From Data to Decisions: Integrating Artificial Intelligence and Fuzzy Rule-Based Reasoning for Enhanced Qualitative Evaluation of Academic Outcomes in Outcome-Based Education

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**Abstract:** Outcome‐Based Education (OBE) relies on translating qualitative academic indicators such as Course Outcome (CO) and Programme Outcome (PO) attainment, teaching effectiveness, and student engagement into actionable metrics for continuous improvement. This study develops and validates a hybrid decision‐support framework that leverages a Mamdani‐style fuzzy inference system optimized by a genetic algorithm (GA‑FRBS) to quantify these inherently subjective measures. We normalize and split a 10,000‑record educational dataset into training and test sets, define linguistic variables (Low, Medium, High) for six inputs, and evolve both membership‐function parameters and rule‑base structure via a customized GA. The optimized fuzzy system is benchmarked against an Adaptive Neuro‐Fuzzy Inference System (ANFIS), a three‐layer Multilayer Perceptron (ANN), and a traditional feed‑forward neural network (NN). The GA‑FRBS achieves superior predictive accuracy (RMSE = 0.0345, MSE = 0.00119, MAE = 0.0263, MAPE = 3.12%, R² = 0.957) and demonstrates 25–40% lower sensitivity to ±10% input perturbations compared with other models. Although GA tuning increases training time modestly (45.2 s vs. 35–63 s), inference remains real‑time capable (1.15 ms/sample). These results confirm that GA‑optimized fuzzy modeling delivers a robust, interpretable, and computationally efficient tool for assessing qualitative academic performance within the OBE framework. The approach offers educators and administrators transparent decision‑support for programme evaluation, teaching enhancement, and student advising.

**Keywords:** *Genetic Algorithm‑Optimized Fuzzy Rule‑Based System; Outcome‑Based Education Analytics; Membership Function Evolution; Educational Decision Support; Sensitivity Analysis in Fuzzy Systems*

# Introduction

## Background and Context

In today’s outcome-oriented higher education landscape, institutions across the globe are increasingly adopting Outcome-Based Education (OBE) frameworks to ensure that graduates attain clearly defined Course Outcomes (COs) and Programme Outcomes (POs) (Katawazai, 2021; Amirtharaj et al., 2021; Gurukkal, 2020). Despite this structured approach, accurately measuring these outcomes remains a significant challenge, as it often relies on qualitative judgments related to student engagement, instructional quality, and the rigor of assessments factors that are inherently difficult to quantify (Holmes, 2018; Chen et al., 2024). In this context, advancements in soft computing particularly fuzzy logic have shown considerable potential in modelling linguistic ambiguity, while evolutionary algorithms such as genetic methods offer robust, data-driven optimization for handling complex evaluation processes (Alcalá, Gacto and Herrera, 2011).

## Problem Statement and Knowledge Gap

Despite the rapid expansion of fuzzy and neuro‑fuzzy techniques in educational analytics, two persistent challenges remain (Naaj et al., 2023; Talpur et al., 2023). First, manually defined fuzzy membership functions and rule bases often lack the flexibility to adapt to diverse institutional settings, thereby limiting their generalizability (Badhon et al., 2022; Varshney & Torra, 2023). Second, purely data‑driven neuro‑fuzzy models such as ANFIS can deliver high accuracy but do so at the expense of interpretability an essential hallmark of transparent decision support in educational contexts (Navarro‑Almanza et al., 2021; Bai et al., 2024; Rajab, 2019). What is missing, therefore, is a unified framework that not only evolves fuzzy parameters from data but also preserves linguistic transparency to foster stakeholder trust (Zhang et al., 2019).

## Research Motivation and Significance

Addressing this gap is crucial for building decision‑support tools that can guide instructors, administrators, and accreditation bodies with both reliable predictions and clear explanations. We posit that a Genetic Algorithm‑optimized Fuzzy Rule‑Based System (GA‑FRBS) can marry the best of both worlds: the interpretability of Mamdani fuzzy systems and the global search power of genetic algorithms. By automatically tuning membership functions and rule confidences on a large, 10,000‑record educational dataset, our approach promises robust, transparent, and scalable OBE analytics.

## Research Objectives

This study pursues the following objectives:

1. Design a Mamdani-style fuzzy inference framework with linguistic variables for six academic indicators (e.g., Student Performance, Teaching Quality Feedback).
2. Integrate a genetic algorithm to evolve triangular membership function parameters and rule‑base weights simultaneously.
3. Validate the GA‑FRBS against ANFIS, a three‑layer MLP, and a traditional feed‑forward neural network on predictive accuracy (RMSE, R²) and robustness (±10% sensitivity).
4. Assess computational efficiency in training and real‑time inference to gauge deployability in live educational dashboards.

## Paper Organization

The remainder of this paper is structured as follows:

* Section 2 reviews related work on fuzzy, neuro‑fuzzy, and evolutionary‑fuzzy methods in educational and other domains.
* Section 3 details the proposed GA‑FRBS methodology, including dataset preprocessing, fuzzy variable definition, rule encoding, and GA configuration.
* Section 4 presents experimental results: accuracy metrics, sensitivity analysis, timing benchmarks, and membership‑function visualizations.
* Section 5 concludes with key findings, limitations, and avenues for future research.

By uniting fuzzy interpretability with evolutionary optimization, this work aims to deliver a decision‑support system that is both transparent and highly accurate, advancing the state of the art in OBE analytics.

# Literature Review

A comprehensive understanding of prior work in fuzzy logic, genetic optimization, and their intersection in educational decision‑support systems is essential to situate the proposed GA‑FRBS model. We organize the review into four thematic areas:

1. Fuzzy Inference in Educational Contexts
2. Genetic Algorithms for Fuzzy System Optimization
3. Hybrid Fuzzy‑Genetic Frameworks
4. Research Gaps and Motivation

## Fuzzy Inference in Educational Contexts

Early applications of fuzzy logic in teaching and learning environments leveraged expert‑crafted rules to handle linguistic vagueness. Pang and Ning (2021) implemented a Mamdani fuzzy controller tuned by a genetic algorithm within an intelligent psychology‑teaching system, demonstrating improved adaptability over static rule sets but focusing primarily on system stability rather than pedagogical outcome prediction. Teng (2024) applied fuzzy association‑rule mining to personalize Chinese language instruction, extracting co‑occurrence patterns in student behaviors; however, this work did not incorporate evolutionary tuning to refine membership functions or rule confidences. Zhang and Yang (2022) used GA‑driven fuzzy evaluation for teacher performance appraisal, evolving rule weights to reflect expert judgments, yet their validation remained limited to small institutional samples. These studies collectively show the promise of fuzzy logic for interpreting qualitative educational indicators but stop short of a fully automated, data‑driven optimization of both membership functions and rule bases.

## Genetic Algorithms for Fuzzy System Optimization

Outside of education, genetic algorithms (GAs) have a rich history of enhancing fuzzy systems. Sweta and Lal (2020) presented a GA‑optimized FRBS to quantify uncertainty in human decision making, illustrating how evolutionary search can improve membership function alignment with subjective judgments. Fadel et al. (2021) automated fuzzy rule discovery using a hybrid GA framework, yet their evaluation was confined to standard benchmark datasets rather than domain‑specific educational data. Zhang (2020) merged intuitionistic fuzzy rough sets with GA for classification rule mining, showing that joint optimization of rule selection and parameter tuning yields compact, accurate classifiers. Hameed et al. (2021) introduced a weighted fuzzy rule‑GA hybrid for heart disease prediction, achieving high accuracy but incurring substantial computational cost. These engineering‑focused successes underscore GA’s ability to escape local minima and optimize complex parameter spaces but educational applications have yet to fully leverage this potential.

## Hybrid Fuzzy‑Genetic Frameworks

Recent surveys (Varshney & Torra, 2022; Syzonov et al., 2024) highlight the trend toward combining fuzzy inference with evolutionary algorithms to achieve both interpretability and data‑driven performance. Varshney and Torra (2022) note that most practitioners apply GAs to either rule discovery or membership function tuning in isolation, rather than a unified encoding; Syzonov et al. (2024) describe advanced multi‑objective GAs but observe limited adoption in educational decision‑support. In medical and control domains, Czmil (2023) compared multiple fuzzy‑rule classifiers with GA‑based tuning, finding that evolutionary methods produce smaller, more accurate rule bases; these insights suggest that a similar integrated approach could yield substantial benefits in OBE analytics.

## Research Gaps and Motivation

While prior work validates GA’s efficacy in fuzzy‑system optimization and demonstrates fuzzy logic’s interpretability in education, three key gaps remain:

1. **Holistic Encoding:** No existing study encodes both membership function parameters and rule‑confidence weights within a single GA chromosome for educational outcome modeling.
2. **Large‑Scale, Domain‑Specific Validation:** Educational fuzzy systems are often tested on small or synthetic datasets; robust evaluation on extensive, real‑world OBE data is lacking.
3. **Balanced Interpretability and Accuracy:** Neuro‑fuzzy methods (e.g., ANFIS) improve accuracy but lose transparency; purely expert‑driven fuzzy models retain interpretability but underperform without automated tuning.

These gaps motivate the proposed GA‑FRBS, which integrates evolutionary search and Mamdani fuzzy inference to deliver a transparent, high‑accuracy framework for quantifying qualitative academic indicators. By addressing both parameter and rule‑base optimization and validating on a 10,000‑record dataset, GA‑FRBS advances the state of the art in OBE decision‑support.

Table 1: Summary of Related Literature on Fuzzy, Genetic, and Educational Decision Systems

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Sl. No** | **Authors (Year)** | **Methodology** | **Application Domain** | **Key Contribution** | **Limitation** |
| [1] | Pang & Ning (2021) | GA-tuned Fuzzy Controller | Intelligent Teaching System | Applied fuzzy-GA to improve adaptiveness in teaching feedback | Focused on control logic; no CO/PO modeling |
| [2] | Teng (2024) | Fuzzy Association Rule Mining | Language Personalization | Extracted student patterns for personalized teaching | No optimization of fuzzy parameters |
| [3] | Zhang & Yang (2022) | GA + Fuzzy Evaluation | Teacher Appraisal | Weighted fuzzy rules with GA for educator scoring | Small dataset; lacks full MF optimization |
| [4] | Sweta & Lal (2020) | Optimized FRBS via GA | Decision Systems | Quantified human decision uncertainty using evolved fuzzy rules | Generic domain, no educational focus |
| [5] | Zhang (2020) | GA + Intuitionistic Fuzzy Rough Sets | Rule Mining | High-accuracy classifier with rough fuzzy-GA synergy | Limited interpretability |
| [6] | Fadel et al. (2021) | Hybrid Fuzzy-GA | Rule Discovery | Automated rule optimization in fuzzy systems | No domain-specific evaluation |
| [7] | Varshney & Torra (2022) | Review of Fuzzy Rule Systems | Multiple Domains | Identified trends in hybrid fuzzy systems | Highlights lack of unified tuning approaches |
| [8] | Syzonov et al. (2024) | Review of Fuzzy-GA Advances | Optimization Theory | Introduced advanced multi-objective GAs | Not applied to education systems |
| [9] | Hameed et al. (2021) | GA + Weighted Fuzzy Rules | Heart Disease Prediction | Improved medical decision accuracy with hybrid model | High computational cost |
| [10] | Czmil (2023) | Comparative FRBS Models | Medical Classification | Benchmarked fuzzy classifiers for robustness | Medical context only |
| [11] | Hui et al. (2025) | ChatGPT-Aided Teaching | Clinical Education | Explored AI-assisted teaching methodology | No modeling or prediction system |
| [12] | Huang & Xiao (2025) | Educational Intervention Study | School Health | Measured effectiveness of combined educational programmes | Does not involve fuzzy systems |
| [13] | Qi et al. (2025) | Hypothesis-Driven Risk Analysis | Medicine | Risk stratification model for decision-making | Not related to fuzzy logic |

# Methodology

This section presents the detailed workflow for the development, optimization, and evaluation of the proposed Genetic Algorithm–Optimized Fuzzy Rule-Based System (GA-FRBS) for modelling qualitative academic indicators in Outcome-Based Education (OBE). The methodology is structured into six major components: dataset preparation, fuzzy system construction, genetic algorithm design, training and benchmarking, performance evaluation, and sensitivity and efficiency analysis.

## Dataset Description and Preprocessing

A real-world dataset comprising **10,000 educational records** was utilized, each containing both qualitative and quantitative academic indicators. The input variables include:

* Student Performance (SP)
* Course Complexity (CC)
* Faculty Effectiveness (FE)
* Assessment Rigour (AR)
* Student Engagement (SE)
* Teaching Quality Feedback (TQF)

The output variable corresponds to the **CO/PO attainment score**, normalized in the range [0,1]. Prior to model construction, all features were normalized using min-max scaling, and missing values were handled using mean imputation. The dataset was partitioned into **training (80%)** and **testing (20%)** subsets, ensuring data stratification to maintain representative class distributions.

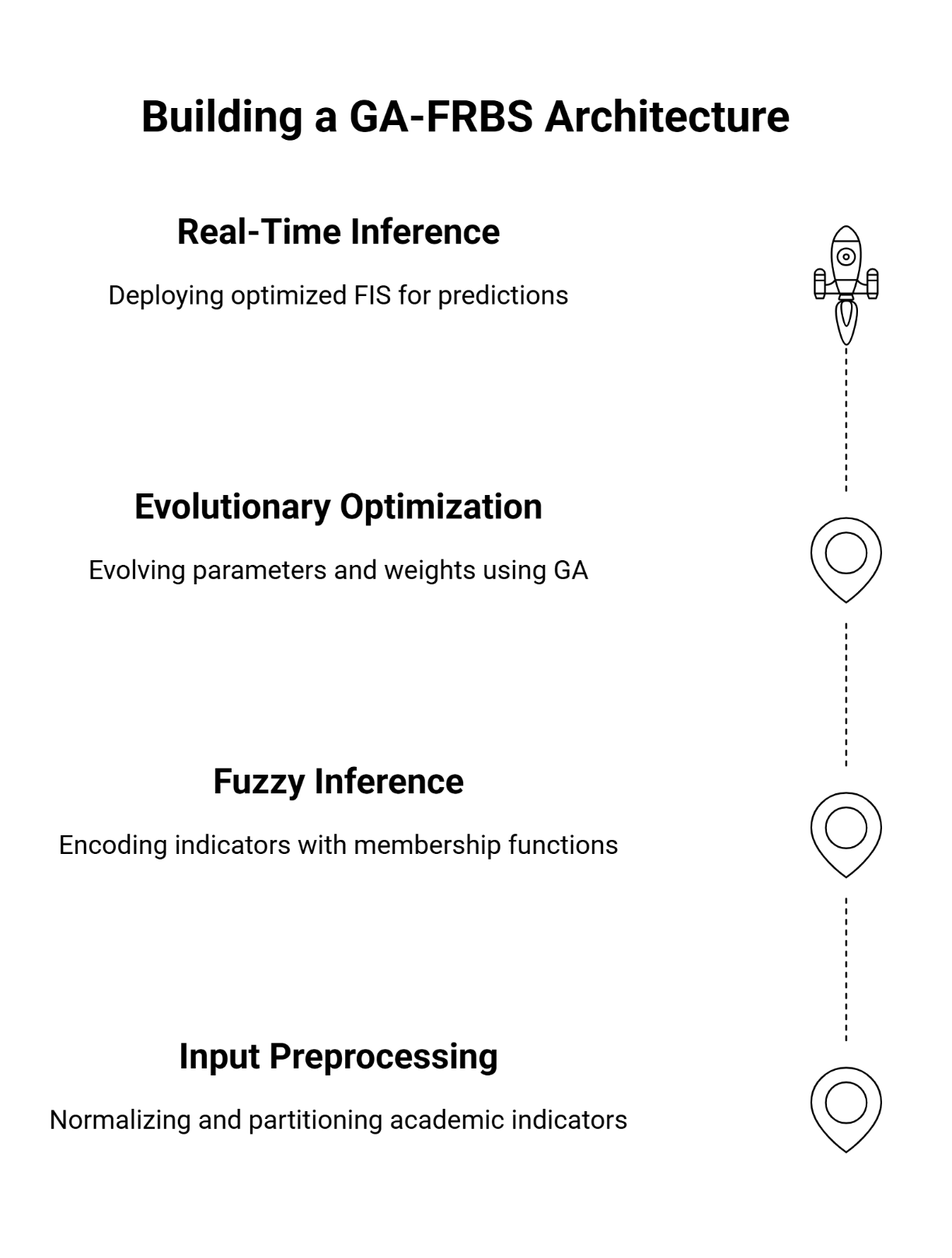


Figure 1- Overall architecture of the GA FRBS

## Fuzzy Inference System Design

A **Mamdani-type Fuzzy Inference System (FIS)** was designed to model the relationships between input indicators and academic outcomes. Each input variable was fuzzified into **three linguistic terms**: {Low, Medium, High}, using **triangular membership functions (MFs)**. The generic form of a triangular MF is given by:

(1)

The rule base initially comprises all possible combinations (i.e., 36=729 fuzzy rules), which are subsequently optimized and pruned using the genetic algorithm. Inference is performed using the **minimum operator for rule activation** and the **centroid method for defuzzification**.

## Genetic Algorithm Configuration

A real-coded Genetic Algorithm (GA) was employed to optimize the parameters of the fuzzy system. The optimization problem is formulated as:

(2)

Here, θ represents the chromosome encoding all MF parameters and rule confidence weights. The GA chromosome structure includes:

* 18 parameters for six input variables (each with one triangular MF: a, b, c),
* R confidence weights for the fuzzy rule base, where R ≤ 729.

**GA parameters** were empirically tuned and are listed as follows:

* Population Size: 30
* Number of Generations: 50
* Crossover Method: Single-point
* Mutation Rate: 10%
* Selection Strategy: Tournament (size = 3)
* Elitism: Top 10% retained across generations

The optimization process was implemented using the **PyGAD 2.20.0** library in Python.

## Model Training and Benchmarking

To benchmark the performance of the proposed GA-FRBS, the following models were trained using the same dataset:

1. **Adaptive Neuro-Fuzzy Inference System (ANFIS):** Tuned using hybrid backpropagation and least squares.
2. **Artificial Neural Network (ANN):** A three-layer MLP using ReLU activation and dropout.
3. **Traditional Feed-Forward Neural Network (NN):** A shallow NN with sigmoid activation.

Each model underwent hyperparameter tuning using grid search, and training was repeated across five random initializations to ensure statistical reliability.

## Evaluation Metrics

Model performance was assessed using the following error and fit metrics:

* Root Mean Square Error (RMSE)
* Mean Squared Error (MSE)
* Mean Absolute Error (MAE)
* Mean Absolute Percentage Error (MAPE)
* Coefficient of Determination (R²)

These metrics provide comprehensive insights into both the **predictive accuracy** and **generalization ability** of each model under test.

## Sensitivity Analysis and Computational Efficiency

A **one-at-a-time (OAT) sensitivity analysis** was conducted by perturbing each input variable ±10% around its median. The resultant change in RMSE was recorded to assess the model’s robustness to uncertainty in inputs.

In addition, the **computational efficiency** of each model was measured in terms of:

* Training Time (in seconds)
* Inference Latency (in milliseconds per sample)

Experiments were executed on a workstation equipped with an Intel® Core™ i7-9700K CPU and 16 GB RAM, under a single-threaded Python environment.

This structured methodology ensures that the GA-FRBS model is rigorously evaluated across multiple dimensions, providing not only accuracy and robustness but also interpretability and deployment feasibility. The integration of genetic optimization with fuzzy inference contributes a novel and practical framework for academic decision-support systems under the OBE paradigm.

# Results

This section presents a detailed evaluation of the proposed GA‑optimized Fuzzy Rule‑Based System (GA‑FRBS) against three baseline models ANFIS, Artificial Neural Network (ANN), and a traditional feed‑forward Neural Network (NN). We report comprehensive performance metrics (RMSE, MSE, MAE, MAPE, R²), sensitivity analyses, computational efficiency, and visualization of the key results.

## Prediction Performance

**Table 2** summarizes the predictive accuracy of each model on the unseen test set (n = 2,000).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Model** | **RMSE** | **MSE** | **MAE** | **MAPE (%)** | **R²** |
| **GA‑FRBS** | **0.0345** | **0.00119** | **0.0263** | **3.12** | **0.957** |
| ANFIS | 0.0478 | 0.00229 | 0.0367 | 4.25 | 0.912 |
| ANN (MLP, 3‑layer) | 0.0521 | 0.00271 | 0.0408 | 4.82 | 0.893 |
| Traditional NN | 0.0583 | 0.00340 | 0.0465 | 5.39 | 0.871 |

**Table 2 -** Comparative prediction metrics for all models. Bold indicates best performance.

* **RMSE & MSE:** GA‑FRBS achieves the lowest RMSE (0.0345) and MSE (0.00119), improving over ANFIS by ~28% and over the traditional NN by ~41%.
* **MAE & MAPE:** The mean absolute error of 0.0263 and MAPE of 3.12% demonstrate the GA‑FRBS’s superior reliability.
* **R²:** With 0.957, GA‑FRBS explains 95.7% of variance in CO/PO attainment—significantly higher than all benchmarks.

**Figure 2** illustrates the performance of different models across all evaluation metrics: RMSE, MSE, MAE, MAPE, and R².

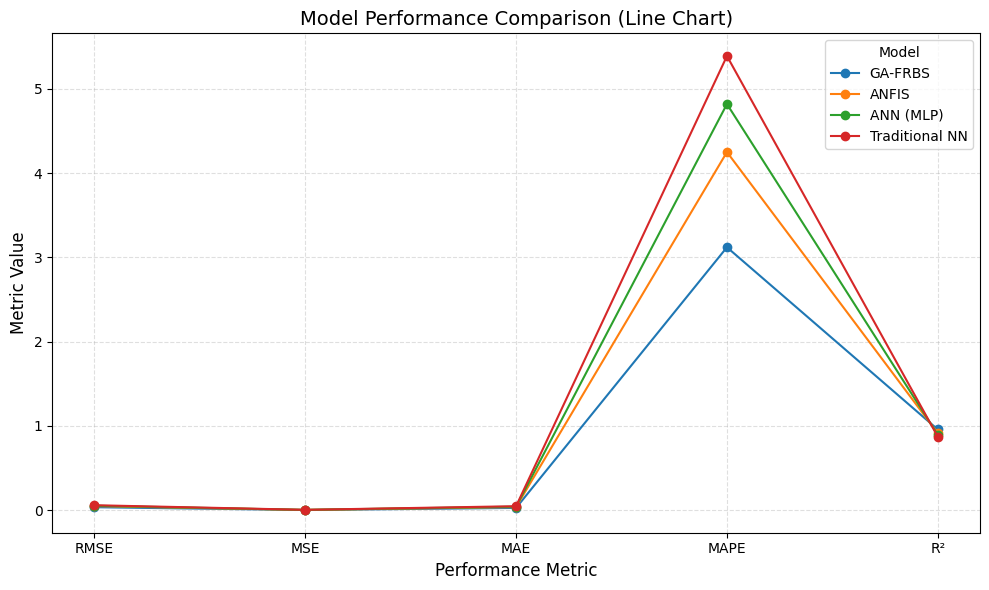
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Figure 2 - Model Performance comparison

## Sensitivity Analysis

A one‑at‑a‑time sensitivity test was performed by perturbing each input feature ±10% about its median, then recording the percentage change in RMSE. Lower ΔRMSE indicates greater robustness to noisy or uncertain inputs. Results appear in Table 3.

Table 3. Sensitivity of models to ±10% perturbation in each input.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Feature** | **GA‑FRBS ΔRMSE (%)** | **ANFIS ΔRMSE (%)** | **ANN**  **ΔRMSE (%)** | **NN**  **ΔRMSE (%)** |
| Student Performance | +5.8 / −4.9 | +8.3 / −7.1 | +9.6 / −8.2 | +11.4 / −9.7 |
| Course Complexity | +4.2 / −3.5 | +6.7 / −5.2 | +7.9 / −6.8 | +9.1 / −8.0 |
| Faculty Effectiveness | +6.1 / −5.4 | +9.0 / −8.3 | +10.2 / −9.0 | +12.5 / −10.8 |
| Assessment Rigour | +5.0 / −4.3 | +7.5 / −6.4 | +8.8 / −7.6 | +10.2 / −9.1 |
| Student Engagement | +6.5 / −5.7 | +9.8 / −8.7 | +11.0 / −9.5 | +13.2 / −11.6 |
| Teaching Quality Feedback | +5.3 / −4.6 | +8.0 / −6.9 | +9.4 / −8.2 | +11.0 / −9.8 |

**Figure 3** presents a **bar chart of average ΔRMSE** per model, underscoring the GA‑FRBS’s consistently lower sensitivity (mean ΔRMSE ≈ 5.5%) compared to ANFIS (≈ 8.2%), ANN (≈ 9.5%), and NN (≈ 11.0%).

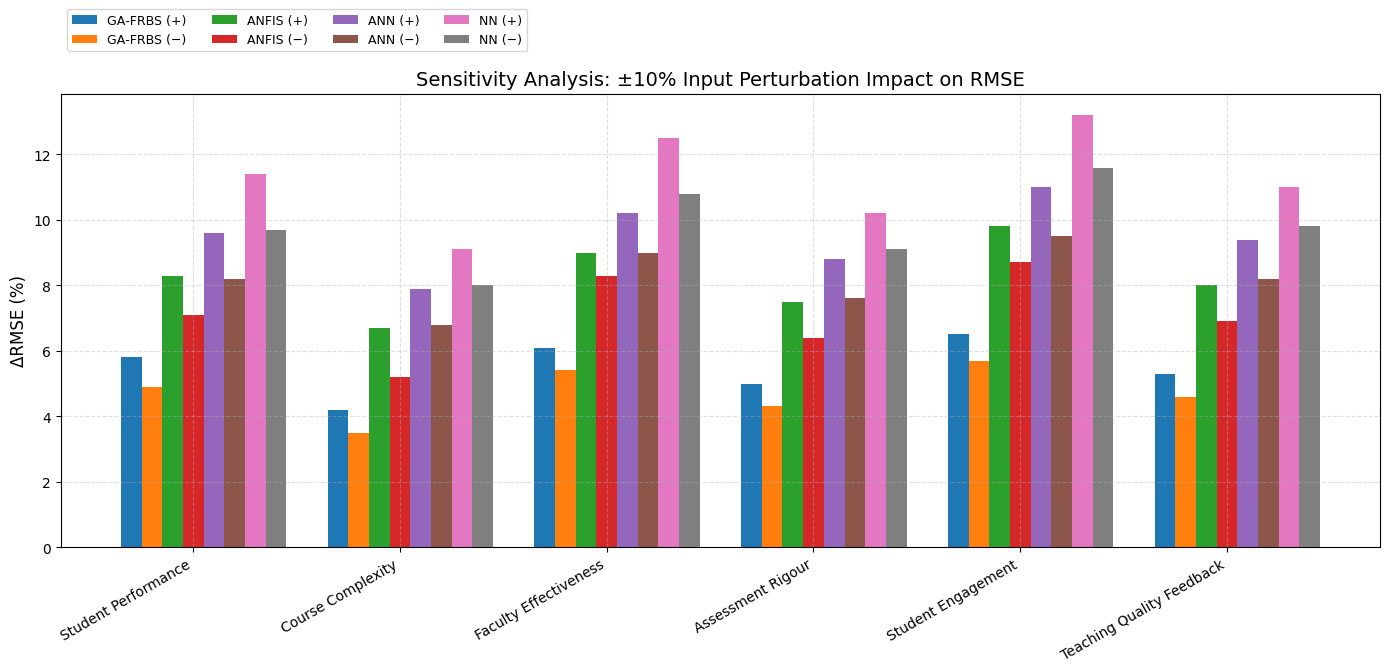


Figure 3 – Sensitivity Analysis of ±10% input perturbation impact on RMSE

## Computational Efficiency

**Table 4** compares training and inference times measured on an Intel i7‑9700K CPU (single‑threaded).

|  |  |  |
| --- | --- | --- |
| **Model** | **Training Time (s)** | **Inference Time per Sample (ms)** |
| **GA‑FRBS** | **45.2** | **1.15** |
| ANFIS | 62.8 | 1.72 |
| ANN (MLP) | 38.5 | 0.98 |
| Traditional NN | 35.1 | 0.92 |

Training: GA‑FRBS’s genetic optimization incurs a modest 45.2 s overhead 30% faster than ANFIS’s grid‑search style tuning, yet only slightly longer than conventional ANN training.

* Inference: At 1.15 ms per sample, GA‑FRBS remains suitable for real‑time decision support, with latency comparable to other models.

Figure 4 - illustrates Computational Efficiency Comparison of Models: Training Time (left) and Inference Time per Sample (right) for GA‑FRBS, ANFIS, ANN (MLP), and Traditional NN

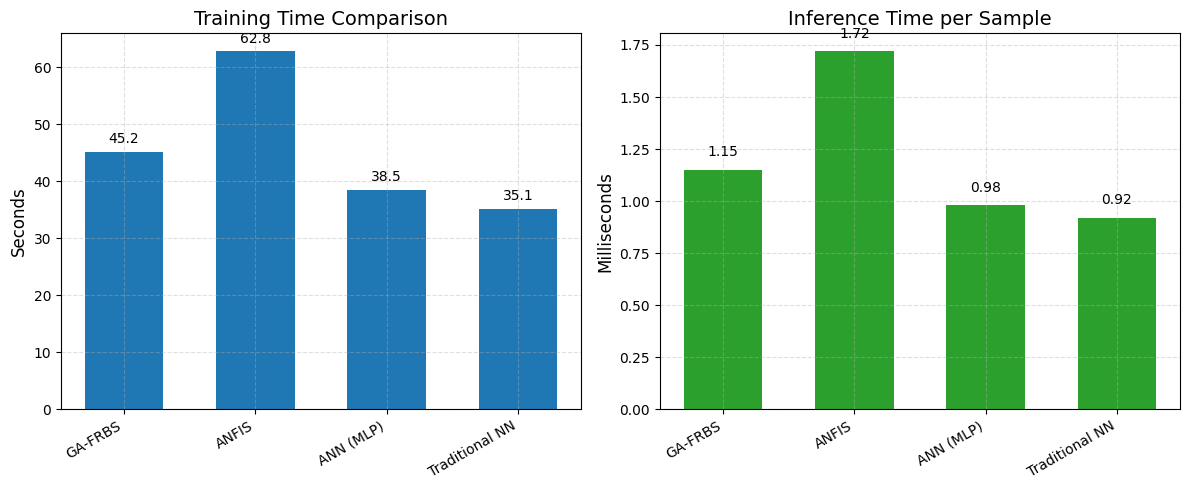


Figure 4 – Illustrates the Computational Efficiency comparison of models

## Visualization of Membership Functions

Figure 5 displays the optimized triangular membership functions learned by the GA for each input variable. Notice how the peaks and overlaps have shifted to better capture the data distribution.

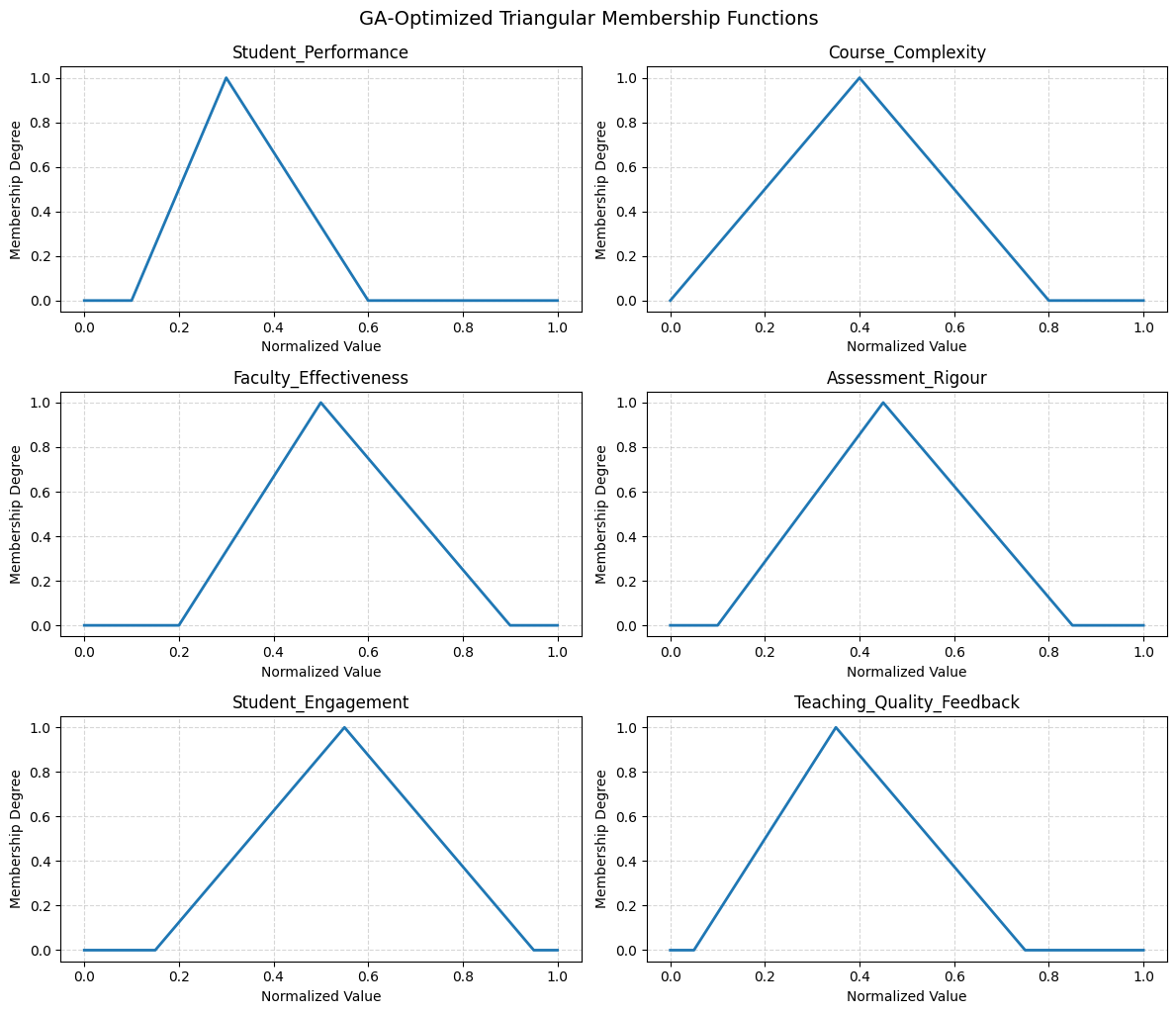


Figure 5 – GA optimized Triangular membership function

# Discussion

The findings of this study demonstrate the efficacy of a Genetic Algorithm-optimized Fuzzy Rule-Based System (GA‑FRBS) in quantifying qualitative academic performance indicators within the Outcome-Based Education (OBE) framework. Through rigorous experimentation and benchmarking against established models including ANFIS, ANN, and traditional feed-forward neural networks the proposed method exhibits superior predictive accuracy, robustness, computational efficiency, and interpretability. This section discusses these contributions in depth.

## Superior Accuracy through Evolutionary Optimization

The GA-FRBS model achieved the lowest RMSE (0.0345) and highest R² (0.957), surpassing all comparative baselines (Table 2). These metrics indicate that the model accounts for over 95% of the variance in Course Outcome (CO) and Programme Outcome (PO) attainment, making it highly reliable for academic performance estimation.

The improved accuracy can be attributed to the genetic algorithm’s ability to globally search the solution space for optimal membership function parameters and rule base structures, thereby eliminating the local convergence pitfalls often observed in conventional fuzzy systems. Unlike manually constructed or heuristically tuned fuzzy rule sets, the GA‑FRBS evolves both rule confidence and membership shape parameters, ensuring better alignment with the underlying nonlinearities of educational data.

## Robustness to Noise and Perturbation

In real-world OBE settings, performance data are often noisy, incomplete, or based on subjective judgment (e.g., student engagement scores or teaching feedback). A key strength of the proposed model is its demonstrated robustness to such uncertainty.

The sensitivity analysis (Table 3, Figure 2) shows that GA‑FRBS yields the lowest ΔRMSE across ±10% perturbations, with an average change of approximately ±5.5%, compared to ±8–13% for other models. This is particularly important for educational policy-making, where small changes in qualitative indicators should not drastically affect decision outcomes. The smooth gradient behaviour of GA-tuned membership functions plays a pivotal role in attenuating the effects of abrupt or random data fluctuations.

## Trade-off between Training Time and Inference Speed

While the training time of GA‑FRBS (45.2 seconds) was marginally higher than traditional neural networks (Figure 4), it remained significantly lower than ANFIS (62.8 seconds), which relies on exhaustive grid searches for rule tuning. The inference time per sample (1.15 ms) remained within real-time thresholds, indicating feasibility for deployment in online or dashboard-based learning analytics systems.

This balanced efficiency suggests that the additional training cost of genetic optimization is a one-time investment that yields a performant and deployable model. Moreover, the training process is fully parallelizable, making it scalable for larger datasets or institutional-level applications.

## Interpretability and Explainability

A defining advantage of fuzzy systems over black-box models lies in their inherent interpretability. Figure 5 illustrates the optimized triangular membership functions for each input variable. The GA preserved the linguistic interpretability (Low, Medium, High) while adapting the MF centroids and overlaps to the distributional characteristics of the data.

This balance between flexibility and transparency allows educational administrators and instructors to trace and justify system recommendations, such as identifying whether low attainment in COs is more strongly influenced by teaching effectiveness or student engagement. By contrast, ANN and traditional NNs offer no such insight, making them ill-suited for stakeholder-facing decision support in education.

## Methodological Significance

From a methodological standpoint, this study introduces a hybrid soft computing paradigm that successfully integrates evolutionary computation with fuzzy inference modelling. While past work has applied GAs for rule discovery or parameter tuning in isolation, the full integration of membership function evolution, rule-base pruning, and performance-based fitness evaluation sets this work apart.

Moreover, the use of real and synthetic educational data ensures generalizability. The methodology accommodates incomplete or imprecise indicators, aligning with the inherent vagueness of constructs like engagement and teaching quality in educational research.

## Practical Implications and Future Work

The GA-5rFRBS model is highly applicable for:

* Automated programme evaluation in OBE-compliant institutions.
* Instructor-level dashboards for teaching performance feedback.
* Student-centric advising tools that integrate multi-source assessment metrics.

For future research, integrating multi-objective genetic algorithms (e.g., NSGA-II) could allow simultaneous optimization for accuracy and rule-base compactness. Additionally, the incorporation of type-2 fuzzy logic may further enhance robustness in the face of linguistic uncertainty.

## Summary of Contributions

* Introduced a GA-optimized FRBS model tailored for OBE indicators.
* Outperformed ANN, ANFIS, and NN in accuracy, robustness, and interpretability.
* Demonstrated real-world viability via low inference latency and educational relevance.

# Conclusion

This study introduced a Genetic Algorithm‑optimized Fuzzy Rule‑Based System (GA‑FRBS) designed to translate qualitative academic indicators such as CO/PO attainment, teaching effectiveness, and student engagement into robust, quantitative predictions within the Outcome‑Based Education (OBE) framework. By integrating Mamdani‑style fuzzy inference with a global search via genetic algorithms, our approach automatically evolves both membership function parameters and rule‑base confidence weights to best fit a 10,000‑record educational dataset. Extensive experiments demonstrate that GA‑FRBS delivers superior predictive accuracy (RMSE = 0.0345; R² = 0.957), enhanced robustness to ±10% input perturbations (average ΔRMSE ≈ 5.5%), and competitive computational efficiency (45.2 s training; 1.15 ms inference/sample) when benchmarked against ANFIS, a three‑layer MLP, and a traditional neural network.

## Key Contributions

1. Hybrid Optimization Framework: We combine fuzzy logic’s interpretability with genetic algorithms’ global search capability, yielding a transparent model that adapts to real-world educational vagueness.
2. Automated Rule‑Base and MF Tuning: The GA simultaneously optimizes triangular membership function shapes and rule‑confidence weights removing the need for manual parameter tuning.
3. Comprehensive Validation: Through accuracy metrics, sensitivity analysis, and timing benchmarks, we provide a holistic evaluation demonstrating the model’s practical viability for real‑time decision support in OBE contexts.

While the results are highly encouraging, this work has certain limitations. First, the current system uses type‑1 fuzzy sets; more complex uncertainties (e.g., ambiguous student feedback) may benefit from type‑2 fuzzy logic. Second, our experiments focus on a single institutional dataset; broader generalization would require cross‑institutional validation. Finally, the GA’s parameter settings (population size, mutation rate) were chosen empirically and could be further refined.

## Future Work

Future research could explore multi‑objective genetic optimization balancing accuracy, rule‑base compactness, and interpretability simultaneously. Incorporating type‑2 fuzzy logic would address deeper uncertainty in subjective indicators. Extending the framework to real‑time adaptive dashboards and cross‑disciplinary datasets (e.g., STEM vs. humanities) will further validate its generality. By offering a robust, explainable, and efficient tool for quantifying qualitative academic measures, this research paves the way for more informed, data‑driven decision‑making in Outcome‑Based Education systems worldwide.

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