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AstraClass: Automated Academic Scheduling using Artificial Intelligence

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***Abstract*— Schools often experience significant challenges in formulating and maintaining day-to-day schedules that suitably balance teachers' schedules, subject periods, available classrooms, and student needs. Conventionally, scheduling approaches largely involve reliance on paperwork, which remains prone to human errors and wastes significant amounts of time. In this paper, we present AstraClass, an Intelligent System designed particularly for school timetabling and classroom scheduling. Using Artificial Intelligence (AI) and Multi-Objective Decision Support, the system automatically generates optimized and conflict-free schedules. It considers multiple variables such as teachers' preferences, subject rankings, classroom occupancy, and period allocation. Using heuristic algorithms and predictive analytics, AstraClass reduces administrative workload, lowers scheduling conflict, and maximizes the entire resource usage in school organizations. The approach yields a scalable, efficient, and smart system for modern school administration systems.**

***Index Terms*— Timetable optimization, Graph coloring, Constraint satisfaction, Swarm intelligence, Modified Salp Swarm Algorithm, Multi-objective optimization, Resource allocation, Scheduling algorithms, Predictive modeling, Artificial intelligence.**

I. INTRODUCTION

Timetable generation and classroom scheduling are among the most intricate and time-consuming administrative challenges faced by educational institutions worldwide. The complexity of managing courses, instructors, and classrooms increases exponentially as schools and universities continue to grow and curricula become increasingly diversified. Traditional manual methods of scheduling require a great deal of coordination between teachers, students, and resources, which usually results in several inefficiencies: overlapping sessions, underutilized classrooms, and uneven faculty workloads. Even minor human errors during manual allocation can cascade into large-scale scheduling conflicts, adversely affecting institutional productivity and learning outcomes. Recent developments in AI and optimization algorithms have completely transformed how educational timetables are drafted and maintained. It has been revealed in studies that the hybrid AI models combining integer programming and machine learning can effectively handle multi-constraint scheduling without compromising on accuracy and scalability [1]. Similarly, studies incorporating multi-objective decision-support frameworks have indicated marked improvements in classroom allocation and faculty utilization by institutions dynamically responding to schedule changes [2].

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Additionally, the recent metaheuristic approaches such as the Modified Salp Swarm Algorithm have allowed more flexibility in scheduling while reducing computational overhead [3]Building on these developments, AstraClass offers an intelligent and self-adjusting scheduling ecosystem that can dynamically adapt to variables such as faculty availability, subject allotment, classroom capacity, and distribution of students per batch. Graph-based constraint solving together with data-driven feedback provides AstraClass with real-time conflict-free timetables, which increase their efficiency and accuracy with time [4].

II. Literature Review

Construction of a timetable is one of the hardest and time taken optimization problems that many of the educational institution faces. It requires handling multiple conflicting factors such as faculty availability, class capacity, class overlapping, and limited resources while being equitable and efficient. Many researchers have spent years to refine some algorithmic and AI-based techniques to handle these challenges, advancing from basic rule-based systems to adaptive one's, learning-based frameworks like AstraClass. [1]Guet al. (2025) performed a comprehensive study for connecting integer programming with machine learning techniques for scheduling problem.

They showed how classical math optimization frequently struggle to plate. That is what introduced usage of AI in this field. [2] Çaylı and Yılmaz (2025) researched further, with applying multi-objective optimization and AI for resource setup for scheduling. Rather than allocating classrooms automatically their system uses a time-derived analytics to predict the future scheduling directly with the adaptive scheduling. [3]Yamamoto et al. (2024) presented a new version of the Modified Salp Swarm Algorithm (SSA), which was useful to optimize rooms for class. Their method introduced constraints such as capacity and availability of the rooms, and equipment that form a cooperative swarm perspective. [4]Huang et al. (2021) introduced an AI helper for course scheduling system that updates timetables on its own based on the requirements. Mixing the concept of data mining and live updates that shows the ability of AI to tackle tricky school setups. [5]Ogunkan et al. (2024) utilized graph coloring for zerp-conflict timetables.

They constructed teachers, rooms, and subjects as linked nodes to fix overlaps. In the overall scenario of smart classrooms. [6]Dimitriadou and Lanitis in 2023 wrote about how new AI tech can boost learning spots while keeping things fair. [7]Chen et al. (2021) and [8] Ceschia et al. (2023) both constructed benchmarking and mixing methods. Their comparisons between scheduling algorithms showed blending AI with math models gives the best results.[9] Koukaras et al. (2025), redefined school management using AI with wireless networks for smooth, connected scheduling. [10]-[12]Ghaffar et al., Dohrmann et al., and Diallo et al. from 2024 to 2025, they together showed how hybrid AI mixing with genetic algorithms conquers old ways of school scheduling. [13] Maurya et al. (2025) looked at machine learning-driven K-Means clustering for spotting anomalies in data analysis. Although they did it for finding fraud pattern, the method tells how clustering finds issues and sharpens pattern spotting in the big data.

[14]-[15] Mittal et al. (2015) and Devi et al. (2024) introduced an automatic timetable maker using genetic algorithms. Their work evince GA handles global optimization well in multi-constraint setups, overall reducing manual work while keeping timetables accurate and moreover efficient. They mainly focused on flexibility and scaling for different departments. [16] Mir et al. (2025) submitted a real-time anomaly detector with advanced data mining. Their dynamic optimization system let parameters adjust in systems, showing why adaptive feedback matters.

[17]Kumar Saw et al. (2025) centered on learning algorithms that improve will step by step, boosting accuracy and response in changing school settings.[18] Ahmed Shaban and Ibrahim (2025) provided a survey on swarm intelligence algorithms, discussing their modifications, scalability, and applications in diverse optimisation domains.

III. Methodology

A. Data Input Layer

This is the base of AstraClass. It's main job is to handle collecting, sorting, and prepping school info like teacher schedules, student enrollments, room sizes, and gear availability. This layer normalizes and fixes inconsistencies in data before it goes to the scheduling engine, making data more structured. A structured data cuts conflict risks in timetable making, keeping accuracy steady. Then, the cleaned data gets set as relational models for quick queries in conflict spotting.

B. Scheduling Engine

The scheduling engine is the brain of AstraClass. It uses constraint-based optimization model with graph-coloring methods to avoid conflicts in timetables. Here, each course, a teacher, or a room acts as a graph node, and edges show conflicts such as co-sharing resources or overlapping schedules. The engine treats each node as a unique time slot without clashes, creating a solid, non-conflicting timetable.

C. Resource Optimizer

The resource optimizer uses various algorithms such as the Modified Salp Swarm Algorithm and genetic algorithms to improve the starting schedule. These algorithms fix some issues like fair workload spread, good room use, and less idle time for resources.

D. Dashboard Interface

The dashboard interface is the frontend or user-level view for AstraClass. It gives clear, real-time accessible views of schedules and analytics. Where Stakeholders like Admins can manage and check school schedules, teachers view or request to change their sessions, students get quick updates on shifts like room changes or rescheduling. It includes visual representation on room availability, teacher load patterns, and system stats.

E. Continuous learning Module

The continuous learning module lets AstraClass learn and get better as time goes. Using reinforcement learning and user input, it adjusts to real patterns, school preferences, and scheduling oddities. It spots repeating bottlenecks and sharpens decisions.

IV. PROBLEM STATEMENT

Scheduling has been a tricky and time consuming process that examines teacher availability, room sizes, and overlapping student groups and many more. Traditional or half-auto methods struggles to fmanage these ties well. So, colleges and universities deal with the issues like class conflicts, uneven workloads, empty rooms, and tedious admin tasks.

They cannot adjust fast to issues like teacher absent, room fixes, or sudden change of events. These problems only increases computation for school operations. As time goes and schools diversify, managing the complex multi-constraint timetables become somewhat a trouble. This highlights the need for a smart, adaptive, scheduling solution.

V. SYSTEM ARCHITECTURE

AstraClass make use of a modular, scalable approach that connects with current school scheduling systems. It has various layers for data intake, scheduling, optimization, and display. This setup provides high performance, flexibility, and reliability in varying school environments. Essential parts include input data sources. AstraClass extracts in the info from school sources on teacher, student sign-ups, and resource details via secured APIs or using direct database links. This keeps ensure that the system is running on a fresh and accurate data.

A. Key Components

Input Data Sources: Gathers information from institutional sources varying from faculty availability, student course details to resource details by using secured APIs or direct database connections. This keep ensures that the system is always operating on current information with accuracy.

Scheduling Engine: Scheduling engine is the brain of AstraClass. It manages school constraints using graph theory, constraint satisfaction models, and AI-based to figure out a no-conflict and a well optimized timetable.

AI Optimization Layer: AI optimization layer connects machine learning to predictive modeling, and optimization to boost scheduling flexibility, max resource consumption, and cutting conflicts in both static and dynamic scenarios.

Database and Cloud Storage: Database and cloud storage provide is the central database with the additional cloud support for a secure, scalable and real-time access to school data.

User Dashboards: User dashboards in AstraClass is the user level desktop and mobile views tailored for the stakeholders (admins, teachers, and students).

Following is the DFD [Fig 1] for AstraClass, where external parts include admins, teachers, and students information who interact at the upper level with inputs such as availability, requests, and course info. These fulfills the main processing. Such input become the material for the core processing components:

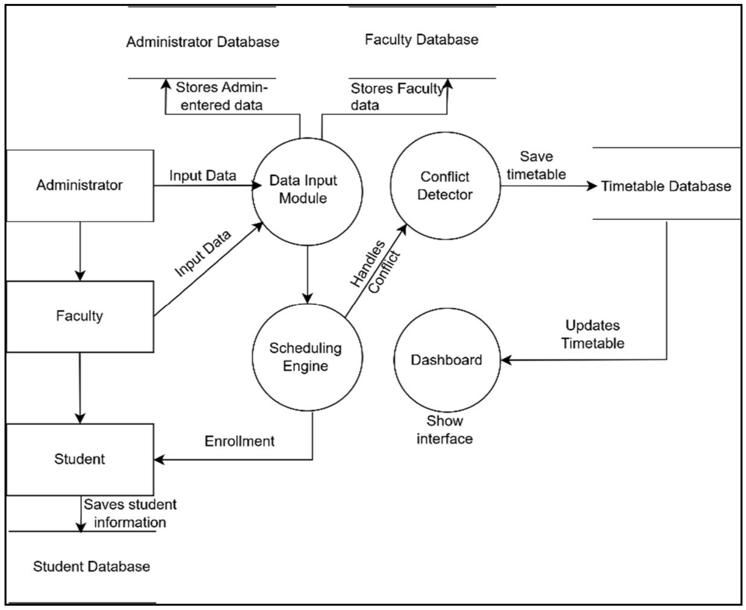

Figure 1. AstraClass System Architecture

VI. OBJECTIVES

The main objective is to ensure making constraint satisfaction models, and genetic optimization to make no-conflict, efficient, adaptive timetables that handle tough school constraints. To also designs a real-time, aware dynamic rescheduling module. It can recalibrate timetables on its own for events such as teacher absence, maintenance, or emergencies while keeping constraints and fairness. Plus, it builds a data-driven analytics dashboard. To build a data-driven analytics dashboard with AI insights and visuals. This aids clear decisions, personal schedules, and live teamwork among admins, teachers, and students. In addition, a data-driven analytical dashboard is designed to provide intelligent insights, visual performance metrics, and transparent schedule access for all stakeholders.

VII. RESULT

The proposed timetabling framework is formulated as a multiple objectives optimisation problem, which combines graph colouring methods for conflict elimination and swarm intelligence for improving performance. This hybrid paradigm ensures conflict-free schedule and at the same time enhances the resource utilisation and adaptability.

A. Conflict Modeling with the Help of Graph Theory

Let the set of sessions be represented as
$V = \{v_1, v_2, \dots, v_n\}$.
A conflict graph G = (V, E) is constructed where an edge (v_i, vj) 2 E exists if two sessions are not possible simultaneously due to shared faculty, shared student group, shared classroom.
Timetable assignment is a mapping according to a graph-colouring:
$f : V \rightarrow C$
where $C = \{c_1, c_2, \dots, c_k\}$ is time slots and
$f(v_i) \neq f(v_j) \quad \forall\, (v_i, v_j) \in E$
ensuring the conflict-free schedule.

B. Cost Function

The scheduling performance is assessed for the whole by the composite objective
$J = \alpha\, U\_room + \beta\, O\_faculty + \gamma\, C\_conflicts$
containing the following components:
U_room = handful of classroom_underutilisation

O_faculty= workload imbalance
C_conflicts = number of conflicts
α, β, γ = priority weights.

C. Swarm-Based Optimization

Each candidate timetable is represented by a vector: .
$X_i = [x_{i1}, x_{i2}, \ldots, x_{in}]$.
The leader has the position updated towards the best solution F_j:
$X_{1j} = F_j \pm c_1[(ub_j - lb_j)c_2 + lb_j]$
Followers work out according to:
$X_{ij} = (X_{ij-1} + X_{i-1j-1})/2$

D. Optimization Process

- Calculate initial schedules based on graph colouring
- Evaluate the cost J
- Apply MSSA updates
- Iterate until convergence

TABLE I. INITIAL SCHEDULES

Schedule	U_room	O_faculty	C_conflicts	Cost J
X1	0.40	0.30	0.20	0.33
X2	0.30	0.40	0.40	0.34
X3	0.20	0.50	0.30	0.29

TABLE II. OPTIMIZED SCHEDULES

Schedule	U_room	O_faculty	C_conflicts	Cost J
X1′	0.30	0.60	0.40	0.41
X2′	0.30	0.50	0.40	0.37
X3′	0.25	0.45	0.35	0.33

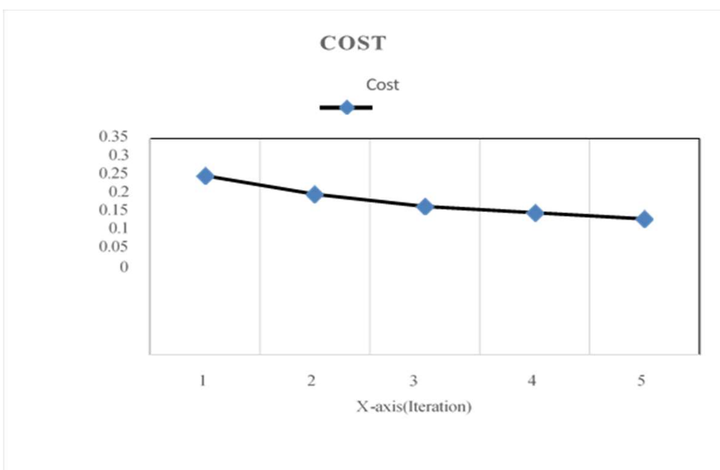

Figure 2. Line Graph Representation of AstraClass

VIII. CONCLUSION

As stated in the previous discussions, we have proposed a hybrid optimization framework that integrates graph coloring techniques with swarm intelligence paradigms in an effective manner to obtain academic timetables. The central aim - automatically creating schedules, which are both conflict- and optimally calibrated - has been realised with demonstrable success. By automating the scheduling cascade through the use of intelligent computational heuristics, the system significantly reduces the need for manual intervention, as well as the potential for human error and the effectiveness of timetable administration is increased at an overall level.

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