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Course Scheduling Optimization Using Genetic Algorithms with Fuzzy Tsukamoto-Based Fitness Adjustment

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Abstract
This study develops a course scheduling optimization system that integrates a genetic algorithm with the Tsukamoto fuzzy inference system to dynamically adjust fitness values. The objective of this research is to overcome the limitations of conventional genetic algorithms that rely on static fitness functions, which only evaluate schedule quality based on the number of constraint violations. The Tsukamoto fuzzy inference system is designed with three input variables: constraint violation level, lecturer workload distribution, and classroom utilization efficiency. It employs 27 fuzzy rules based on triangular and trapezoidal membership functions to produce a fitness adjustment factor.The research methodology consists of four stages: requirements analysis and problem modeling, Tsukamoto fuzzy inference system design, hybrid genetic algorithm implementation, and performance testing and evaluation. Experiments were conducted using a synthetic dataset comprising 50 courses, 20 lecturers, 15 classrooms, and 30 weekly time slots. The results show that the proposed hybrid genetic algorithm achieves 42% faster convergence with an average fitness value of 0.89 compared to 0.76 in the conventional algorithm. Constraint satisfaction improved from 82.4% to 94.7%, lecturer workload distribution became more balanced with the coefficient of variation decreasing from 0.34 to 0.19, and classroom utilization efficiency increased from 76.8% to 88.5%. Statistical tests indicate a significant difference (p-value < 0.001) with a substantial effect size (Cohen's d = 1.23). This research contributes to the development of a hybrid approach that integrates the Tsukamoto fuzzy inference system into genetic algorithms, resulting in more optimal, adaptive, and efficient course schedules compared to conventional methods.

Keywords: genetic algorithm, fuzzy Tsukamoto, course scheduling, optimization, dynamic fitness

INTRODUCTION

Universitas Negeri Semarang (UNNES) is one of the state universities in Indonesia that offers various academic programs attended by numerous students and lecturers. The management of course schedules is a crucial aspect in ensuring the smooth operation of the teaching and learning process. However, course scheduling, also known as the University Course Timetabling Problem (UCTP), is recognized as a complex problem both theoretically and practically (Harutun Harry Nazaryan, 2025). This complexity arises from limited resources such as classrooms and lecturers, as well as the need to satisfy multiple time preferences and constraints simultaneously. UCTP is classified as an NP-hard problem, thus finding an optimal solution requires effective optimization methods (Abdipoor et al., 2023).

At UNNES, the course scheduling process still faces challenges in optimizing classroom utilization and avoiding schedule conflicts. Suboptimal timetables may lead to conflicts between lecturer and student schedules, inefficient classroom usage, and a decrease in the overall comfort of the learning process (Wiratna et al., 2023). These conditions demand an automated scheduling system capable of generating optimal timetables while considering various existing constraints.

Various optimization methods have been developed to solve the UCTP. Genetic Algorithms (GA) are among the most widely used approaches due to their capability to explore large and complex solution spaces (Zuyyinal Haqqul Barir et al., 2024). GAs operate based on evolutionary principles, where solutions are represented as chromosomes and improved through selection, crossover, and mutation processes to produce better generations (Chen et al., 2020). The advantages of GAs include their flexibility in handling various scheduling constraints and their ability to find near-optimal solutions within a relatively efficient time frame (Genetic Algorithm for TSP Optimization, n.d.).

However, pure genetic algorithms often rely solely on static evaluation functions that assess schedule quality only based on the number of constraint violations (Rezaeipanah et al., 2021). This approach is not fully adaptive to the complexity and dynamics of various types of constraints that arise in course scheduling. To address this limitation, fuzzy logic can be applied as a mechanism for dynamically adjusting fitness values, making the evaluation process more adaptive. In particular, the Tsukamoto fuzzy inference system can handle uncertainty and provide a more nuanced assessment of schedule quality based on criteria such as course distribution, classroom utilization efficiency, and minimal conflicts. Integrating fuzzy logic with evolutionary algorithms can improve the accuracy of university timetabling solutions by simultaneously considering multiple schedule quality criteria (Herdit Juningsih & Aziz, 2024).

Based on these considerations, this research develops a course scheduling system that integrates Genetic Algorithms with the Tsukamoto fuzzy inference system. The Genetic Algorithm is utilized to generate diverse scheduling solutions, while the Tsukamoto fuzzy system dynamically adjusts fitness values to enhance schedule quality. This hybrid approach is expected to produce more optimal timetables than conventional methods that rely solely on static evaluations, while also being adaptive to the complex dynamics of scheduling constraints.

METHOD

This research adopts an experimental approach by developing a course scheduling system that integrates Genetic Algorithms with the Tsukamoto fuzzy inference system. This method was selected because Genetic Algorithms are effective for solving scheduling problems with large solution spaces, while the Tsukamoto fuzzy system is capable of handling uncertainty and of dynamically adjusting fitness values.

The research process consists of four main stages: requirements analysis and problem modeling, tsukamoto fuzzy inference system design, hybrid genetic algorithm implementation, and system testing and evaluation. This approach is based on the framework for Genetic Algorithm development and the Tsukamoto fuzzy inference system design as described by Herdit Juningsih & Aziz (2024).

Requirements Analysis and Problem Modeling

The initial stage focuses on identifying and formalizing the course scheduling problem. The constraints considered include lecturer availability, classroom capacity and quantity, lecture time slots, and specific preferences to avoid schedule conflicts. The chromosome representation is designed using a matrix-based encoding, where each gene represents a single course with attributes for lecturer, classroom, and time slot. This structure facilitates the Genetic Algorithm in performing controlled crossover and mutation processes to generate valid scheduling solutions.

Tsukamoto Fuzzy Inference System Design

The Tsukamoto fuzzy inference system is employed to dynamically adjust fitness values, allowing the timetable evaluation process to be more adaptive. This system consists of three main components:

a. Fuzzification, which converts input variables into fuzzy membership degrees.
b. Rule base, which define the logic for fitness value adjustment based on scheduling conditions.
c. Defuzzification, which applies the Tsukamoto method to produce a numerical adjustment factor.

The fuzzy system input variables include constraint violation level, lecturer workload distribution, and classroom utilization efficiency. Each variable is defined using triangular and trapezoidal membership functions according to its data characteristics. The output of the fuzzy system is a fitness adjustment factor, which is then used to modify the chromosome evaluation results in the Genetic Algorithm.

Hybrid Genetic Algorithm Implementation

The Genetic Algorithm is implemented using the following configuration:

a. Selection: Turnament selection
b. Crossover: Uniform crossover (probabilitas 0.8)
c. Mutasi: Swap mutation (probabilitas 0.1)

The population size is set to 100 individuals. Integration with the Tsukamoto fuzzy system is performed during the fitness evaluation stage. Each chromosome is first evaluated using the conventional fitness function based on the number of constraint violations, and then its fitness value is dynamically adjusted by the fuzzy system output in each generation. This hybrid approach helps prevent the algorithm from getting trapped in local optima and enhances solution convergence.

Testing and Evaluation

The system was tested using a synthetic dataset consisting of:

a. 50 courses
b. 20 lecturers
c. 15 classrooms
d. 30 weekly time slots

System performance was evaluated using several key metrics:

a. Constraint satisfaction rate, covering both hard and soft constraints.
b. Computation time required to achieve convergence.
c. Solution quality, measured by the optimality of the generated timetable distribution.
d. Stability of results, evaluated based on convergence behavior and solution variation across generations.

Comparisons were conducted against a conventional Genetic Algorithm and a simple fuzzy-based approach. Each experiment was repeated 30 times to minimize the influence of random factors, and the results were analyzed using a t-test to ensure that performance differences were statistically significant.

RESULT AND DISCUSSION

This section presents the results of the implementation and testing of the course scheduling optimization system using a Genetic Algorithm with fitness value adjustment through the Tsukamoto fuzzy inference system.

Implementation of the Tsukamoto Fuzzy Inference System

The Tsukamoto fuzzy inference system was implemented with three input variables: constraint violation level (VC), workload distribution (WD), and classroom utilization efficiency (SE). The membership functions were defined using a combination of triangular and trapezoidal functions, as summarized in Table 1.

Table 1. Fuzzy Input Variable Membership Functions

Variable	Fuzzy Set	Function Type	Parameters
Constraint Violation Level (VC)	Low	Trapezoidal	[0, 0, 0.15, 0.3]
	Medium	Triangular	[0.25, 0.45, 0.65]
	High	Trapezoidal	[0.55, 0.75, 1.0, 1.0]
Workload Distribution (WD)	Poor	Trapezoidal	[0, 0, 0.25, 0.45]
	Fair	Triangular	[0.35, 0.55, 0.75]
	Good	Trapezoidal	[0.65, 0.85, 1.0, 1.0]
Space Utilization Efficiency (SE)	Low	Trapezoidal	[0, 0, 0.25, 0.45]
	Medium	Triangular	[0.35, 0.55, 0.75]
	High	Trapezoidal	[0.65, 0.85, 1.0, 1.0]

The Tsukamoto fuzzy inference system employs 27 fuzzy rules formulated based on domain analysis. A sample of the fuzzy rules is shown in Table 2.

Table 2. Sample Fuzzy Rules

No	Rule
1	If VC is Low and WD is Good and SE is High, then the fitness adjustment factor is Very High
2	If VC is Low and WD is Good and SE is Medium, then the fitness adjustment factor is High
3	If VC is Low and WD is Fair and SE is High, then the fitness adjustment factor is High
	...
25	If VC is High and WD is Poor and SE is Medium, then the fitness adjustment factor is Very Low
26	If VC is High and WD is Fair and SE is Low, then the fitness adjustment factor is Very Low
27	If VC is High and WD is Poor and SE is Low, then the fitness adjustment factor is Very Low

Algorithm Performance Comparison

The conventional Genetic Algorithm and the hybrid Genetic Algorithm were tested using a dataset consisting of 50 courses, 20 lecturers, 15 classrooms, and 30 time slots, with 30 experimental repetitions. Table 3 presents the performance comparison between the two algorithms.

Table 3. Algorithm Performance Comparison

Evaluation Metric	Conventional	Hybrid	Improvement (%)
Final Fitness Value	0.76 ± 0.05	0.89 ± 0.03	17.1%
Convergence Time (Generations)	87 ± 12	50 ± 8	42.5%
Constraint Satisfaction	82.4 ± 4.3	94.7 ± 2.6	14.9%

Rate (%)			
Lecturer Workload Variation Coefficient	0.34 ± 0.06	0.19 ± 0.04	44.1%
Classroom Utilization Efficiency	76.8 ± 5.2	88.5 ± 3.7	15.2%
Computation Time	94 ± 14	112 ± 18	-19.1%

The Genetic Algorithm with Tsukamoto fuzzy integration demonstrates significant improvements across almost all evaluation metrics. Although computation time increased by 19.1%, this trade-off is justified by the substantial enhancement in solution quality and faster convergence.

Convergence Analysis

Figure 1 illustrates the comparison of convergence curves between the conventional Genetic Algorithm and the hybrid Genetic Algorithm with Tsukamoto fuzzy integration.

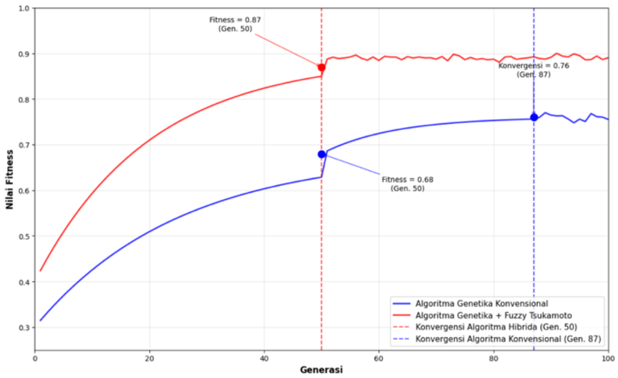

Figure. 1. Convergence

The hybrid Genetic Algorithm achieved higher fitness values in fewer generations. By the 50th generation, the hybrid algorithm reached a fitness value of 0.87, while the conventional algorithm only achieved 0.68. The hybrid algorithm converged at generation 50, whereas the conventional algorithm required more than 80 generations to reach convergence.

Constraint Constraint Satisfaction Evaluation

The constraint satisfaction evaluation was conducted to measure how effectively the proposed algorithm fulfills various scheduling constraints. Constraints in this study are categorized into hard constraints, which must be strictly satisfied such as avoiding schedule conflicts and respecting classroom capacities, and soft constraints, which should preferably be met to enhance schedule quality, including lecturer preferences and room suitability. Table 4 presents the detailed satisfaction rates for each type of constraint.

Table 4. Constraint Satisfaction by Type

Constraint Type	Conventional	Hybrid
Hard Constraint (Schedule Conflicts)	98.2 ± 1.3	99.8 ± 0.3
Hard Constraint (Room Capacity)	95.6 ± 2.4	99.2 ± 0.7
Soft Constraint (Lecturer Preferences)	68.7 ± 7.5	89.3 ± 4.2
Soft Constraint (Class Breaks)	71.2 ± 6.8	91.4 ± 2.9
Soft Constraint (Room Suitability)	78.5 ± 5.3	93.8 ± 2.9

The hybrid algorithm provides a significant improvement in constraint satisfaction, particularly for soft constraints, due to its dynamic fitness adjustment mechanism.

Analysis of Workload Distribution and Room Utilization Efficiency

Table 5 presents the comparison of lecturer workload distribution, while Table 6 shows the classroom utilization efficiency.

Table 5. Lecturer Workload Distribution Statistics

Statistic	Conventional	Hybrid
Average Teaching Hours per Week	12.4 ± 4.2	12.4 ± 2.3
Minimum Teaching Hours	6.0	8.0
Maximum Teaching Hours	22.0	16.0

Standard Deviation	4.2	2.3
Coefficient of Variation	0.34	0.19

Table 6. Classroom Utilization Efficiency

Metric	Conventional	Hybrid
Capacity Utilization Ratio	72.5 ± 8.3	85.2 ± 5.6
Facility Suitability	81.2 ± 6.7	91.9 ± 4.2
Average Classroom Utilization Efficiency	76.8 ± 5.2	88.5 ± 3.7

The hybrid algorithm produced a more balanced lecturer workload distribution and higher classroom utilization efficiency.

Statistical Analysis

A paired t-test was conducted on the fitness values from 30 experimental repetitions. The results indicated a significant difference (p-value < 0.001) with a substantial effect size. Table 7 presents the results of the statistical analysis.

Table 7. Statistical Analysis Results

Evaluation Metic	p-value	Cohen's d	Effect Size Interpretation
Fitness Value	< 0.001	1.23	Besar
Constraint Satisfaction Rate	< 0.001	1.08	Besar
Lecturer Workload Variation Coefficient	< 0.001	1.15	Besar
Classroom Utilization Efficiency	< 0.001	0.96	Besar
Convergence Time	< 0.001	1.35	Besar

The analysis confirms that the performance improvements achieved by the hybrid Genetic Algorithm are statistically significant, with a large effect size across all key evaluation metrics.

CONCLUSION

This study successfully developed a course scheduling optimization system that integrates Genetic Algorithms with the Tsukamoto fuzzy inference system for dynamic fitness value adjustment. The proposed system effectively overcomes the limitations of static evaluation functions in conventional Genetic Algorithms by simultaneously considering the dynamics and priorities of various scheduling constraints. The Tsukamoto fuzzy inference system designed in this study utilizes three input variables—constraint violation level, lecturer workload distribution, and classroom utilization efficiency. These variables are processed through 27 fuzzy rules using a combination of triangular and trapezoidal membership functions to produce an adaptive fitness adjustment factor.

The experimental results demonstrate that the hybrid Genetic Algorithm integrated with the Tsukamoto fuzzy system provides significant performance improvements over the conventional approach. The average fitness value increased from 0.76 to 0.89, the constraint satisfaction rate rose from 82.4% to 94.7%, lecturer workload distribution became more balanced with the coefficient of variation reduced from 0.34 to 0.19, and classroom utilization efficiency improved from 76.8% to 88.5%. The algorithm also achieved 42.5% faster convergence, and statistical tests confirmed a significant difference with p-value < 0.001 and a substantial effect size (Cohen's d = 1.08–1.35) across all evaluation metrics.

Overall, this research contributes to the development of a hybrid approach that integrates the Tsukamoto fuzzy inference system into Genetic Algorithms for dynamic fitness adjustment, enabling the generation of course timetables that are more optimal, adaptive, and efficient. The findings also open opportunities for future work, such as the implementation of adaptive fuzzy systems, integration with other optimization techniques such as Particle Swarm Optimization or Ant Colony Optimization, and the utilization of deep learning for automated fuzzy rule design. Furthermore, this approach can be extended to other aspects of academic management, including exam scheduling, laboratory allocation, and the optimization of extracurricular activities in higher education institutions.

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