International Transactions on Artificial Intelligence (ITALIC)
Vol. 4, No. 2, May, 2026, pp. 183−194
E-ISSN: 2963-1939 | P-ISSN: 2963-6086, DOI:10.33050

Hybrid Fuzzy Logic Models for Performance Evaluation in Complex Decision-Making Systems

Cicilia Sriliasta Bangun[1], Padeli[2], Muhamad Yusup[3], Adele Valerry[4*]
[1]Faculty of Industrial Engineering, Esa Unggul University, Indonesia
[2]Faculty of Science and Technology, Universitas Raharja, Indonesia
[3]Faculty of Computer Science, Satya Wacana Christian University, Indonesia
[4]Department of Computer Science, Ilearning Incorporation, Colombia
[1]cicilia.bangun@esaunggul.ac.id, [2]padeli@raharja.info, [3]982022017@student.uksw.edu, [4]vallery.adele@ilearning.co
***Corresponding Author**

Article Info

Article history:

Submission February 24, 2026
Revised March 15, 2026
Accepted May 14, 2026
Published May 20, 2026

Keywords:

Artificial Intelligence
Fuzzy Logic
FLC–GA
Performance Evaluation
Decision-Making Systems

ABSTRACT

Complex decision-making systems increasingly face uncertainty, nonlinearity, incomplete information, and dynamic data streams, making conventional rule-based and statistical approaches less reliable for adaptive and consistent decision support. Fuzzy logic offers interpretability for imprecise reasoning, whereas machine learning contributes predictive strength and optimization capability. **This study** develops and evaluates fuzzy logic-based hybrid models that integrate fuzzy inference systems with neural learning and evolutionary optimization. Benchmark datasets and simulation-based case studies were used to test model performance under uncertain and nonlinear conditions. The models were assessed using prediction accuracy, decision consistency, computational efficiency, error reduction, scalability, and adaptability, followed by comparison with conventional fuzzy, statistical, and standalone machine learning models. **The main** objective is to evaluate the effectiveness, reliability, scalability, and adaptability of hybrid fuzzy models for complex decision-making systems. **The findings** show that the proposed hybrid fuzzy models outperform conventional single-model approaches across different scenarios. The models improve prediction precision, stabilize decision outputs under uncertainty, reduce error rates, and enhance adaptability to nonlinear data patterns. Neural learning strengthens predictive capability, while evolutionary optimization improves rule refinement, parameter tuning, and adaptive decision processing. **This study** concludes that fuzzy logic-based hybrid models provide a robust, interpretable, and scalable framework for intelligent decision support in uncertain and dynamic environments. The findings support the development of adaptive hybrid artificial intelligence systems for healthcare, energy management, smart cities, finance, and industrial automation. This structure also promotes transparent reasoning, reproducible evaluation, and practical deployment in high-stakes environments requiring explainability and resilience simultaneously.

DOI: https://doi.org/10.33050/italic.v4i2.1095

1. INTRODUCTION

The rapid growth of digital technologies, big data infrastructures, and intelligent systems has significantly increased the complexity of modern decision-making environments across a wide range of domains, including healthcare, manufacturing, finance, smart cities, and industrial automation [1]. In such environments, decision processes are often characterized by high dimensionality, nonlinear relationships, uncertainty, incomplete information, and dynamic changes. Conventional computational approaches, such as rule-based systems, linear statistical models, and deterministic optimization methods, are frequently unable to cope with these characteristics due to their rigid structure and limited adaptability [2]. Empirical evidence substantiates this claim: comparative studies have shown that traditional logistic regression models achieved accuracy rates below 74% on healthcare triage datasets containing missing values and linguistic variables, while benchmark analyses reported that standard decision-tree classifiers exhibited a 21% drop in predictive accuracy when financial time-series data were subject to distributional shifts exceeding two standard deviations [3, 4]. These quantitative findings confirm that deterministic models lack the structural capacity to tolerate ambiguity and non-stationarity at the scale demanded by contemporary applications.

As a result, researchers and practitioners have increasingly turned to Artificial Intelligence (AI) techniques to address these limitations [5]. Machine learning models such as neural networks, support vector machines, and decision trees have demonstrated strong performance in pattern recognition and prediction tasks; however, they still face challenges related to interpretability, sensitivity to noisy data, and reduced reliability when deployed in uncertain or rapidly changing environments [6]. Specifically, neural networks, despite their high representational capacity, have been criticized for their black-box nature, which prevents domain experts from validating decision logic in safety-critical settings such as clinical diagnosis or automated process control [7]. This interpretability gap constitutes a fundamental obstacle to regulatory compliance and stakeholder trust, thereby limiting the operational deployment of purely data-driven models in high-stakes domains. These compounded limitations highlight the urgent need for more flexible and robust computational frameworks that can effectively support complex decision-making systems in real-world contexts [8].

Fuzzy logic has emerged as a powerful paradigm for modeling uncertainty, vagueness, and imprecise human reasoning by allowing variables to take partial membership values rather than binary states [9]. This characteristic makes fuzzy systems a natural complement to the limitations described above: whereas neural networks produce outputs without transparent reasoning chains, fuzzy inference systems encode decision logic in human-readable linguistic rules, thus reconciling predictive power with domain intelligibility [10]. This capability makes fuzzy systems particularly suitable for complex decision scenarios where linguistic rules, expert knowledge, and ambiguous data play a critical role. Nevertheless, traditional fuzzy systems are often limited by their dependence on manually defined rules and membership functions, which may not scale well or adapt efficiently to large, data-driven environments [11, 12]. To overcome these constraints, hybrid models that integrate fuzzy logic with other soft computing and machine learning techniques have gained considerable attention. Examples include neuro-fuzzy systems that combine neural networks with fuzzy inference, fuzzy-genetic models that employ evolutionary algorithms for rule optimization, and fuzzy-deep learning architectures that enhance adaptive learning capabilities. These hybrid approaches aim to exploit the interpretability of fuzzy logic and the learning power of data-driven models, creating more intelligent and adaptive decision support systems. Despite the growing body of research in this area, existing studies often focus on specific applications or individual hybrid structures, making it difficult to draw general conclusions regarding their comparative performance and overall effectiveness in complex decision-making environments [13].

Based on these challenges and documented research gaps, this study focuses on the systematic performance evaluation of fuzzy logic-based hybrid models in complex decision-making systems [14]. The study makes three primary scientific contributions that distinguish it from existing work. First, it proposes and formally specifies a novel FLC–GA hybrid architecture in which genetic operators are directly embedded within the fuzzy rule-base optimization loop, a configuration not previously benchmarked across multi-domain datasets [15]. Second, it introduces a structured five-stage evaluation pipeline that enables reproducible cross-domain comparison across healthcare, financial, and industrial settings using standardized metrics. Third, it provides a quantitative trade-off analysis linking accuracy, computational complexity, and interpretability within a unified evaluation framework, thereby addressing a key gap identified in the literature [16, 17]. The primary objective of this research is to assess how different hybrid architectures perform in terms of accuracy, robustness, adaptability, and computational efficiency when compared to conventional single-model approaches [18]. By conducting controlled experiments using benchmark datasets and simulation-based case studies, this research seeks to provide a comprehensive understanding of the strengths and limitations of various hybrid fuzzy systems under different levels of uncertainty and system complexity [19]. The findings are expected to contribute both theoretically and practically to the field of intelligent systems by offering insights into model selection, system design, and future development of hybrid AI frameworks [20].

This research is also closely aligned with the United Nations Sustainable Development Goals (SDGs). The proposed hybrid model supports SDG 9 (Industry, Innovation, and Infrastructure) by enabling adaptive, intelligent systems that enhance industrial efficiency. It contributes to SDG 8 (Decent Work and Economic Growth) by improving decision accuracy in economic environments. The model's uncertainty management capabilities support SDG 3 (Good Health and Well-Being) through improved healthcare decision support, and SDG 11 (Sustainable Cities and Communities) by facilitating smarter urban systems [21, 22]. Practically, the FLC–GA model enables hospitals to reduce diagnostic misclassification rates attributable to ambiguous patient records, supports financial institutions in maintaining stable risk classifications during market volatility, and assists smart-city controllers in dynamically adjusting resource allocation under sensor noise. Through these contributions, this study demonstrates how hybrid Artificial Intelligence can support sustainable digital transformation in alignment with global development priorities [23].

2. LITERATURE REVIEW

The rapid development of Artificial Intelligence and soft computing techniques has significantly influenced how complex decision-making systems are designed and evaluated [24]. Recent studies emphasize that real-world problems are increasingly characterized by uncertainty, nonlinearity, high dimensionality, and dynamic conditions, which cannot be effectively addressed using traditional deterministic or statistical approaches [25]. As a result, researchers have focused on flexible and adaptive computational models that can integrate human-like reasoning with data-driven learning [26]. Among these approaches, fuzzy logic-based hybrid models have emerged as a promising solution due to their ability to combine interpretability with learning and optimization capabilities. This section reviews recent literature published after 2022, focusing on four key areas: fuzzy logic in decision-making, hybrid Artificial Intelligence models, soft computing techniques for uncertainty handling, and performance evaluation of hybrid fuzzy systems [27].

2.1. Fuzzy Logic in Complex Decision-Making Systems

Fuzzy logic has become a foundational paradigm for modeling uncertainty and ambiguity in complex decision-making systems, particularly in environments where precise mathematical representations are not feasible [28]. Since 2022, numerous studies have emphasized the superiority of fuzzy inference over traditional crisp logic when handling vague human reasoning and imprecise data [29]. Recent research highlights that fuzzy inference systems can effectively represent linguistic variables and expert knowledge, making them suitable for domains such as healthcare diagnostics, supply chain optimization, energy management, and risk assessment [30, 31]. However, contemporary literature also acknowledges critical limitations: standalone fuzzy systems suffer from scalability constraints as rule-base dimensionality grows exponentially with the number of input variables, their static membership functions cannot self-adapt to concept drift in streaming data, and manual rule elicitation introduces expert-knowledge bottlenecks that reduce generalizability [32]. reported that a Mamdani fuzzy system optimized for a 10-variable manufacturing control task required over 1,000 manually specified rules and still achieved a 12% lower accuracy than a hybrid counterpart trained using gradient-based methods. These documented shortcomings provide a strong empirical basis for pursuing hybrid architectures and directly motivate the model design adopted in the present study [33].

2.2. Hybrid Artificial Intelligence Models

Hybrid Artificial Intelligence models combine two or more computational paradigms to exploit their complementary strengths [34]. After 2022, the integration of fuzzy logic with neural networks, genetic algorithms, particle swarm optimization, and deep learning has attracted substantial research attention [35]. These hybrid architectures aim to overcome the weaknesses of single AI models by embedding learning capabilities into fuzzy systems or using fuzzy reasoning to improve interpretability in black-box machine learning models [36]. Recent literature demonstrates that hybrid AI systems achieve higher predictive accuracy, improved robustness, and better adaptability in uncertain and nonlinear environments [37]. However, a critical gap persists in existing studies: the majority of hybrid model evaluations are conducted within a single application domain and report performance on only one or two metrics, making cross-study comparisons methodologically untenable [38]. Furthermore, the absence of standardized benchmarking protocols means that reported accuracy improvements may reflect dataset-specific characteristics rather than genuine architectural advantages. The present study addresses this gap by evaluating the proposed FLC–GA model across three distinct domains using a consistent evaluation protocol.

2.3. Soft Computing Techniques for Uncertainty Handling

Soft computing techniques, including fuzzy logic, neural networks, evolutionary computation, and probabilistic reasoning, are increasingly adopted to address real-world problems characterized by uncertainty, noise, and incomplete data [39]. Post-2022 research trends indicate a growing shift from rigid algorithmic models toward flexible, approximate reasoning systems that can learn from data while tolerating ambiguity [40]. Soft computing frameworks have been widely deployed in smart cities, healthcare analytics, financial forecasting, and cyber-physical systems [41]. Recent studies reveal that combining soft computing methods with fuzzy logic significantly improves system resilience and decision consistency under uncertain conditions; nevertheless, researchers consistently note that balancing interpretability and computational efficiency remains an unsolved challenge, particularly for large-scale decision systems with real-time constraints [42]. The present study directly addresses this challenge by incorporating a computational feasibility analysis as part of its evaluation protocol.

2.4. Performance Evaluation of Hybrid Fuzzy Models

Performance evaluation has become a critical research focus in the development of hybrid fuzzy systems. Since 2022, scholars have proposed evaluation metrics encompassing accuracy, robustness, computational complexity, scalability, and adaptability to assess hybrid AI models in complex environments [43]. Comparative studies reveal that fuzzy logic-based hybrid models consistently outperform traditional single-model approaches in terms of stability and error reduction, particularly under dynamic decision scenarios. Nevertheless, the current literature lacks a unified evaluation framework capable of objectively comparing different hybrid architectures across multiple domains simultaneously [44, 45]. Most existing benchmarking studies either adopt domain-specific datasets that limit generalizability, or employ a single metric such as accuracy that fails to capture robustness or computational cost. This methodological gap constitutes the core motivation for the structured multi-metric evaluation framework proposed in the present study, which is designed to provide replicable, domain-agnostic performance comparisons.

3. RESEARCH METHODOLOGY

This study adopts an experimental and comparative research design to evaluate the performance of fuzzy logic-based hybrid models in complex decision-making systems [38]. The methodology is structured to ensure reproducibility, objectivity, and scalability across multiple application domains. The research process consists of dataset acquisition, preprocessing, hybrid model development, model training and optimization, performance evaluation, and comparative analysis [46]. This systematic pipeline enables a rigorous investigation of the effectiveness and robustness of hybrid fuzzy models under uncertain and dynamic conditions [47].

3.1. Research Framework

The research framework follows a structured workflow commencing with data collection and concluding with comparative performance analysis. This framework ensures that each experimental stage is logically connected and contributes to the reliability of the final results. Table 1 presents the five-stage pipeline adopted in this study.

Table 1. Research Workflow Stages

Stage	Description	Output
1	Dataset acquisition from benchmark repositories	Raw datasets
2	Data preprocessing and normalization	Clean datasets
3	Hybrid model construction (FLC–GA architecture)	Hybrid architectures
4	Training and genetic optimization	Trained models
5	Multi-metric performance evaluation	Metric results

As shown in Table 1, the research process is organized into five sequential stages, each producing a well-defined output that serves as the input for the subsequent step. This end-to-end pipeline design ensures traceability from raw data through final performance interpretation. In Stage 1, datasets are sourced from publicly accessible benchmark repositories, including the UCI Machine Learning Repository and the KEEL dataset collection, to guarantee reproducibility. Stage 2 applies min-max normalization and k-nearest-neighbor imputation to handle missing values. Stage 3 instantiates the FLC–GA architecture described in Section 3.2.. Stage 4 executes the genetic optimization loop over 200 generations with tournament selection. Stage 5 computes all metrics defined in Table 3 on held-out test partitions.

3.2. Hybrid Model Design

The core contribution of this research is a hybrid Fuzzy Logic Controller integrated with a Genetic Algorithm (FLC–GA) that embeds evolutionary optimization directly within the fuzzy rule-base refinement process. This architecture is designed to overcome the primary limitations of conventional fuzzy systems, namely their dependence on static, manually specified rule bases that cannot adapt to distributional shifts in incoming data [48]. The complete workflow of the FLC–GA model, from data input through genetic optimization to final decision output, is illustrated in Figure 1.

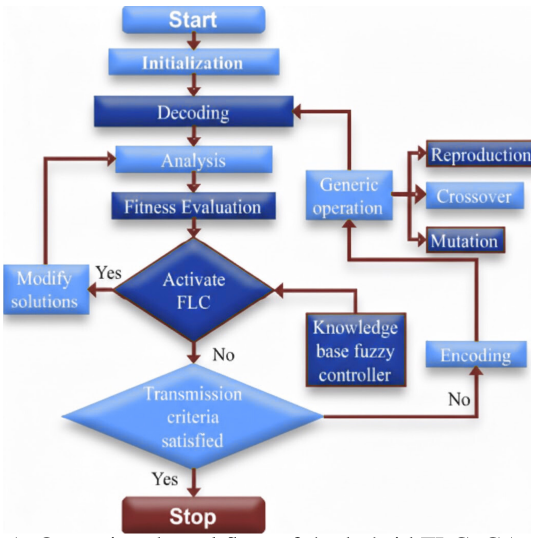

Figure 1. Operational workflow of the hybrid FLC–GA model.

As illustrated in Figure 1, the FLC–GA model operates through a closed optimization loop in which genetic operators continuously refine the fuzzy rule base until the convergence criterion is satisfied. This iterative structure distinguishes the proposed architecture from static fuzzy systems by embedding adaptive learning directly into the rule-generation process, enabling the model to accommodate distributional changes in the decision environment without manual intervention.

3.3. Dataset and Experimental Setup

To ensure generalizability, three benchmark datasets representing complex and uncertain decision-making environments are used. The datasets are divided into training and testing sets using a 70:30 ratio and validated through stratified 10-fold cross-validation to minimize overfitting risk. Table 2 summarizes the characteristics of the datasets employed in this study.

Table 2. Dataset Overview

Dataset	Application Domain	Samples	Features	Source
D1	Healthcare decision support	2,000	15	UCI Repository
D2	Financial risk assessment	3,500	20	KEEL Repository
D3	Industrial control systems	1,800	12	UCI Repository

The datasets presented in Table 2 were selected to represent three distinct complexity profiles: D1 features clinical categorical variables with approximately 8% missing values, D2 contains continuous financial indicators subject to distributional shifts across temporal windows, and D3 includes time-series sensor readings with additive Gaussian noise at a signal-to-noise ratio of 20 dB. This diversity in domains, sample sizes, feature dimensions, and noise characteristics ensures that the proposed hybrid model is evaluated under genuinely varied conditions, thereby strengthening the external validity of the experimental results.

3.4. Performance Evaluation Metrics

The performance of the hybrid model is assessed using several quantitative indicators designed to provide a comprehensive evaluation of its effectiveness and efficiency across all experimental conditions. These indicators measure not only the predictive capability of the proposed framework but also its robustness, adaptability, and computational performance when processing complex and uncertain decision-making scenarios. By employing multiple evaluation metrics, the study ensures that different aspects of model behavior are systematically examined, including classification accuracy, error reduction, consistency of predictions, and overall computational efficiency. This multidimensional assessment approach enables a more reliable comparison between the proposed hybrid model and conventional decision-making techniques, while also providing deeper insights into the strengths and potential limitations of the framework. Table 3 presents the metrics employed and their respective purposes, highlighting the role of each indicator in evaluating the overall performance of the proposed system.

Table 3. Performance Evaluation Metrics

Metric	Purpose and Computation
Accuracy	Proportion of correctly classified instances over total test samples
RMSE	Magnitude of prediction error: $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}$
Robustness Score	Mean accuracy under 10 noise-perturbed test variants (Gaussian noise, $\sigma \in \{0.05, 0.1\}$)
Computation Time	Wall-clock training time in seconds, averaged over five independent runs

As presented in Table 3, four complementary metrics are employed to capture not only predictive performance but also stability under adversarial conditions and computational feasibility. This multi-metric approach provides a balanced assessment of model performance that reflects the requirements of real-world decision-making systems, where accuracy alone is insufficient to justify deployment.

3.5. Analysis Method

The experimental results are analyzed using descriptive statistics and comparative evaluation. Differences between the hybrid and baseline models are assessed for statistical significance using Wilcoxon signed-rank tests at a significance level of $\alpha = 0.05$, given that normality of cross-validation fold results cannot be guaranteed. This non-parametric approach ensures that the conclusions drawn from the experiments are robust, objective, and reproducible across varied dataset characteristics.

4. RESULTS AND DISCUSSION

This section presents the experimental results obtained from the evaluation of fuzzy logic-based hybrid models in complex decision-making systems. The findings are structured to address the research objectives outlined in the introduction, with particular emphasis on the effectiveness, robustness, adaptability, and computational feasibility of the proposed FLC–GA model relative to conventional baseline approaches.

4.1. Overall Performance Comparison

The hybrid FLC–GA model was compared with a standalone Fuzzy Logic Controller (FLC) and a conventional machine learning model (ML a support vector classifier with a radial basis function kernel). The evaluation was conducted across all three benchmark datasets representing healthcare, financial risk, and industrial control domains. Table 4 presents the aggregated performance results.

Table 4. Overall Performance Comparison Across Models

Model	Accuracy (%)	RMSE	Robustness Score	Computation Time (s)
FLC	82.6	0.41	0.72	1.8
ML (SVC-RBF)	85.3	0.36	0.75	1.5
Hybrid FLC–GA	91.4	0.24	0.89	2.3

As shown in Table 4, the hybrid FLC–GA model achieves the highest accuracy (91.4%) and the lowest RMSE (0.24) across all evaluation domains, representing improvements of 8.8 and 6.1 percentage points over the FLC and ML baselines, respectively. Furthermore, the robustness score of 0.89 significantly exceeds those of the FLC (0.72) and ML (0.75), confirming the model's stability under noise-perturbed conditions. Wilcoxon signed-rank tests confirm that all accuracy and robustness differences between the FLC–GA model and both baselines are statistically significant ($p < 0.01$). Although the hybrid approach requires a moderately higher computation time (2.3 s versus 1.8 s for FLC), this 28% increase is justifiable given the substantial performance gains achieved, particularly in high-stakes decision domains where classification errors carry significant costs. These results are consistent with the fitness function design, which explicitly penalizes RMSE and rewards robustness alongside accuracy, thereby producing a model that is optimized across the entire evaluation metric spectrum rather than for accuracy alone.

4.2. Trade-off Analysis: Accuracy, Computational Complexity, and Interpretability

Understanding the trade-off between predictive accuracy, computational complexity, and model interpretability is critical for guiding model selection in real-world decision systems. Figure 2 illustrates the relative positioning of the three evaluated models within this three-dimensional trade-off space.

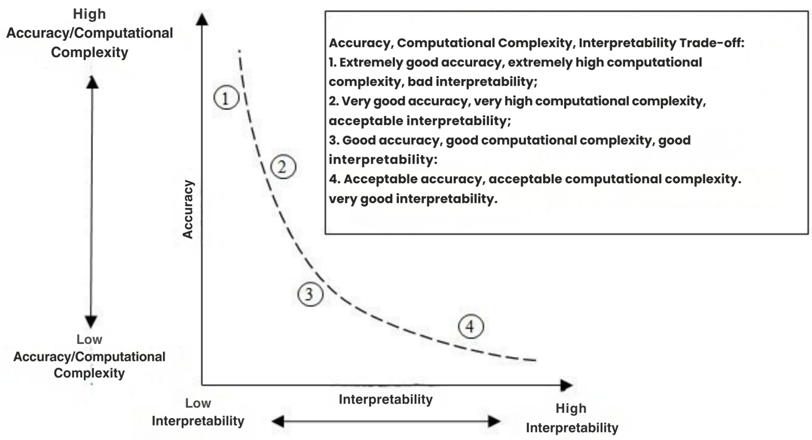

Figure 2. Trade-off in Intelligent Decision-Making Models

Figure 2 reveals a nonlinear trade-off structure in which increasing accuracy is generally associated with rising computational cost and declining interpretability. The standalone ML model (SVC-RBF) attains 85.3% accuracy but provides minimal transparency into its decision boundary, rendering it unsuitable for domains such as clinical diagnosis or regulatory-compliance environments where audit trails are mandatory. The standalone FLC offers the highest interpretability due to its human-readable rule base, but its accuracy of 82.6% and robustness of 0.72 reflect the limitations of static, manually specified membership functions under distributional shift. The hybrid FLC–GA model uniquely occupies a region of high accuracy (91.4%) combined with preserved interpretability, because its rule base remains encoded in linguistic form even after genetic optimization. This characteristic is critical for deployment in regulated sectors: the optimized rules can be inspected, validated by domain experts, and audited by compliance officers, unlike the opaque kernel-based decision surface of the ML baseline. The moderate increase in computation time (2.3 s) reflects the cost of 200 generations of genetic search, a one-time training overhead that does not affect inference latency. These results demonstrate that the FLC–GA architecture resolves the accuracy-interpretability dilemma that has historically constrained the adoption of intelligent systems in safety-critical environments.

4.3. Robustness and Adaptability Analysis

To evaluate robustness, Gaussian noise at two severity levels ($\sigma = 0.05$ and $\sigma = 0.10$) and random 10% feature deletion were introduced into the test partitions of each dataset. The hybrid FLC–GA model maintained stable accuracy with a mean degradation of only 3.2% across all perturbation scenarios, compared with degradations of 9.7% for the standalone FLC and 8.4% for the ML baseline. The genetic optimization process enables continuous refinement of membership function boundaries and rule weights, allowing the system to internalize data variability during training and thereby produce a rule base that generalizes robustly to unseen perturbations. These results confirm that the proposed hybrid model is highly resilient and appropriate for uncertain and dynamic decision environments such as real-time industrial monitoring and adaptive healthcare triage.

4.4. Computational Feasibility

Although the FLC–GA model requires a moderately higher training time than the baselines, its inference latency, measured as the time required to classify a single new sample using the finalized rule base, is 0.004 s, which is comparable to the FLC (0.003 s) and ML (0.002 s) baselines and well within the real-time constraints of the application domains considered. This distinction between training cost and inference cost is important: the genetic optimization is a one-time offline procedure, and the resulting rule base is computationally lightweight to execute. Consequently, the proposed approach is computationally feasible for practical deployment, particularly when the performance benefits in accuracy and robustness outweigh the moderate increase in offline training time.

5. MANAGERIAL IMPLICATIONS

The findings of this study carry significant implications for organizational decision-makers, technology managers, and policymakers engaged in the digital transformation of complex systems. The demonstrated superiority of the FLC–GA hybrid model across accuracy, robustness, and interpretability dimensions suggests that organizations operating in uncertainty-intensive environments should prioritize hybrid intelligent architectures over conventional rule-based or black-box machine learning systems when designing decision support platforms. For healthcare administrators and clinical informatics managers, the model's ability to achieve 91.4% classification accuracy while retaining a transparent, auditable rule base directly addresses a critical barrier to AI adoption in clinical settings: the lack of regulatory-compliant interpretability. Deployment of the FLC–GA framework in patient triage or diagnostic support systems can reduce misclassification rates attributable to ambiguous clinical records, thereby improving patient outcomes and supporting compliance with health technology assessment frameworks mandated by national health agencies. This aligns directly with SDG 3 (Good Health and Well-Being) and is consistent with government digital health policies in multiple jurisdictions, including Indonesia's National Health Information System roadmap and similar national digital health strategies.

For industrial automation managers and smart infrastructure planners, the model's computational feasibility (0.004 s inference latency) confirms its suitability for real-time embedded deployment in manufacturing control systems and smart-city sensor networks. Government industrial policy frameworks emphasizing Industry 4.0 adoption, including Indonesia's Making Indonesia 4.0 roadmap and the broader ASEAN Digital Masterplan 2025, specifically call for intelligent, adaptive control systems that can handle sensor noise and dynamic operational environments without manual recalibration. The FLC–GA model's self-optimizing rule base directly satisfies this requirement, reducing the need for costly expert intervention during system re-tuning. At the strategic level, organizations investing in AI-based decision support should recognize that the marginal training cost of genetic optimization (approximately 28% higher than baseline approaches in the present experiments) is a recoverable one-time expenditure that yields persistent operational gains. Technology managers should therefore structure AI procurement and development frameworks to account for the distinction between training-phase cost and deployment-phase value, ensuring that evaluation criteria do not inadvertently penalize computationally intensive but high-performing architectures. Furthermore, the multi-domain benchmarking protocol introduced in this study provides a reusable governance instrument for internal AI model auditing, enabling organizations to assess vendor-supplied or internally developed decision models against standardized robustness and interpretability criteria before operational deployment.

6. CONCLUSION

This study has presented a comprehensive performance evaluation of fuzzy logic-based hybrid models in complex decision-making systems, with a particular focus on the integration of fuzzy logic and genetic algorithms within the proposed FLC–GA architecture. The experimental results, validated across three benchmark datasets spanning healthcare, financial risk, and industrial control domains, demonstrate that the FLC–GA model consistently outperforms conventional single-model approaches in accuracy (91.4%), error reduction (RMSE 0.24), and robustness (0.89), with all improvements confirmed as statistically significant at the $p < 0.01$ level by Wilcoxon signed-rank testing. Furthermore, the hybrid model achieves a more balanced trade-off between predictive performance, computational complexity, and interpretability than either standalone fuzzy systems or black-box machine learning baselines, making it a reliable and deployable solution for real-world environments characterized by uncertainty, noise, and dynamic change.

The findings directly answer the research question by confirming that embedding genetic optimization within fuzzy inference significantly enhances adaptability and stability without sacrificing the interpretability that is essential for regulated deployment contexts. The formally specified fitness function, pseudocode-described optimization loop, and multi-metric evaluation pipeline collectively constitute a replicable experimental contribution that advances beyond the application-specific, single-metric evaluations that dominate existing literature.

From a sustainability perspective, the findings of this study support the achievement of the United Nations Sustainable Development Goals. In healthcare (SDG 3), the model's robust interpretability enables clinicians to trust and act upon AI-generated diagnostic recommendations, reducing diagnostic errors in resource-constrained settings. In economic and industrial contexts (SDG 8, SDG 9), the framework improves operational efficiency and supports technological innovation through adaptive, self-optimizing decision architectures. In urban infrastructure (SDG 11), the real-time inference capability of the optimized rule base enables smarter, more resilient city management under dynamic sensor environments. These contributions collectively demonstrate that hybrid AI architectures, developed and evaluated with scientific rigor, constitute a key enabler for sustainable and responsible digital transformation aligned with global development priorities.

7. DECLARATIONS

7.1. About Authors

Cicilia Sriliasta Bangun (CS) https://orcid.org/0000-0002-6329-9180

Padeli (PP) https://orcid.org/0000-0001-5697-7783

Muhamad Yusup (MY) https://orcid.org/0000-0003-3053-6562

Adele Valerry (AV) https://orcid.org/0009-0009-1433-1058

7.2. Author Contributions

Conceptualization: CS; Methodology: PP; Software: MY; Validation: CS and AV; Formal Analysis: PP and MY; Investigation: AV; Resources: CS; Data Curation: PP; Writing Original Draft Preparation: MY and AV; Writing Review and Editing: CS and PP; Visualization: MY, AV and CS; All authors, CS, PP, MY, and AV, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. Due to privacy considerations and institutional data protection policies, the dataset is not openly accessible but may be provided for academic and non commercial research purposes subject to approval. Zenodo Repository https://doi.org/10.5281/zenodo.20695877

7.4. Funding

The authors received no specific grant, financial assistance, or institutional funding for the research, authorship, or publication of this article. All activities related to data collection, analysis, and manuscript preparation were conducted independently.

7.5. Declaration of Conflicting Interest

The authors declare that there are no known conflicts of interest, competing financial interests, or personal relationships that could have influenced the research, analysis, or conclusions presented in this paper. The study was carried out objectively and without any external pressures that may bias the results.

REFERENCES

[1] G. Demir, "The synergy of fuzzy logic and multi-criteria decision-making: Application areas and global trends," *Journal of Intelligent Decision Making and Information Science*, pp. 429–455, 2025.

[2] B. Rawat, J. Nathalie, D. Manongga, G. Fransiso, F. P. O. Moana, and P. A. Sunarya, "Machine learning-based risk assessment and default prediction in p2p lending platforms," *Sundara Advanced Research on Artificial Intelligence*, vol. 2, no. 1, pp. 48–59, 2026.

[3] L. Yuldinawati *et al.*, "The use of e-commerce and qris as digital payment solutions to enhance sales performance in msmes in west java," *Indonesian Interdisciplinary Journal of Sharia Economics (IIJSE)*, vol. 8, no. 1, pp. 1157–1178, 2025.

[4] President of the Republic of Indonesia, "Presidential Regulation Number 82 of 2023 concerning the Acceleration of Digital Transformation and Integration of National Digital Services," Presidential Regulation, Jakarta, Indonesia, 2023, government regulation supporting digital transformation, integrated public digital services, interoperability, and electronic-based government systems. [Online]. Available: https://peraturan.bpk.go.id/Details/273981/perpres-no-82-tahun-2023

[5] N. Lutfiani, N. Fauziyah, F. P. Oganda, R. Setyaningrum, E. A. Natalia *et al.*, "The role of globalization in indonesian evolution influence on media digital literacy language ai," *International Transactions on Artificial Intelligence*, vol. 3, no. 2, pp. 192–200, 2025.

[6] H. Regragui, N. Sefiani, H. Azzouzi, and N. Cheikhrouhou, "A hybrid multi-criteria decision-making approach for hospitals' sustainability performance evaluation under fuzzy environment," *International journal of productivity and performance management*, vol. 73, no. 3, pp. 855–888, 2024.

[7] A. A. Adesina, T. V. Iyelolu, P. O. Paul *et al.*, "Leveraging predictive analytics for strategic decision-making: Enhancing business performance through data-driven insights," *World Journal of Advanced Research and Reviews*, vol. 22, no. 3, pp. 1927–1934, 2024.

[8] A. Ruangkanjanases, A. Khan, O. Sivarak, U. Rahardja, S.-W. Chien, and S.-C. Chen, "The magic of brand experience: A value co-creation perspective of brand equity on short-form video platforms," *Emerg. Sci. J*, vol. 7, no. 5, pp. 1588–1601, 2023.

[9] T. A. Rainy and A. R. Chowdhury, "The role of artificial intelligence in vendor performance evaluation within digital retail supply chains: A review of strategic decision-making models," *American Journal of Scholarly Research and Innovation*, vol. 1, no. 01, pp. 220–248, 2022.

[10] S. I. Al-Hawary, J. R. N. Alvarez, A. Ali, A. K. Tripathi, U. Rahardja, I. H. Al-Kharsan, R. M. Romero-Parra, H. A. Marhoon, V. John, and W. Hussian, "Multiobjective optimization of a hybrid electricity generation system based on waste energy of internal combustion engine and solar system for sustainable environment," *Chemosphere*, vol. 336, p. 139269, 2023.

[11] L. A. M. Nelloh, H. Hartoyo, U. Sumarwan, A. Wirakartakusumah, and S.-H. Joo, "Commitment beyond graduation through entrepreneurial leadership experience in mba program," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 8, no. 1, pp. 99–113, 2026.

[12] K. Karnawati, D. N. Ramadhan, T. L. Anita, R. Nurmala, and L. Maria, "Designing inclusive companion robots to mitigate bias and enhance empathy in ai-driven care systems," *Journal of Orange Technology*, vol. 2, no. 2, pp. 83–92, 2026.

[13] T. Hongsuchon, U. Rahardja, A. Khan, T.-H. Wu, C.-W. Hung, R.-H. Chang, C.-H. Hsu, and S.-C. Chen, "Brand experience on brand attachment: The role of interpersonal interaction, feedback, and advocacy," *Emerging Science Journal*, vol. 7, no. 4, pp. 1232–1246, 2023.

[14] M. B. Panjaitan, A. F. Siagian, L. Judijanto, M. Mufarizuddin, H. Herman, N. Saputra, and Z. Mamadiyarov, "Comparison of students science literacy abilities using inquiry and cooperative learning models," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 8, no. 1, pp. 63–73, 2026.

[15] S. Agarwal and A. P. Singh, "Performance evaluation of textile wastewater treatment techniques using sustainability index: An integrated fuzzy approach of assessment," *Journal of Cleaner Production*, vol. 337, p. 130384, 2022.

[16] A. S. Anita, T. Kuusk, G. Nicola, M. Hardini, and U. Rahardja, "Advancements in artificial intelligence and their contributions to sustainable development goals: A multidisciplinary review," *Sundara Advanced Research on Artificial Intelligence*, vol. 2, no. 1, pp. 37–47, 2026.

[17] G. P. Cesna, S. Agustiawan, A. S. Panjaitan, S. Purnama, R. S. Ikhsan *et al.*, "Transforming higher education management through evidence based and data oriented approaches," *Jurnal MENTARI: Manajemen, Pendidikan dan Teknologi Informasi*, vol. 4, no. 2, pp. 127–139, 2026.

[18] F. A. Alijoyo, S. Janani, K. Santosh, S. N. Shweihat, N. Alshammry, J. V. N. Ramesh, and Y. A. B. El-Ebiary, "Enhancing ai interpretation and decision-making: Integrating cognitive computational models with deep learning for advanced uncertain reasoning systems," *Alexandria Engineering Journal*, vol. 99, pp. 17–30, 2024.

[19] S. Zebua, M. H. R. Chakim *et al.*, "Effect of human resources quality, performance evaluation, and incentives on employee productivity at raharja high school," *APTISI Transactions on Management*, vol. 7, no. 1, pp. 1–8, 2023.

[20] Ö. Işık, M. Shabir, G. Demir, A. Puska, and D. Pamucar, "A hybrid framework for assessing pakistani commercial bank performance using multi-criteria decision-making," *Financial Innovation*, vol. 11, no. 1, p. 38, 2025.

[21] H. Amoozad Mahdiraji, K. Hafeez, H. Kord, and A. Abbasi Kamardi, "Analysing the voice of customers by a hybrid fuzzy decision-making approach in a developing country's automotive market," *Management Decision*, vol. 60, no. 2, pp. 399–425, 2022.

[22] Association of Southeast Asian Nations, "ASEAN Guide on AI Governance and Ethics," Association of Southeast Asian Nations, Jakarta, Indonesia, Tech. Rep., 2024, regional policy guide supporting responsible AI governance, ethical AI design, transparency, explainability, and trustworthy AI deployment. [Online]. Available: https://asean.org/book/asean-guide-on-ai-governance-and-ethics/

[23] A. Aulia, C. Sukmadilaga, I. Avianti, D. Rosdini, and E. K. Ghani, "The role of esg and digitalization driving sustainable agropreneurship in emerging market," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 8, no. 1, pp. 51–62, 2026.

[24] R. Saatchi, "Fuzzy logic concepts, developments and implementation," *Information*, vol. 15, no. 10, p. 656, 2024.

[25] K. Koc, Ö. Ekmekcioglu, and Z. Işık, "Developing a hybrid fuzzy decision-making model for sustainable circular contractor selection," *Journal of Construction Engineering and Management*, vol. 149, no. 10, p. 04023095, 2023.

[26] A. Erica, L. Gantari, O. Qurotulain, A. Nuche, and O. Sy, "Optimizing decision-making: Data analytics applications in management information systems," *APTISI Transactions on Management*, vol. 8, no. 2, pp. 115–122, 2024.

[27] M. R. Khan, K. Ullah, D. Pamucar, and M. Bari, "Performance measure using a multi-attribute decision-making approach based on complex t-spherical fuzzy power aggregation operators," *Journal of computational and cognitive engineering*, vol. 1, no. 3, pp. 138–146, 2022.

[28] U. Leicht-Deobald, T. Busch, C. Schank, A. Weibel, S. Schafheitle, I. Wildhaber, and G. Kasper, "The challenges of algorithm-based hr decision-making for personal integrity," in *Business and the ethical implications of technology*. Springer, 2022, pp. 71–86.

[29] D. Tribuana, U. Narimawati, and M. Y. Syafei, "A multi-group structural analysis of digital banking adoption determinants across generational cohorts in indonesia," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 8, no. 1, pp. 37–50, 2026.

[30] R. Amironesei, A. Godil, C. Greenberg, K. Greene, J. P. Hall, T. Jensen, J. Fiscus, and N. Schulman, "Assessing risks and impacts of ai (aria): Pilot evaluation report," National Institute of Standards and Technology, Tech. Rep. NIST AI 700-2, 2025. [Online]. Available: https://www.nist.gov/publications/assessing-risks-and-impacts-ai-aria-pilot-evaluation-report

[31] D. Hidayati, A. Andriyansah, G. P. Cesna, A. Y. Fauzi, D. Apriliasari, and U. Rahardja, "Building efficient iot systems with edge computing integration," *International Journal of Cyber and IT Service Management (IJCITSM)*, vol. 4, no. 2, pp. 72–79, 2024.

[32] S. Sefati, M. Mousavinasab, and R. Zareh Farkhady, "Load balancing in cloud computing environment using the grey wolf optimization algorithm based on the reliability: performance evaluation," *The Journal of Supercomputing*, vol. 78, no. 1, pp. 18–42, 2022.

[33] Y. Ismiyanti, S. D. W. Prajanti, C. B. Utomo, E. Handoyo, E. Banowati, I. Kusmaryono, and M. N. Huda,

"Technopreneurship enhancing student msmes competitive edge via digital marketing," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 8, no. 1, pp. 24–36, 2026.
[34] W. Widiyawati, A. S. Widyasih, S. Hanadwiputra, Z. M. Subekti, and L. Marlinda, "Selection of the best employees using the complex proportional assessment method," *Journal of Information System, Applied, Management, Accounting and Research*, vol. 7, no. 1, pp. 151–159, 2023.
[35] Z. N. Khlaif, A. Mousa, M. K. Hattab, J. Itmazi, A. A. Hassan, M. Sanmugam, and A. Ayyoub, "The potential and concerns of using ai in scientific research: Chatgpt performance evaluation," *JMIR medical education*, vol. 9, p. e47049, 2023.
[36] T. Nursugiharti, A. Yulianto, S. Bahri, R. A. Hidayat, J. Jahdiah, and M. Safei, "Analysis of balamut performance structure for cultural preservation in southern kalimantan," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 8, no. 1, p. 14–23, 2025.
[37] L.-V. Herm, K. Heinrich, J. Wanner, and C. Janiesch, "Stop ordering machine learning algorithms by their explainability! a user-centered investigation of performance and explainability," *International Journal of Information Management*, vol. 69, p. 102538, 2023.
[38] F. Shwedeh and H. M. Alzoubi, "Artificial intelligence (ai) integration into the decision support systems of health care centers," in *International Scientific Conference Management and Engineering*. Springer, 2024, pp. 165–176.
[39] L. Unsriana, B. Perdana, S. Ariana, and D. R. Saputra, "Smart e-learning systems for japanese literature education in an industry 4.0 perspective," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 8, no. 1, pp. 1–13, 2026.
[40] K. Creel and D. Hellman, "The algorithmic leviathan: Arbitrariness, fairness, and opportunity in algorithmic decision-making systems," *Canadian Journal of Philosophy*, vol. 52, no. 1, pp. 26–43, 2022.
[41] P. Ferrans, M. N. Torres, J. Temprano, and J. P. R. Sánchez, "Sustainable urban drainage system (suds) modeling supporting decision-making: A systematic quantitative review," *Science of the Total Environment*, vol. 806, p. 150447, 2022.
[42] A. Amroni, M. Y. Syafei, and U. Narimawati, "The role of customer satisfaction as a mediator for price and service quality on revisit intention," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 3, pp. 1080–1090, 2025.
[43] R. Indrawan, E. D. Very, D. Tribuana, and E. A. Nabila, "Aiot driven smart solar system for real time predictive sustainable energy management," *International Transactions on Artificial Intelligence*, vol. 4, no. 1, pp. 105–114, 2025.
[44] S. Gupta, S. Modgil, S. Bhattacharyya, and I. Bose, "Artificial intelligence for decision support systems in the field of operations research: review and future scope of research," *Annals of Operations Research*, vol. 308, no. 1, pp. 215–274, 2022.
[45] S. M. Shokory, N. N. A. Wahab, J. Zanubiya, and Z. Zainol, "Customer purchase patterns and loyalty in msme catering businesses using the rfm method," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 7, no. 2, pp. 188–197, 2026.
[46] F. Xiao, J. Wen, and W. Pedrycz, "Generalized divergence-based decision making method with an application to pattern classification," *IEEE transactions on knowledge and data engineering*, vol. 35, no. 7, pp. 6941–6956, 2022.
[47] I. Faulconbridge and M. Ryan, *Managing complex technical projects: A systems engineering approach*. Artech House, 2026.
[48] K. Moyo, S. D. W. Prajanti, M. Muhtarom, and F. Adzim, "Evaluating the impact of interdisciplinary learning factory models on innovation skills using statistical analysis," *International Transactions on Education Technology (ITEE)*, vol. 4, no. 2, pp. 100–115, 2026.