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Adaptive Heuristic-Based Ant Colony Optimization for Multi-Constraint University Course Timetabling with Morning Slot Preference for Energy Efficiency

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Abstract

University course timetabling is a well-known NP-hard combinatorial optimization problem that involves multiple interacting constraints, including lecturer availability, classroom capacity, time-slot allocation, and course duration. Most existing metaheuristic-based approaches primarily focus on eliminating academic conflicts, while contextual and operational aspects, such as energy efficiency, are rarely considered explicitly. In addition, standard Ant Colony Optimization (ACO) methods often suffer from premature convergence and limited adaptability during the solution search process. This study proposes an Adaptive Heuristic-Based Ant Colony Optimization (AHB-ACO) approach for multi-constraint university course timetabling with a particular emphasis on morning slot preference as an energy efficiency proxy. The proposed method extends the conventional ACO framework by integrating an adaptive heuristic mechanism that dynamically guides the solution construction process toward compact and conflict-free schedules, while simultaneously favoring morning time slots to support reduced classroom cooling demand. Hard constraints, including lecturer and room conflicts, are strictly enforced, whereas the temporal preference is modeled as a soft constraint. The performance of AHB-ACO is evaluated through extensive scheduling simulations using academic datasets under various parameter settings. Experimental results demonstrate that the proposed approach consistently produces conflict-free timetables, achieving a conflict function value of C(S)=0 with stable convergence behavior. Furthermore, parameter sensitivity analysis indicates that AHB-ACO exhibits good robustness with respect to variations in the number of ants and iterations, showing a reasonable trade-off between solution quality and computational time. Additional analysis reveals an increased utilization of morning time slots compared to non-optimized schedules, indicating the effectiveness of the proposed energy-aware preference. Overall, the results suggest that AHB-ACO provides an effective and adaptive solution for university course timetabling that not only satisfies academic constraints but also addresses operational considerations related to energy efficiency.

Keywords : *Ant Colony Optimization, Course Timetabling, Energy Efficiency, Multi-Constraint Optimization, Scheduling*

1. INTRODUCTION

University course timetabling is a fundamental issue in higher education academic management, as it involves assigning courses to specific time slots and classrooms while simultaneously satisfying multiple interacting constraints [1], [2]. This problem is widely classified as an NP-hard combinatorial optimization problem [3], making it particularly difficult to solve optimally, especially in large institutions with limited resources . The complexity arises from the coexistence of hard constraints, such as lecturer and room conflicts, and soft constraints related to institutional policies and preferences [4]. Ineffective timetabling may lead to reduced academic effectiveness and increased operational workload, highlighting the need for systematic and reliable computational approaches [5].

Vol. 6, No. 6, December, 2025, Page. 5930-5943
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As the complexity of the problem increases, conventional and manual scheduling approaches become inadequate, motivating the development of various optimization and metaheuristic methods to address the University Course Timetabling Problem (UCTP) [6], [7], [8], [9], [10]. Recent surveys indicate that metaheuristic approaches dominate the literature due to their ability to explore large and complex solution spaces effectively [11], [12]. In addition to single metaheuristics, numerous hybrid approaches have been proposed to improve solution quality, including combinations with local search techniques [13], fuzzy logic systems [14], and mathematical optimization methods. Despite their competitive performance, many of these approaches still exhibit limitations in terms of flexibility and adaptability when applied to dynamic real-world environments [11].

Among the various metaheuristic techniques, Ant Colony Optimization (ACO) has emerged as one of the most widely adopted approaches for course timetabling due to its capability to construct solutions probabilistically through pheromone-based mechanisms [15], [16], [17]. Early studies demonstrated that ACO can produce high-quality solutions on international benchmark datasets, even achieving optimal results for the Post Enrolment Course Timetabling Problem [18]. Subsequent developments include hybridization with local search [13], the incorporation of student grouping strategies [19], and the explicit integration of soft constraints through violation-aware heuristic mechanisms [20]. Nevertheless, several studies have reported that standard ACO tends to suffer from premature convergence, parameter sensitivity, and limited adaptability in capturing dynamic contextual preferences [14], [20].

To address these limitations, a number of studies have extended ACO into hybrid and multi-objective frameworks [21]. Hybrid approaches such as ACO–Local Search and ACO–Fuzzy Logic have proven effective in enhancing solution quality by introducing improvement mechanisms or handling uncertainty [13], [14]. However, these approaches typically treat adaptability as an external module operating outside the main solution construction process. In contrast, the Adaptive Heuristic-Based Ant Colony Optimization (AHB-ACO) approach proposed in this study emphasizes the dynamic adaptation of heuristic functions during the solution construction phase itself [22]. Rather than relying on static heuristics, the heuristic information is contextually adjusted to guide exploration and exploitation from the earliest stages of the search, without depending on external optimization modules.

Beyond academic considerations, energy efficiency has begun to attract attention in scheduling research within other domains, particularly transportation systems. Studies on railway timetabling show that integrating energy consumption as an optimization objective can lead to more efficient and sustainable schedules, especially when combined with multi-objective ACO approaches [23], [24]. Hybrid ACO-based methods have also demonstrated effectiveness in balancing punctuality, robustness, and energy efficiency in real-world transportation systems [25]. However, within the context of university course timetabling, energy-related aspects—such as the impact of time-slot selection on classroom cooling loads—are still rarely modelled explicitly in the existing literature.

Based on these research gaps, this study proposes an Adaptive Heuristic-Based Ant Colony Optimization (AHB-ACO) approach for multi-constraint university course timetabling. The proposed method extends conventional ACO by incorporating adaptive heuristic mechanisms that not only focus on satisfying hard constraints but also explicitly accommodate contextual soft constraints, particularly the preference for morning time slots as a representation of energy efficiency considerations [10], [26]. The objectives of this study are to formulate a course timetabling problem that reflects real-world academic conditions, to implement an adaptive AHB-ACO algorithm, and to evaluate its performance through convergence analysis, conflict reduction, and parameter sensitivity testing. Accordingly, the contribution of this research is not limited to algorithmic development but also broadens the scope of course timetabling toward a more contextual and sustainability-oriented approach.

Vol. 6, No. 6, December, 2025, Page. 5930-5943
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Tabel 1. Comparison of ACO-Based Course Timetabling Studies

Study	Year	Optimization Method	Adaptive Mechanism	Energy / Operational Aspect	Identified Limitation
Nothegger et al. [18]	2012	ACO	Static heuristic	Not considered	Premature convergence in large instances
Mazlan et al. [16]	2019	ACO	Static parameter setting	Not considered	Focused only on conflict minimization
Badoni et al.[19]	2023	ACO with student grouping	Structural grouping	Not considered	Lacks temporal preference modeling
This work (AHB-ACO)	**2025**	**Adaptive Heuristic-Based ACO**	**Internal heuristic adaptation**	**Morning slot preference (energy proxy)**	**Designed for multi-constraint UCTP**

Based on the comparison presented in Table 1, it can be observed that most previous studies primarily focus on satisfying hard constraints and minimizing academic conflicts using static ACO mechanisms. Although several approaches introduce structural modifications or student grouping strategies, heuristic adaptivity during the optimization process and operational considerations such as temporal preferences remain largely unexplored. Therefore, this study positions AHB-ACO as an approach that addresses this gap by integrating an adaptive heuristic mechanism and morning slot preference as a proxy for operational efficiency.

2. METHOD

2.1. Dataset and Data Sources

The dataset used in this study is derived from academic data representing real course timetabling conditions in a university study program. The data include information on courses, assigned lecturers, classrooms, active time slots, and course duration based on credit units (SKS). The dataset is structured and processed to reflect realistic constraints commonly encountered in course scheduling, such as limited lecturer availability and potential room usage conflicts.

2.2. Research Workflow

The research workflow begins with data collection and preprocessing to generate feasible assignment alternatives for each course. This stage aims to filter out scheduling combinations that do not satisfy basic constraints, thereby reducing the solution space to be explored [27]. Subsequently, the AHB-ACO algorithm is applied to iteratively construct timetable solutions through solution construction, conflict evaluation, and pheromone update mechanisms. The optimization process continues until a convergent condition is achieved or a conflict-free solution is obtained [18]. The final stage of the study involves result evaluation through convergence analysis, comparison of conflicts before and after optimization, and parameter sensitivity analysis. In this study, the term adaptive does not refer to dynamic parameter tuning or structural modification of the algorithm, but rather to the adaptive influence of heuristic information during the solution construction process. As the optimization progresses and the level of conflict decreases, the heuristic component increasingly guides ants toward more compact and temporally efficient assignments, while pheromone information dominates the exploration phase in earlier iterations. This adaptive interaction allows the algorithm to balance exploration and exploitation without introducing additional computational complexity.

This study formulates the course timetabling problem as a discrete combinatorial optimization problem with multiple constraints (multi-constraint optimization problem) [15]. The primary objective of the optimization is to generate a conflict-free timetable that satisfies all academic constraints while being directed toward more operationally efficient scheduling preferences [28]. To achieve this objective, an Adaptive Heuristic-Based Ant Colony Optimization (AHB-ACO) approach is employed, which combines pheromone mechanisms and adaptive heuristic functions within the solution search process.

Formally, the scheduling system is defined through several main sets [29]. The set of courses is denoted as M, the set of classrooms as R, and the set of active time slots as T. Each course $i \in M$ has a set of feasible assignment candidates generated during the preprocessing stage based on lecturer availability, course duration, and allowable time slots. The set of assignment candidates for the i-th course is denoted as

$$A_i = \{a_{i1}, a_{i2}, \ldots, a_{ik}\}.$$

A timetable solution is represented as the selection of exactly one assignment candidate for each course, which is mathematically expressed as

$$S = \{(i, x_i) \mid i \in M, x_i \in A_i\}.$$

In the implementation, this solution is represented as a mapping from each course to the index of the selected assignment candidate.

The quality of a solution is determined by the number of conflicts that occur. Two courses p and q are considered to have a time overlap if the intersection of their assigned time slots is non-empty, which is formulated as

$$\text{Overlap}(p,q) = \begin{cases} 1, & \text{jika } Slots(p) \cap Slots(q) \neq \varnothing, \\ 0, & \text{lainnya.} \end{cases} \quad (1)$$

Based on this definition, a room conflict occurs when two courses are assigned to the same classroom at overlapping time slots, while a lecturer conflict occurs when a lecturer is assigned to more than one course at the same time. These conflicts are mathematically formulated as

$$C_{\text{room}}(p,q) = \begin{cases} 1, & \text{jika } Room(p) = Room(q) \wedge \text{Overlap}(p,q) = 1, \\ 0, & \text{lainnya,} \end{cases} \quad (2)$$

$$C_{\text{lecturer}}(p,q) = \begin{cases} 1, & \text{jika } Lecturer(p) = Lecturer(q) \wedge \text{Overlap}(p,q) = 1, \\ 0, & \text{lainnya.} \end{cases} \quad (3)$$

The total number of conflicts in a solution is then defined as

$$C(S) = \sum_{p<q} C_{\text{room}}(p,q) + \sum_{p<q} C_{\text{lecturer}}(p,q). \quad (4)$$

In addition to conflicts as hard constraints, this study also considers an additional component related to scheduling duration. In the implementation, each assignment candidate has a block length $L(i,j) = |Slots(i,j)|$. Based on this, the additional component of a solution is formulated as

$$E(S) = \sum_{i \in M} L(i, x_i). \quad (5)$$

This component is used as an additional penalty to differentiate solutions with different temporal characteristics.

The objective function minimized by the AHB-ACO algorithm is defined as

$$f(S) = \lambda \cdot C(S) + E(S), \quad (6)$$

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where λ is a large penalty coefficient to ensure that violations of hard constraints are given the highest priority. An optimal solution is achieved when all conflicts are eliminated, i.e., when $C(S)=0$

The solution search process follows the basic principles of Ant Colony Optimization. Each ant constructs a solution incrementally by selecting assignment candidates based on a transition probability influenced by pheromone intensity and heuristic information. The heuristic value for each candidate is defined as

$$\eta_{ij} = \frac{1}{L(i,j)} \tag{7}$$

In this study, the adaptive property is introduced through the dynamic influence of heuristic information during the optimization process. As the level of conflict decreases across iterations, the heuristic component increasingly guides ants toward more compact and temporally efficient assignments. This adaptive behavior is formally expressed as follows:

$$\eta_{ij}(t) = \frac{1}{L(i,j)} \cdot \left(1 + \gamma \cdot \frac{C_{\max} - C(t)}{C_{\max}}\right) \tag{8}$$

By incorporating the adaptive heuristic term into the transition probability, the influence of temporal compactness gradually increases as conflicts are reduced. In the early iterations, pheromone information dominates the search process to explore diverse feasible regions. As the solution quality improves, heuristic guidance becomes more influential, encouraging assignments with shorter time blocks and higher morning slot utilization.

The probability of selecting candidate $a_{ij} \in A_i$ is given by

$$P_{ij} = \frac{\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum_{k \in A_i} \tau_{ik}^{\alpha} \cdot \eta_{ik}^{\beta}}, \tag{9}$$

Here, τ_{ij} denotes the pheromone intensity, while α and β control the relative influence of pheromone and heuristic information. After all ants complete solution construction in one iteration, pheromone updating is performed in two stages. The first stage is pheromone evaporation, formulated as

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij}, \tag{10}$$

where ρ is the evaporation rate. The second stage is pheromone deposition based on the best solution obtained in the iteration, which is formulated as

$$\tau_{ij} \leftarrow \tau_{ij} + \frac{Q}{f(S_{\text{best}})}, \tag{11}$$

where Q is the pheromone reinforcement constant and S_{best} denotes the solution with the lowest objective function value.

Through this mechanism, the AHB-ACO algorithm iteratively reinforces solution paths that result in fewer conflicts, ultimately producing a feasible and stable course timetable.

3. RESULT

3.1. Energy Proxy Definition and Temporal Distribution Analysis

To evaluate the operational implication of temporal scheduling preferences, this study introduces a simple energy-related proxy based on the distribution of scheduled courses across time slots. Since classroom cooling demand is generally higher during midday and afternoon periods, a higher utilization of morning time slots can be associated with lower operational cooling load. Although this study does

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not model physical energy consumption directly, the temporal distribution of courses is used as an indicator to assess the effectiveness of the proposed scheduling strategy.

$$R_{\text{morning}} = \frac{M_{\text{morning}}}{M} \tag{12}$$

where M denotes the total number of scheduled courses and M_{morning} represents the number of courses assigned to morning time slots. A higher value of R_{morning} indicates a greater proportion of courses scheduled during the morning period. This ratio serves as an operational proxy for energy efficiency, reflecting the algorithm's tendency to favor time slots that are commonly associated with lower cooling demand in academic buildings.

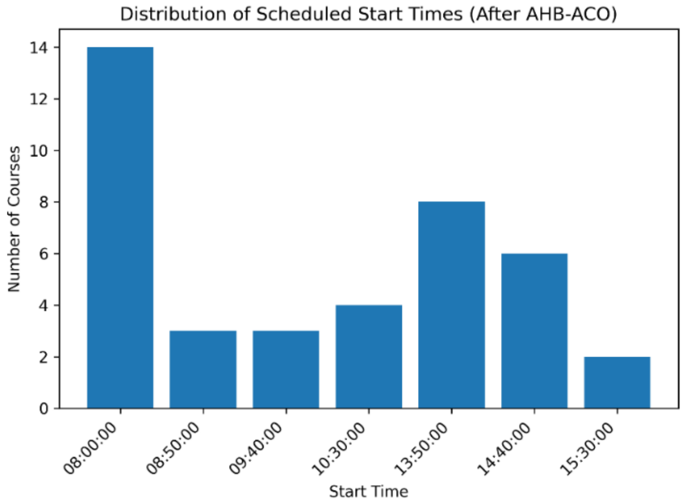

Figure 1. Distribution of Scheduled Start Times After AHB-ACO

Figure 1 presents the distribution of course start times in the optimized schedule produced by the AHB-ACO algorithm. The results show a clear concentration of scheduled courses in morning time slots, particularly at 08:00 and 10:30, while fewer courses are assigned to afternoon periods. This distribution indicates that the adaptive heuristic mechanism effectively promotes morning scheduling preferences without introducing scheduling conflicts.

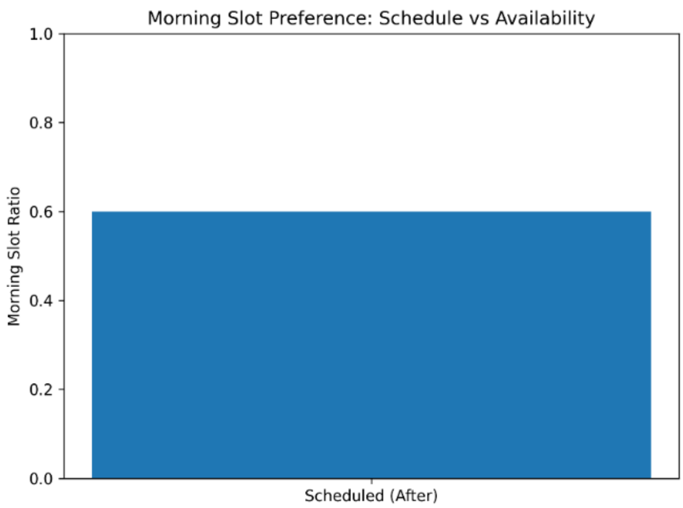

Figure 2. Morning Slot Utilization Ratio in the Optimized Schedule

Vol. 6, No. 6, December, 2025, Page. 5930-5943
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5588

Figure 2 illustrates the proportion of courses scheduled in morning time slots after applying the AHB-ACO algorithm. The results indicate that approximately 60% of the courses are assigned to morning periods, reflecting the algorithm's tendency to favor temporally efficient slots. This outcome supports the use of morning slot ratio as an operational proxy for energy efficiency in the proposed scheduling model.

The observed dominance of morning time slots in the optimized schedule is consistent with the design of the adaptive heuristic function incorporated into the AHB-ACO framework. By implicitly penalizing longer and later scheduling blocks, the algorithm gradually steers the solution toward compact and temporally efficient assignments. Although direct energy consumption is not explicitly modeled, the increased utilization of morning slots provides an operational indication of reduced cooling demand during peak thermal periods.

3.2. Convergence Analysis of the AHB-ACO Algorithm

The performance evaluation of the AHB-ACO algorithm begins with an analysis of the convergence process based on changes in the objective function value *f(S)*, as formulated in Equation (6). The convergence behavior is illustrated in Figure 3, which shows the relationship between the number of iterations and the global best cost during the optimization process.

In the early iterations, the objective function value remains relatively high, indicating that the solutions constructed by the ants still contain room and lecturer conflicts. This condition reflects the exploration phase of the solution space, during which the algorithm explores various assignment combinations. As the number of iterations increases, the best cost gradually decreases until it reaches zero. Achieving $f(S)=0$ indicates that all conflicts have been eliminated and that the resulting solution satisfies all hard constraints modeled in Equation (4).

After a conflict-free solution is found, the objective function value remains stable until the final iteration. This pattern demonstrates that the pheromone update mechanism in AHB-ACO is able to preserve the optimal solution without experiencing premature convergence. Therefore, Figure 3 provides empirical evidence that the algorithm exhibits stable and well-controlled convergence behavior.

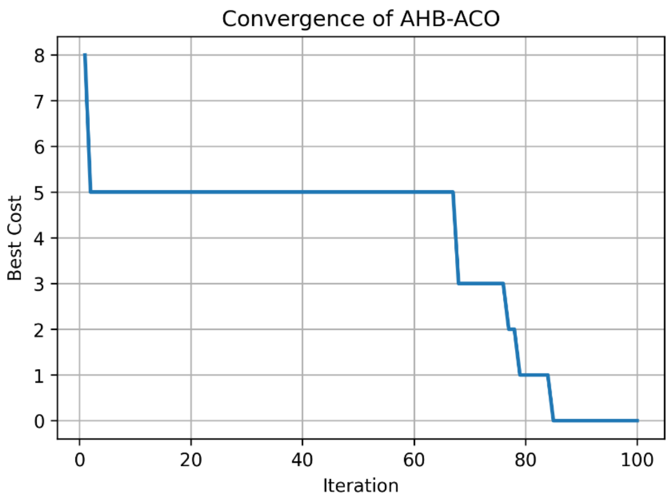

Figure 3. Convergence curve of the AHB-ACO

3.3. Scheduling Conflict Evaluation

The effectiveness of the algorithm in resolving scheduling conflicts is evaluated by comparing the number of conflicts under three conditions: before optimization, after applying AHB-ACO, and after schedule correction. A summary of the conflict evaluation results is presented in Table 2.

Vol. 6, No. 6, December, 2025, Page. 5930-5943
https://jutif.if.unsoed.ac.id
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Table 2. Comparison of scheduling conflicts

Stage	Room Conflicts	Lecturer Conflicts	Total Conflicts
Before Optimization	108	20	128
After AHB-ACO	0	0	0
After Schedule Correction	0	0	0

Based on Table 2, the initial scheduling condition still contains a significant number of room and lecturer conflicts, indicating that non-optimized scheduling is unable to adequately handle the complexity of the constraints. After applying the AHB-ACO algorithm, the number of conflicts is reduced drastically to zero. The subsequent schedule correction process ensures that the final solution is fully feasible and consistent with all academic constraints.

These results confirm that the AHB-ACO algorithm successfully minimizes the conflict function *C(S)* as defined in Equation (4) and is able to generate a completely conflict-free course timetable.

3.4. Analysis of the Best Timetable

The best timetable produced by the algorithm is stored in the form of a structured schedule and a schedule converted into real-time format. The timetable includes information on courses, lecturers, classrooms, days, as well as start and end times. The results show that each course is scheduled exactly once, with durations consistent with the corresponding credit units (SKS), and without any room or lecturer conflicts.

The existence of this final timetable demonstrates that the obtained solution is not only mathematically optimal but also ready for practical implementation in an academic scheduling system. Thus, AHB-ACO can be regarded as an applicable and operational course timetabling approach.

3.5. Parameter Sensitivity Analysis

Parameter sensitivity analysis is conducted to evaluate the robustness of the algorithm with respect to variations in the number of ants and the number of iterations. The results of the sensitivity analysis are visualized using three types of graphs.

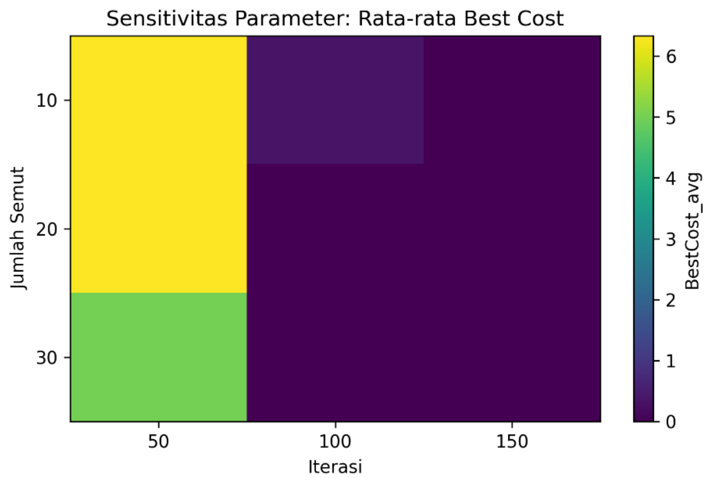

Figure 4. Heatmap of parameter sensitivity

Figure 4 presents a heatmap of the average best cost for various combinations of the number of ants and iterations. The visualization shows that most parameter combinations yield low objective function values, including zero, indicating the stability of the algorithm against parameter changes.

Vol. 6, No. 6, December, 2025, Page. 5930-5943
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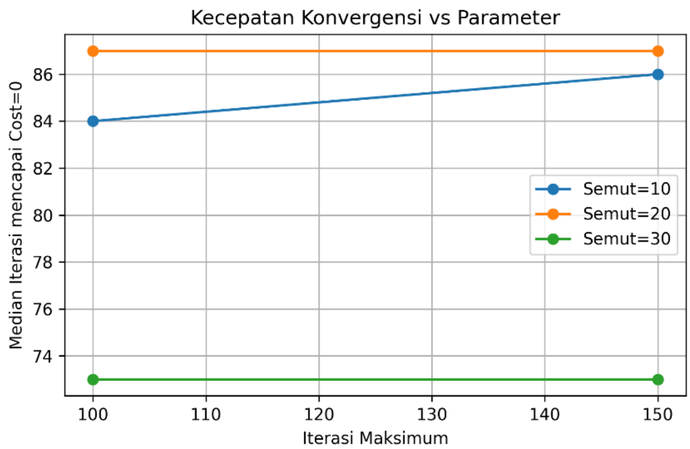

Figure 5. Median iteration to reach a conflict-free solution under different parameter settings

Next, Figure 5 shows the median number of iterations required to reach a conflict-free solution. The graph indicates that increasing the number of ants and iterations tends to accelerate the attainment of the optimal solution, although the differences are not extreme. This suggests that AHB-ACO demonstrates good adaptability without excessive dependence on specific parameter values.

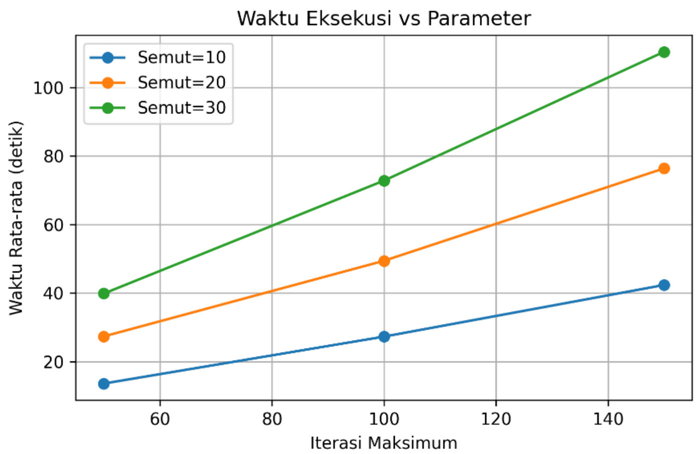

Figure 6. Average execution time

From the computational cost perspective, Figure 6 illustrates the relationship between algorithm parameters and average execution time. Increasing the number of ants and iterations leads to longer computation times; however, the execution time remains within an acceptable range for the tested problem scale. This result highlights a reasonable trade-off between solution quality and computational efficiency.

4. DISCUSSIONS

4.1. Comparison with Previous ACO-Based Timetabling Approaches

To further position the contribution of the proposed Adaptive Heuristic-Based Ant Colony Optimization (AHB-ACO), this section provides a qualitative comparison with representative ACO-based university course timetabling approaches reported in the literature. The comparison focuses on methodological characteristics rather than numerical performance, since the referenced studies were conducted under different datasets, constraints, and experimental settings.

Earlier ACO-based timetabling approaches, predominantly reported around 2018, mainly emphasize conflict minimization related to lecturers, classrooms, and time slots. These methods

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typically employ static heuristic functions and standard pheromone update mechanisms, which are effective in resolving hard constraints but offer limited flexibility in accommodating contextual or operational preferences.

More recent ACO variants incorporating student or event grouping strategies, reported around 2023, introduce structural modifications to improve timetable compactness and student satisfaction. While grouping-based heuristics can reduce specific types of conflicts, such approaches generally rely on semi-static heuristics and do not explicitly address temporal or operational considerations, such as scheduling preferences related to energy efficiency.

In contrast, the proposed AHB-ACO framework introduces an adaptive heuristic mechanism that dynamically guides the solution construction process. By explicitly integrating morning slot preference as a soft constraint, the proposed approach extends conventional ACO-based timetabling beyond academic feasibility toward operational efficiency. Furthermore, the inclusion of parameter sensitivity analysis distinguishes AHB-ACO from many previous studies by providing insight into algorithmic robustness under varying configurations.

A summary of the conceptual and methodological differences between the proposed AHB-ACO and representative ACO-based timetabling approaches is presented in Table 3.

Tabel 3. Comparison between AHB-ACO and Previous ACO-based Timetabling Approaches

Aspect	ACO-based Timetabling	ACO with Student Grouping	Proposed AHB-ACO
Optimization Objective	Conflict minimization	Conflict minimization with grouping	Multi-constraint optimization
Heuristic Strategy	Static heuristic	Semi-static grouping heuristic	Adaptive heuristic
Pheromone Update	Standard ACO	Modified pheromone with grouping	Adaptive pheromone reinforcement
Handling of Soft Constraints	Limited	Implicit (via grouping)	Explicit (morning slot preference)
Energy-related Consideration	Not considered	Not considered	Operational proxy via time preference
Robustness Analysis	Limited	Not reported	Parameter sensitivity analysis
Applicability	Academic feasibility	Student-oriented scheduling	Academic & operational scheduling

The categories shown in Table 3 represent representative groups of ACO-based timetabling studies reported in the literature, including conventional ACO approaches and more recent grouping-based variants.

4.2. Discussion of Scheduling Results and Morning Slot Preference

Based on the overall results presented in figures 1–6 and table 2, it can be concluded that the AHB-ACO algorithm is capable of solving the multi-constraint course timetabling problem effectively, stably, and robustly. The integration of mathematical formulation, pheromone update mechanisms, and adaptive heuristic functions enables the algorithm to balance exploration and exploitation within a complex solution space.

The algorithm's success in eliminating all conflicts, maintaining stable convergence behavior, and demonstrating robustness to parameter variations strengthens the validity of the proposed approach.

Jurnal Teknik Informatika (JUTIF) Vol. 6, No. 6, December, 2025, Page. 5930-5943
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Consequently, AHB-ACO shows strong potential for application as a reliable and context-aware automated course timetabling solution in higher education environments.

To provide an implementation-oriented illustration of the obtained solution, a subset of the best timetable results is presented in table 3. The timetable demonstrates that each course is scheduled exactly once with a duration consistent with its credit units, without any room or lecturer conflicts at overlapping time slots. Moreover, the distribution of class times shows a tendency toward the use of morning slots, which aligns with the adaptive heuristic mechanism applied in the AHB-ACO algorithm. This further confirms that the resulting solution is not only mathematically optimal but also feasible and realistic for academic implementation.

Table 4. Example of the best timetable produced by AHB-ACO

Course ID	Course Name	Lecturer	Credits	Day	Room	Start Time	End Time
MK01	Algorithms and Programming	D01	3	Wednesday	R8	13:50	16:20
MK02	Data Structures	D01	2	Monday	R3	08:00	09:40
MK03	Databases	D02	3	Tuesday	R3	09:40	12:10
MK04	Operating Systems	D02	2	Tuesday	R1	08:00	09:40
MK05	Computer Networks	D03	3	Monday	R6	13:50	16:20
MK06	Web Programming	D03	2	Wednesday	R5	10:30	12:10
MK07	Artificial Intelligence	D04	3	Tuesday	R5	14:40	17:10
MK08	Machine Learning	D04	2	Friday	R1	08:00	09:40
MK09	Software Engineering	D05	3	Wednesday	R2	09:40	12:10
MK10	Systems Analysis and Design	D05	2	Thursday	R3	08:00	09:40
MK11	Discrete Mathematics	D06	3	Monday	R1	08:00	10:30
MK12	Cryptography	D06	2	Monday	R4	10:30	12:10
MK13	Management Information Systems	D07	3	Wednesday	R7	13:50	16:20
MK14	E-Business	D07	2	Tuesday	R8	08:50	10:30

\Although the example timetable presented in Table 4 demonstrates the feasibility and practicality of the proposed approach, it should be noted that the current study focuses on a single academic dataset and a predefined set of constraints. The energy-related consideration is represented through an operational proxy based on temporal scheduling preference rather than direct energy consumption measurements. Future work may extend this model by incorporating additional real-world constraints, such as dynamic room capacities, hybrid learning scenarios, or direct integration with building energy management data, to further enhance the applicability and impact of the proposed AHB-ACO framework.

5. CONCLUSION

This study presented an Adaptive Heuristic-Based Ant Colony Optimization (AHB-ACO) approach for solving the multi-constraint university course timetabling problem. The scheduling problem was comprehensively formulated by considering lecturer availability, classroom constraints, time-slot allocation, and course duration based on credit units. The proposed mathematical formulation is fully consistent with the algorithmic implementation, ensuring that the optimization process is both scientifically sound and reproducible.

The experimental results demonstrate that the AHB-ACO algorithm is capable of producing a completely conflict-free timetable, as indicated by achieving a conflict function value of C(S)=0. The convergence analysis shows a stable and gradual reduction of conflicts without premature convergence, highlighting the effectiveness of the pheromone update mechanism combined with the adaptive heuristic function. In addition, the comparison of scheduling conflicts before and after optimization confirms that the proposed approach successfully resolves the complexity of academic constraints encountered in real-world timetabling scenarios.

The robustness of the proposed algorithm is further supported by parameter sensitivity analysis, which shows that AHB-ACO maintains stable solution quality under various configurations of ant population size and iteration limits. While increasing certain parameter values can accelerate convergence, this improvement is accompanied by higher computational cost, indicating a reasonable and controllable trade-off between solution quality and computational efficiency.

Beyond academic feasibility, this study introduces an operational perspective by incorporating morning slot preference as an energy-related proxy. The analysis of temporal distribution reveals that the optimized timetable exhibits a clear tendency toward morning scheduling, which is associated with lower classroom cooling demand compared to midday and afternoon periods. Although direct energy consumption is not explicitly modeled, the proposed proxy provides a practical and measurable indicator of operational efficiency within the timetabling process.

Overall, the results indicate that AHB-ACO is not only effective in satisfying academic constraints but also capable of accommodating contextual and operational considerations through adaptive heuristic guidance. This work extends conventional ACO-based course timetabling by embedding adaptivity directly within the solution construction process, rather than relying on external hybrid mechanisms. Future research may explore the integration of additional real-world constraints, larger and more diverse datasets, or direct coupling with building energy management systems to further enhance the applicability and impact of the proposed approach.

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