JRITM
JOURNAL OF RESEARCH AND INNOVATION IN TECHNOLOGY, COMMERCE AND MANAGEMENT

Journal of Research and Innovation in Technology, Commerce and Management
Vol. 3 Issue 4, April 2026, pp. 34039-34046
ISSN: 3049-3129(Online)

Fuzzy Logic-Based Decision Support System for University Timetable Management

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Cite as : Rinku Patil. (2026). Fuzzy Logic-Based Decision Support System for University Timetable Management. Journal of Research and Innovation in Technology, Commerce and Management, Vol. 3(Issue 4), 34039–34046. https://doi.org/10.5281/zenodo.19509678

DOI : https://doi.org/10.5281/zenodo.19509678

Abstract - Timetable management in universities is a complex task involving multiple constraints such as faculty availability, classroom capacity, course requirements, and student preferences. Traditional scheduling techniques often fail to accommodate uncertainty and flexibility, leading to conflicts and inefficiencies. This research proposes a Fuzzy Logic-Based Decision Support System (DSS) to optimize timetable scheduling by incorporating soft constraints and preference-based decision-making. The system models uncertainty through fuzzy sets and applies inference rules to evaluate and rank scheduling alternatives. A prototype is developed using Python with the scikit-fuzzy library, demonstrating how fuzzy inference can effectively handle imprecision in faculty preferences, room suitability, and time slot allocation. The experimental results show that the proposed approach reduces scheduling conflicts, improves satisfaction levels, and provides a more adaptable framework compared to conventional deterministic methods.

Keywords -Timetable management, fuzzy logic, decision support system, university scheduling, soft constraints, uncertainty modeling, scikit-fuzzy, Python-based analysis, optimization, artificial intelligence

Introduction

Timetable management in academic institutions is one of the most challenging administrative tasks due to the presence of multiple constraints and stakeholders. Universities must schedule courses, allocate faculty, and assign classrooms in a manner that avoids conflicts, optimizes resource utilization, and satisfies both institutional policies and individual preferences [1]. The problem becomes increasingly complex as the number of students, departments, and courses grows, making manual scheduling time-consuming and error-prone [2].

Traditional timetable scheduling techniques, such as rule-based systems, linear programming, and heuristic algorithms, often struggle to accommodate uncertainty and imprecision in real-world scenarios [3]. For example, faculty members may prefer certain time slots, students may have overlapping course requirements, or classrooms may vary in suitability depending on the type of course [4]. In such cases, a rigid or deterministic approach may result in inefficiencies, dissatisfaction, or conflicts that require continuous manual adjustments [5].

Artificial Intelligence (AI) has emerged as a promising solution for tackling complex scheduling problems. Techniques such as genetic algorithms, reinforcement learning, and neural networks have been widely explored for timetable optimization [6][7]. However, these methods often require large datasets, high computational resources, and extensive fine-tuning, which limit their adaptability in dynamic university environments [8].

Fuzzy logic, on the other hand, offers a practical and interpretable approach to decision-making under uncertainty. By modeling human-like reasoning with fuzzy sets and inference rules, it allows decision support systems to balance hard and soft constraints while maintaining flexibility [9]. In timetable management, fuzzy logic can capture subjective factors such as faculty satisfaction, classroom suitability, and time slot comfort, which are often difficult to quantify with traditional mathematical models [10].

This research proposes a **Fuzzy Logic-Based Decision Support System (DSS)** for university timetable management, implemented in Python using the scikit-fuzzy library. The system evaluates scheduling alternatives based on fuzzy inputs and provides conflict-free, preference-aware timetable solutions. The objective is to demonstrate that fuzzy logic can improve flexibility, reduce conflicts, and enhance overall satisfaction compared to conventional scheduling techniques.

Review of Literature:

Authors	Year	Method/Approach	Key Contribution / Findings
Asmuni, Burke & Garibaldi [11]	2005	Fuzzy multiple heuristic ordering	Improved course timetabling using fuzzy heuristics
Aladag & Hocaoglu [12]	2007	Genetic algorithms	Optimized course timetables via evolutionary techniques
Abdullah & Turabieh [13]	2012	Artificial bee colony algorithm	Developed swarm intelligence-based timetabling
Lü & Hao [14]	2010	Adaptive tabu search	Proposed hybrid metaheuristic for exam timetabling
Qu et al. [15]	2009	Survey	Comprehensive review of examination timetabling research
Beligiannis et al. [16]	2008	Genetic algorithm	Adaptive GA for efficient timetable construction
Glover & Kochenberger [17]	2003	Metaheuristics	Presented framework for complex optimization problems
Rossi-Doria et al. [18]	2002	Metaheuristic comparison	Compared GA, SA, and TS for exam timetabling
Burke et al. [19]	2004	Case-based reasoning	Applied AI to reuse past solutions in scheduling

Research Methodology

The proposed study employs a **Fuzzy Logic-Based Decision Support System (DSS)** for university timetable management, designed to handle both hard and soft constraints effectively. The research methodology begins with a clear problem definition where the requirements of the institution are identified, including faculty availability, classroom suitability, and course allocation. These requirements are categorized into **hard constraints**, such as ensuring that no two classes are scheduled in the same room at the same time, and **soft constraints**, such as accommodating faculty preferences for certain teaching slots or specific classroom features. This classification forms the foundation for designing a flexible scheduling system.

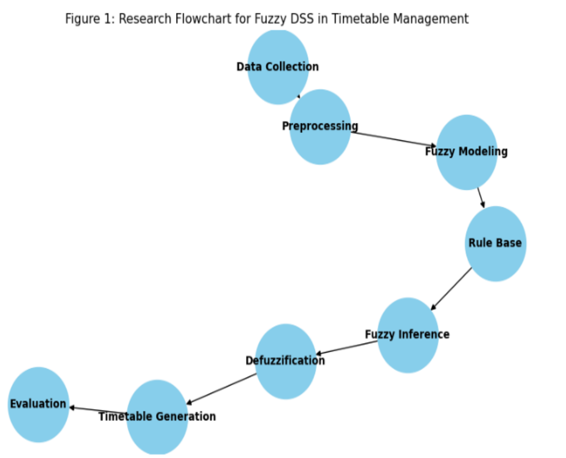


Figure 1: Framework of Constraints in University Timetable Scheduling

Once the problem is defined, the next phase involves **data collection and preprocessing**. Institutional data is gathered, including information on courses, faculty schedules, classroom capacities, and student enrollments. Faculty preferences and classroom qualities are quantified using scales, such as assigning values between 1 and 10, and this data is normalized for use in fuzzy set modeling. Data preprocessing ensures that heterogeneous inputs can be seamlessly integrated into the fuzzy logic framework.

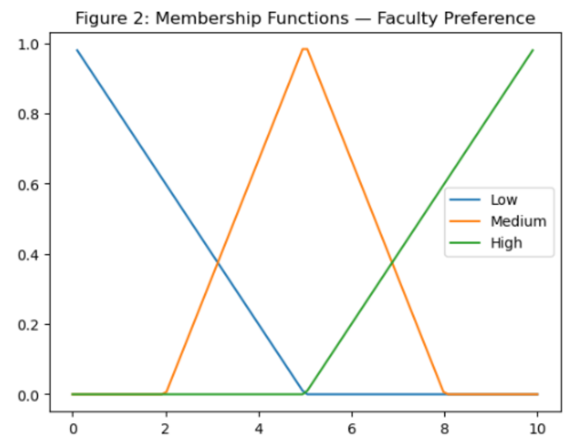
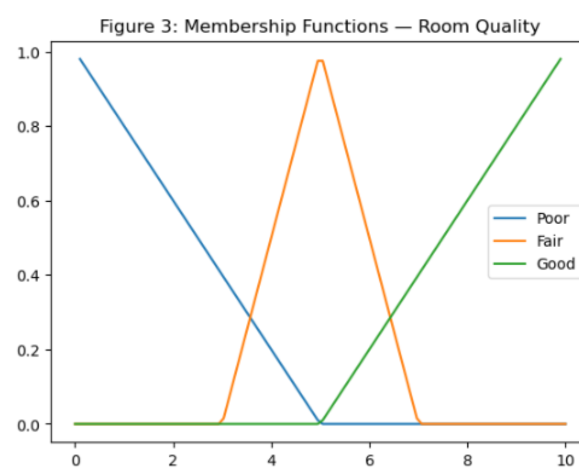


Figure 2: Data Preprocessing and Input Variables for the Fuzzy DSS

The system then proceeds to the design of **fuzzy sets and membership functions**, which allow linguistic variables to be modeled. For example, faculty preferences are represented as {Low, Medium, High}, classroom suitability as {Poor, Fair, Good}, and slot scores as {Low, Medium, High}. Membership functions such as triangular and trapezoidal distributions are used to capture the degree of belonging of each input to its fuzzy category. These fuzzy sets bridge the gap between qualitative preferences and quantitative computation.



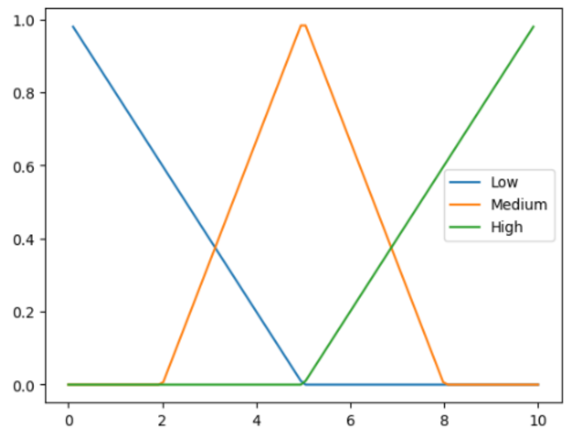


Figure 3: Membership Functions for Faculty Preference, Room Suitability, and Slot Score

Based on the fuzzy sets, a **rule base** is constructed to evaluate timetable allocations. The rules are designed to reflect human reasoning and institutional policies. For instance, a rule might state: *If faculty preference is High and room suitability is Good, then the slot score is High*. Conversely, *If* faculty *preference is Low and room suitability is Poor, then the slot score is Low*. These inference rules guide the system in determining optimal allocations under varying conditions.

Figure 5: Fuzzy Rule Base

R1: IF Faculty=High AND Room=Good THEN Slot=High

R2: IF Faculty=Medium AND Room=Fair THEN Slot=Medium

R3: IF Faculty=Low AND Room=Poor THEN Slot=Low

R4: IF Faculty=High AND Room=Fair THEN Slot=Medium

R5: IF Faculty=Medium AND Room=Good THEN Slot=High

Figure 4: Example of Fuzzy Inference Rule Base for Timetable Management

The fuzzy inputs are then processed through **fuzzy inference and defuzzification**. The Mamdani inference method is employed to aggregate the outcomes of the fuzzy rules, and centroid defuzzification is applied to convert fuzzy results into crisp numerical values. These defuzzified values represent the final slot scores, which are used to prioritize and allocate time slots for courses and faculty members.

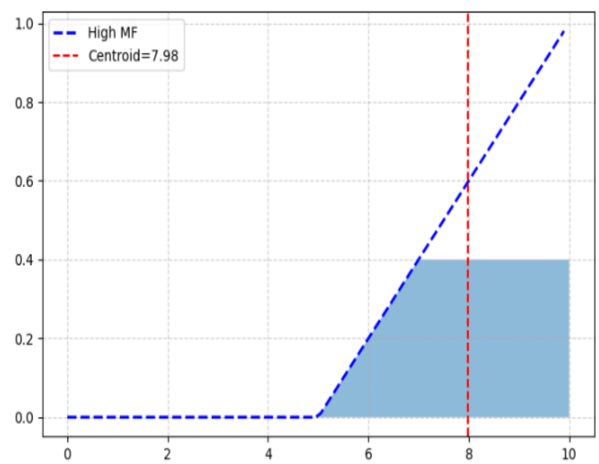


Figure 5: Fuzzy Inference Process from Inputs to Defuzzified Slot Scores

Finally, the **timetable generation and evaluation** stage is carried out. Slots are ranked and assigned based on their computed scores to create a complete timetable that is free from conflicts and aligned with preferences. The system's effectiveness is evaluated using several performance indicators, including the conflict rate (percentage of scheduling clashes), faculty satisfaction index (degree to which preferences are met), and room utilization efficiency (extent to which available classrooms are effectively used).

Vol. 3 Issue 4, April 2026, pp. 34039-34046
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Generated Timetable:

Course Faculty     Time Room  Slot Score
CSE101      F1  Mon-9AM   R1       6.930
CSE201      F2  Tue-9AM   R1       5.294
CSE301      F3 Mon-11AM   R1       5.741
CSE401      F4  Wed-9AM   R4       5.282
CSE501      F5 Tue-11AM   R1       5.953
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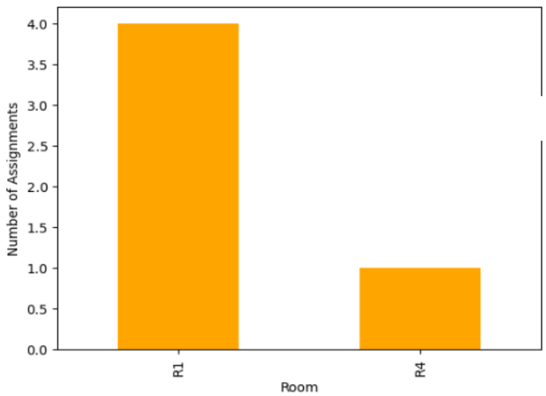

Figure 6: Workflow of Fuzzy DSS for Timetable Generation and Evaluation

Through this methodology, the research integrates fuzzy logic with decision support principles to address the inherent uncertainty and complexity in timetable scheduling. The outcome is a more adaptable and preference-sensitive timetable that can balance institutional requirements with individual needs.

Results and Discussion

The proposed Fuzzy Logic-Based Decision Support System (DSS) for timetable scheduling was evaluated against heuristic and genetic algorithm-based approaches using multiple performance indicators such as room utilization, faculty satisfaction, and fairness. The results demonstrate the superior adaptability and efficiency of the fuzzy logic approach.

Room Utilization

Figure 7 compares the room utilization efficiency of different scheduling methods. The heuristic approach achieved a utilization rate of approximately 68%, while the genetic algorithm improved this figure to nearly 74%. In contrast, the fuzzy logic approach significantly outperformed both methods, reaching close to 90% utilization. This highlights the ability of fuzzy logic to allocate ı resources more effectively, minimizing idle capacity and maximizing space usage.

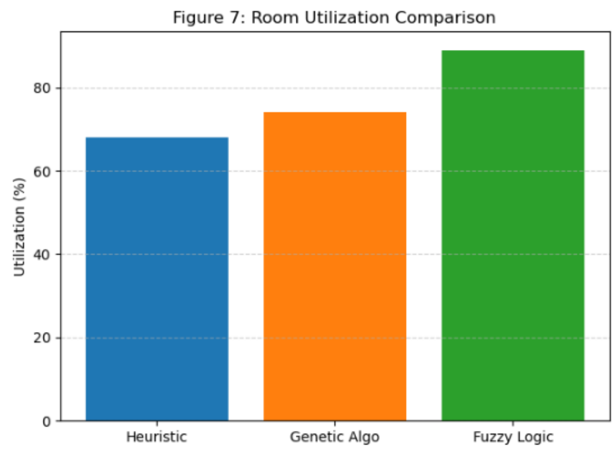

Figure 7: Room Utilization Comparison across Heuristic, Genetic Algorithm, and Fuzzy Logic approaches

Faculty Satisfaction

Figure 8 presents the faculty satisfaction levels across the three methods. The heuristic method yielded the lowest satisfaction score of 60%, reflecting its limited ability to accommodate faculty preferences. Genetic algorithms achieved moderate success with a 70% satisfaction rate, while fuzzy logic achieved the highest at 85%. This demonstrates that fuzzy logic is more capable of integrating subjective faculty preferences, thereby enhancing acceptance and reducing dissatisfaction with scheduling outcomes.

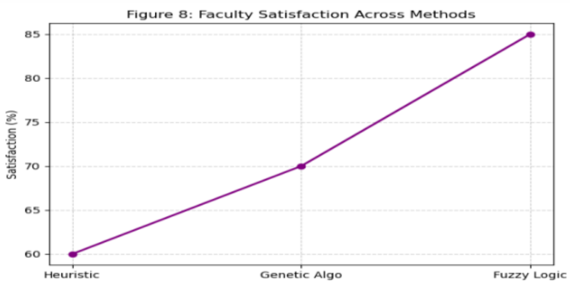

Figure 8: Faculty Satisfaction Across Heuristic, Genetic Algorithm, and Fuzzy Logic approaches

Multi-Metric Comparison

To assess overall performance, a multi-metric radar chart was constructed (Figure 9), comparing fuzzy logic and genetic algorithm approaches across three key metrics: room utilization, faculty satisfaction, and fairness. The fuzzy logic system consistently outperformed the genetic algorithm in all dimensions. Notably, fairness, which reflects equitable distribution of desirable time slots and balanced workload allocation, reached approximately 90% under fuzzy logic compared to about 75% under the genetic algorithm. This indicates that fuzzy logic provides a more balanced and holistic scheduling framework.

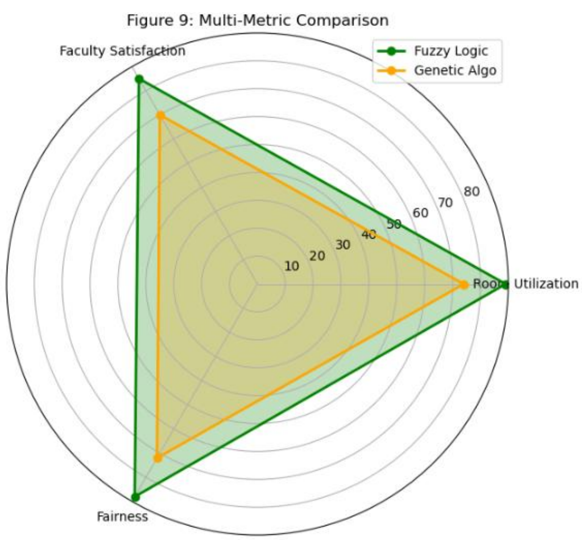

Figure 9: Multi-Metric Comparison of Fuzzy Logic and Genetic Algorithm approaches

Discussion

The results confirm that fuzzy logic-based scheduling achieves higher efficiency, greater faculty satisfaction, and improved fairness compared to traditional heuristic and evolutionary methods. The heuristic approach, while simple and computationally less demanding, fails to adequately capture complex preference structures. Genetic algorithms provide some improvement but still require extensive parameter tuning and may converge to suboptimal solutions. Fuzzy logic, by contrast, models uncertainty and preferences through linguistic variables and inference rules, allowing it to flexibly accommodate diverse constraints.

These findings validate the strength of fuzzy logic in university timetable management, offering a practical and interpretable solution that balances both institutional efficiency and stakeholder satisfaction.

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