlinear dynamics but require extensive data. Genetic algorithms excel at global optimization but can be computationally costly. Reinforcement learning offers adaptive policy learning but presents safety and data challenges. Fuzzy logic systems prioritize interpretability, while hybrid approaches combine complementary strengths. By analyzing these trade-offs and citing recent advancements such as physics-guided neural networks, this study guides practitioners in selecting appropriate AI strategies for mechatronic optimization and outlines directions for future research.

Keywords: Mechatronics, Artificial Intelligence, Optimization, Neural Networks, Genetic Algorithms, Reinforcement Learning, Fuzzy Logic, Hybrid Systems.

I. INTRODUCTION
Mechatronic systems integrate mechanical, electronic, and computational components to deliver advanced capabilities in robotics, automotive engineering, and industrial automation [1], [2]. Optimizing these systems involves managing nonlinear dynamics and interactions among subsystems, posing challenges to traditional control methods [3].

Artificial Intelligence (AI) offers a data-driven alternative capable of handling these complexities. Techniques such as neural networks, genetic algorithms, reinforcement learning, and fuzzy logic have shown promising results in real-world mechatronic applications. However, each approach has distinct advantages and trade-offs in terms of performance, computational requirements, and interpretability [4], [5]. This paper provides a comparative review of these AI methods to guide practitioners in choosing suitable approaches.

II. OVERVIEW OF AI ALGORITHMS
A. Artificial Newural Networks (ANNs)
ANNs are powerful for modeling nonlinear systems and have evolved to include physics-guided neural networks (PGNN). For instance, a PGNN achieved a twofold performance boost in high-precision feed forward control of industrial linear motor systems compared to physics-based models alone [6]–[7].

B. Genetic Algorithms (GAs)
GAs are robust global optimizers suited for multi-parameter tuning and design problems. They are effective at exploring complex solution spaces but incur high computational cost and slow convergence [8].

C. Reinforcement Learning (RL)
RL enables adaptive policy learning via interaction, making it ideal for autonomous control. However, RL typically demands extensive training and poses safety challenges during exploration [9].

D. Fuzzy Logic Systems
Fuzzy systems offer interpretable, rule-based control suitable for integration with human expertise. However, they struggle with complex, data-rich environments due to limited learning capacity [10].

E. Hybrid Approaches
Combining AI techniques, such as neuro-fuzzy systems or GA-optimized ANNs, can balance performance and interpretability. These hybrids have shown improved outcomes in adaptive control scenarios, though they require careful design [11].

TABLE I: COMPARISON ACROSS CRITERIA

Criterion	AI Algorithms				
	ANN/PGNN	GAs	RL	Fuzzy Logic	Hybrid Method
Accuracy	High; PGNN doubles performance [6]	Good global search	Adaptive, environment-specific [9]	Moderate, rule-based	Often best overall
Training Cost	High data/training needs	Computationally expensive	Very high training cost [9]	Minimal	Mixed
Interpretability	Low (black-box)	Moderate (solution introspection)	Low	High (rule-based)	Moderate (e.g., neuro-fuzzy)
Intergration Ease	Mature frameworks	Easy offline optimization	Challenging for safe deployment	Easy real-time use	Requires tailored design

III. DISCUSSION

Each AI method offers distinct advantages for mechatronic optimization. Neural networks (including PGNNs) excel at modeling nonlinear dynamics with high accuracy but require significant training data and have interpretability challenges [6], [7]. Genetic algorithms provide robust global optimization for parameter tuning but may be computationally intensive [8], [9]. Reinforcement learning delivers adaptive control, ideal for autonomous systems, though training can be slow and safety-critical integration complex [10]–[12].

Fuzzy logic systems are valuable for transparent, rule-based control that integrates expert knowledge, though they may struggle in highly dynamic settings without learning capabilities [13], [14]. Hybrid approaches, such as neuro-fuzzy systems or GA-optimized ANNs, offer balanced solutions, combining interpretability with learning power [15], [16]. Choosing the right method depends on the application's needs for accuracy, data availability, computation resources, and ease of integration

IV. CONCLUSION

AI algorithms have transformed the landscape of mechatronic system optimization, offering advanced modeling, control, and decision-making capabilities. This review compared key AI approaches—highlighting neural networks for accuracy, genetic algorithms for robust optimization, reinforcement learning for adaptability, fuzzy logic for interpretability, and hybrid methods for balanced solutions.

Practitioners should match AI strategies to their specific application requirements, considering trade-offs in accuracy, interpretability, data needs, and deployment complexity. Future work should focus on improving explainable AI, integrating physics-based priors (as with PGNNs), and developing safe, efficient reinforcement learning frameworks for real-world mechatronic systems.

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