Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 5s (2025)

Nonlinear Optimization Framework for Educational Timetable Scheduling using Differential Evolution

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Article History:

Received: *14-10-2024*

Revised: *25-11-2024*

Accepted: *11-12-2024*

Abstract:

This research presents a nonlinear model for optimizing educational timetables using the Differential Evolution algorithm. The model manages complex scheduling tasks by considering various constraints, including teacher availability, course requirements, classroom features, and institutional rules. It processes data through feature engineering to quantify factors like time slots, teacher expertise, and course priorities. The algorithm dynamically explores multiple timetable configurations, evaluating their suitability based on hard constraints like teacher availability and classroom occupancy, and soft constraints such as minimizing idle periods and meeting preferences. Experimental analysis shows that the model improves scheduling by resolving conflicts, reducing idle hours, and utilizing classroom space more efficiently. The findings highlight a structured approach to balancing institutional needs and logistical challenges in timetable generation.

Keywords: Teacher Schedules; Classroom Attributes; Time Slots Transformation; Constraints Module; Hard Constraints; Optimization Core Module.

1. INTRODUCTION

The scheduling of educational timetables represents a perennial challenge for academic institutions worldwide. This complex task requires balancing a multitude of conflicting requirements, including but not limited to teacher availability, course sequencing, classroom capacity, and institutional policies [1]. Traditional approaches to timetable scheduling often rely on manual compilation, which is not only time-consuming but also prone to errors and inefficiencies. With the advent of computational optimization techniques, there is a growing interest in developing more sophisticated, automated methods that can navigate the intricate landscape of educational scheduling with greater precision and flexibility [2].

The importance of optimizing educational timetables cannot be overstated. An efficiently designed timetable directly contributes to the effective management of educational resources, enhances the learning experience by aligning with pedagogical best practices, and accommodates the preferences and constraints of faculty and students alike [3]. Moreover, in the context of increasing institutional complexities and diverse educational offerings, the need for an advanced scheduling solution has become more pronounced.

This article proposes a comprehensive framework for the optimization of educational timetables, leveraging the principles of multidimensional scheduling to address the various constraints and preferences inherent to academic institutions. At the heart of this framework is a robust optimization core, which employs iterative processes to explore and refine potential scheduling solutions. The framework is designed to be adaptable, capable of accommodating a wide range of scheduling scenarios and institutional requirements.

The introduction of this framework is motivated by the recognition that effective timetable optimization must account for a broad spectrum of factors. These include not only the logistical aspects of scheduling but also the pedagogical considerations that influence the effectiveness of educational delivery. By integrating these factors into a cohesive optimization model, the proposed framework aims to generate timetables that are not only feasible and efficient but also conducive to an enhanced educational environment.

In detailing the components of this framework, this article explores the methodologies employed for data collection and preprocessing, feature engineering, constraint definition and integration, and the optimization process itself. The objective is to present a structured approach to educational timetable optimization that is grounded in the realities of academic institutions, providing a viable solution to one of the most pressing administrative challenges in education today.

2. RELATED WORK

Gore et al. [4] presented a solution for the intricate task of creating an extensive timetable for academic institutions. The proposed automated timetable generation system, employing Genetic Algorithm, multiple context reasoning, and a hybrid evolutionary approach, addresses the challenges faced by physical scheduling means. The article offers valuable insights into related work, discussing various algorithms and approaches while highlighting practical applications in both academic and commercial settings. The experimental results showcase the system's ability to generate optimized timetables, considering constraints and maintaining lecture hours. Visual representations of system components, including login and timetable pages, further elucidate the proposed solution's efficacy, making a significant contribution to the field of academic scheduling.

Alghamdi et al. [5] contributed a comprehensive review of optimization algorithms applied to university course timetabling scheduling. The article illuminates the complexities of this NP-hard problem, emphasizing heuristic techniques and meta-heuristics due to the vast search space and numerous constraints. The primary objective is to provide an in-depth explanation of the optimization algorithms, evaluating their effectiveness and discussing the features of the university course timetabling problem. The review encompasses various techniques, such as meta-heuristics, heuristic algorithms, hybrid algorithms, and multi-objective algorithms, offering a thorough analysis of their strengths, weaknesses, and applicability to different constraints. This article serves as a valuable resource for researchers, practitioners, and students interested in university course timetabling, identifying research gaps and informing future studies.

Ambhore et al. [6] introduced an innovative automatic timetable generator system to address the complexities of creating timetables in academic institutions. The system, incorporating evolutionary algorithms, tabu search, simulated annealing, and scatter search, offers a dynamic solution for generating timetables across various semesters. By considering constraints such as predefined university schemes and faculty workload, the proposed system proves to be applicable and efficient, potentially reducing the workload for faculty members and administration. The article provides valuable insights into the challenges faced by educators and proposes a scalable solution with practical applications.

D'souza et al. [7] tackle the multi-constraint satisfaction and solution optimization challenges inherent in timetable generation. The article introduces a genetic algorithm-based approach to generate timetables that adhere to various constraints, including lecturer and course availability, maximum teaching hours, and consecutive hour limitations. The proposed system aims to automate the timetable generation process, providing a cost-effective solution for educational institutes. The article emphasizes the need for user feedback and intermediate result storage, fostering adaptability and allowing users to modify generated timetables. Overall, this article contributes an innovative solution to the complex problem of timetable generation, overcoming the limitations of existing software solutions.

Vinodhini et al. [8] presented an auto-time table automation tool utilizing genetic algorithms to address the recurrent timetable generation problem in colleges. The tool aims to generate error-free timetables efficiently, considering inputs such as courses, lecture halls, departments, and lecturers. The article highlights the tool's advantages, emphasizing its cost-effectiveness, time efficiency, and ability to minimize errors with minimal manual intervention. Additionally, it provides references to related works in automated timetabling and university timetable scheduling, positioning the proposed tool as a valuable contribution to revolutionizing college timetable generation and scheduling problems.

Techie-Menson et al. [9] presented a detailed exploration of the design and implementation of a web-based timetable system tailored for higher education institutions. The article categorizes university timetabling problems, addressing challenges associated with activities allocation within time constraints. The proposed web-based system offers accessibility to administrators, faculty, and students, promoting real-time collaboration and error reduction. Methodologies like graph heuristics, hill climbing, tabu search, and simulated annealing are discussed, providing a comprehensive guide for improving efficiency and effectiveness in higher education institutions.

Ying Ying et al. [10] introduced a novel genetic algorithm, the timetable scheduling system using genetic algorithm for the School of Computing (tsuGA), aimed at optimizing timetable scheduling for the School of Computing (SC). The system efficiently resolves hard constraints, minimizing conflicts, and presents an interface accessible to users with varying access levels. The article contributes by proposing a new genetic algorithm, detailing the system's design and development, and providing pseudocodes for key genetic operators. Experimental results demonstrate the system's efficiency, meeting hard constraints for the majority of students and showcasing the potential for further enhancements.

Otaninyenuwa Helen et al. [11] addressed the manual challenges of timetable management for students in institutions. The article proposes an automated solution technique based on genetic algorithms, emphasizing the limitations of traditional trial-and-error methods. The objective is to develop a web-based student timetable management system, leveraging genetic algorithms to generate optimal timetables. The article makes significant contributions to academic administration by presenting a reliable and efficient automated solution, providing insights into genetic algorithm models and representation methods. The proposed system opens avenues for integrating technology into academic administration, potentially streamlining and improving the efficiency of the academic management process.

Patil et al. [12] introduced an algorithm that combines genetic and scheduling algorithms to automatically generate optimal and non-redundant course schedules for educational institutions. The algorithm, validated with successful test cases, follows a systematic approach, addressing challenges in real-world timetabling scenarios. The primary objective is to enhance existing timetabling systems, ensuring the production of conflict-free schedules consistently across diverse universities and educational institutions. The proposed algorithm efficiently allocates suitable time for staff, students, and facilities, contributing to the improvement of timetabling processes in educational institutions.

Singh et al. [13] presented a solution to the time-consuming and burdensome task of manual timetable creation by designing and implementing an automatic timetable generator software. Utilizing HTML, CSS, JavaScript, and PHP, the software offers a user-friendly interface and incorporates intelligent algorithms to optimize the timetable creation process. It addresses factors like subject duration, faculty availability, and user-defined constraints, providing an efficient and accurate solution for educational institutions, corporate organizations, and event management teams. The research contributes significantly to education and event management by offering an innovative and efficient solution that saves time and effort compared to manual methods. The software's adaptability to different requirements further enhances its utility, making it a valuable contribution to the field.

3. METHODS AND MATERIALS

3.1. Data Layer Module

Data Layer encompasses the initial stage where comprehensive data collection takes place. This includes gathering extensive information on teacher schedules, course requirements, classroom availability, and institutional constraints. The preprocessing component within this layer is crucial for ensuring the uniformity and precision of the input data as shown in table 1. It involves meticulous data cleaning to remove inconsistencies and inaccuracies, encoding of categorical variables to transform qualitative data into a machine-readable format, and normalization of numerical values to ensure data across various scales can be compared and processed effectively.

Table 1: Features in the Data Layer for Teacher Timetable Generation

Feature Category	**Feature Description**
Teacher Schedules	Availability of each teacher, including days and times they are available to teach.
Course Requirements	Details about each course, such as course code, title, required hours, and level.
Classroom Availability	Information on classrooms, including location, capacity,

	and available time slots.
Institutional Constraints	Rules and policies that affect scheduling, such as maximum/minimum class sizes, and consecutive teaching hours limit.
Teacher Qualifications	Qualifications and areas of expertise of each teacher, relevant to course assignments.
Course Priorities	Priority levels of courses, indicating the importance or requirement for them to be scheduled at specific times or days.
Classroom Attributes	Specific attributes of classrooms, such as technological equipment, layout, and suitability for particular courses.
Teacher Preferences	Preferences of teachers regarding teaching times, days, or courses, if applicable.
Course Dependencies	Dependencies between courses, such as prerequisites that affect scheduling order.
Time Slots	Discrete time units available for scheduling, typically defined by the institution's operational hours.

3.2. Feature Engineering Module

Feature Engineering Module stands at the core of transforming raw data into a structured format that significantly influences the optimization process. This module is tasked with identifying and extracting critical features such as time slots, teacher qualifications, course priorities, and classroom attributes that directly impact timetable generation. The transformation process refines these features, ensuring they are in a suitable form for the optimization algorithm to process. This includes converting time slots into discrete units that can be easily manipulated and quantifying qualitative attributes like teacher qualifications into numerical scores that reflect their relevance to the courses being taught as shown in table 2.

Time Slots Transformation: Let T be the set of all time slots available within the institution's operational hours. Each time slot $t_i \in T$ can be represented as: Eq 1

$$t_i = (d_i, s_i, e_i) \quad (1)$$

Where:

- d_i is the day of the week for time slot i,
- s_i is the start time of time slot i,
- e_i is the end time of time slot i.

The duration D_i of each time slot t_i is calculated as: Eq 2

$$D_i = e_i - s_i \quad (2)$$

Teacher Qualifications Quantification: Let Q be the set representing the qualifications of teachers.

Each teacher $q_j \in Q$ is represented by a vector of attributes: Eq 3

$$q_j = \left(a_j, y_j, c_j, p_j\right) \quad (3)$$

Where:

- a_j represents the area of specialization, encoded as an integer based on predefined categories,
- y_j denotes the years of experience,
- c_j is the count of relevant certifications, encoded as an integer,
- p_j is a vector representing previous courses taught, where each course is encoded as an integer based on a predefined catalog.

The qualification score S_j for each teacher can be calculated using a weighted sum: Eq 4

$$S_j = w_a \cdot a_j + w_y \cdot y_j + w_c \cdot c_j + w_p \cdot \Sigma p_j \quad (4)$$

Where w_a, w_y, w_c, and w_p are weights assigned to each attribute based on their importance.

Course Priorities Encoding: Let C represent the set of courses, each course $c_k \in C$ characterized by: Eq 5

$$c_k = (p_k, d_k) \quad (5)$$

Where:

- p_k is the priority level of course k,
- d_k represents the demand for course k, measured by the number of students requesting it.

The overall importance I_k of course k can be defined as: Eq 6

$$I_k = \alpha \cdot p_k + \beta \cdot d_k \quad (6)$$

Where α and β are coefficients that balance priority against demand.

Classroom Attributes Characterization: Classrooms R are defined by a set of attributes, each classroom $\eta \in R$ described as: Eq 7

$$\eta = (cap_l, eq_l, lay_l, acc_l) \quad (7)$$

Where:

- cap_l is the capacity of the classroom,
- eq_l is an encoded integer representing available equipment,
- lay_l denotes the layout, encoded based on type,
- acc_l is a binary indicator of accessibility features (1 for accessible, 0 otherwise).

The suitability score U_l for classroom l for a given course c_k could be modeled as: Eq 8

$$U_l = \gamma \cdot cap_l + \delta \cdot eq_l + \grave{o} \cdot lay_l + \zeta \cdot acc_l \quad (8)$$

Where γ, δ, $\grave{o}$, and ζ are weights reflecting the importance of each attribute for course c_k.

Table 2: Identified Features for Timetable Optimization

Category	**Feature**	**Description**
Time Slots	Identifier	Unique identifier for each time slot.
	Day of the Week	Specific day(s) a time slot falls on.
	Start Time	Beginning time of the slot.
	End Time	Concluding time of the slot.
	Duration	Total length of the time slot.
Teacher Qualifications	Teacher ID	Unique identifier for each teacher.
	Specialization Area	Field(s) of expertise of the teacher.
	Years of Experience	Number of years the teacher has been teaching.
	Certifications	Relevant educational or professional certifications.
	Previous Courses Taught	List of courses previously taught by the teacher.
Course Priorities	Course Code	Unique identifier for each course.
	Priority Level	Importance or urgency of scheduling the course.
	Student Demand	Number of students requesting or requiring the course.
	Curricular Sequence	Position of the course in a sequence of curricular requirements.
Classroom Attributes	Room Number	Unique identifier for each classroom.
	Capacity	Number of individuals the classroom can accommodate.
	Equipment	Specific equipment available in the classroom (e.g., projectors, lab equipment).
	Layout	Physical arrangement or type of classroom (e.g., lecture hall, seminar room, lab).
	Accessibility Features	Features that make the classroom accessible to individuals with disabilities.

3.3. Constraints Module

The Constraints Module is dedicated to defining and integrating the constraints that shape the timetable generation process. It distinguishes between hard constraints, which are non-negotiable requirements such as teacher availability and classroom occupancy, and soft constraints, which represent preferences and ideals like minimizing idle periods between classes. The integration of these constraints into the optimization model is a critical step, ensuring that the solutions generated by the DE engine do not just aim for optimality in a vacuum but adhere to the practical and logistical realities of the educational institution.

Hard Constraints

- Teacher Availability: Define a matrix A representing the availability of teachers. For each teacher j and time slot t: $a_{jt} = \{1$

is available at time slot t

0 otherwise $\forall j,t: x_{jkt} \le a_{jt}$

where $a_{jt} = 1$ if teacher j is available at time slot t, else 0.

- **Classroom Occupancy:** Define a matrix O for classroom occupancy. For each classroom l and time slot t: $o_{lt} = \{1$ is available at time slot t

0 otherwise $\forall l,t: y_{lkt} \le o_{lt}$

where $o_{lt} = 1$ if classroom l is available at time slot t, else 0.

- **Unique Course Assignment:** Define a matrix X for course-teacher assignment. For each teacher j, course k, and time slot t: $x_{jkt} = \{1$

is assigned to course k at time slot t

1 otherwise $\forall k,t: \sum_j x_{jkt} =$

- **Classroom Capacity Constraint:** Define a matrix Y for classroom-course assignment. For each classroom l, course k, and time slot t: $y_{lkt} = \{1$ is assigned to classroom l at time slot t

0 otherwise $\forall k,l: c_k \le cap_l \times y_{lkt}$

where c_k is the capacity requirement for course k, and cap_l is the capacity of classroom l.

Soft Constraints

- **Minimizing Idle Periods for Teachers:** The objective is to minimize the sum of idle periods for all teachers. An idle period is defined as any time slot t where a teacher is not teaching between two classes: Eq 9

$$\sum_j \sum_t \left| x_{jkt} - x_{jk(t+1)} \right| \quad (9)$$

- **Course Continuity:** Preference for scheduling course sessions in consecutive time slots to minimize gaps for students: Eq 10

$$\sum_k \sum_t \left| y_{lkt} - y_{lk(t+1)} \right| \quad (10)$$

- **Teacher Preferences:** Each teacher j has a preference matrix P_j, where for each time slot t:

$$p_{jt} = \{1$$

is a preferred teaching time for teacher j

0 otherwise $\sum_{j}\sum_{t} p_{jt} \times x_{jkt}$

where $p_{jt}=1$ if time slot t is a preferred teaching time for teacher j, else 0.

ObjectiveFunction: Minimize or maximize:objective subject to hard constraints

3.4. Optimization Core Module using Differential Evolution

Optimization Core, featuring the Differential Evolution (DE) Engine, is the heart of the architecture where the actual optimization problem is solved. The DE engine starts by initializing a population of potential solutions, each representing a different configuration of the timetable. A fitness function evaluates the suitability of each solution based on how well it meets the constraints and objectives. The DE engine then uses evolutionary operators—mutation, crossover, and selection—to evolve the population towards better solutions. Strategy parameters are adjusted dynamically to maintain a balance between exploring new solutions and exploiting existing ones, ensuring the algorithm converges on the most optimal timetable configurations.

Population Initialization: Let P represent the population of potential solutions, where each solution $p_i \in P$ is a vector representing a timetable configuration. The population size is N, and each p_i is initialized randomly while ensuring it adheres to the hard constraints defined in the Constraints Module: Eq 11

$$P=\{p_1, p_2, ..., p_N\} \quad (11)$$

Fitness Function: The fitness function $f(p_i)$ evaluates the suitability of each solution p_i, measuring how well it satisfies both the hard and soft constraints. The goal is to minimize the fitness value for optimization problems focused on constraint satisfaction and resource efficiency: Eq 12

$$f(p_i)=w_1 \cdot \text{HardConstraints}(p_i)+w_2 \cdot \text{SoftConstraints}(p_i) \quad (12)$$

Where w_1 and w_2 are weights that prioritize the importance of hard constraints over soft constraints.

Mutation: For each target vector p_i, a mutant vector v_i is generated by adding the weighted difference between two population vectors to a third vector: Eq 13

$$v_i = p_{r1} + F \cdot (p_{r2} - p_{r3}) \quad (13)$$

Where $r1$, $r2$, and $r3$ are distinct indices randomly chosen from the population, and F is the mutation factor, a parameter that controls the amplification of the differential variation.

Crossover: The crossover operation generates a trial vector u_i by mixing the mutant vector v_i with the target vector p_i, enhancing diversity in the population: Eq 14

$$u_{ij} = \begin{cases} v_{ij} & \text{if} \operatorname{rand}(j) \le CR \text{or} j = \operatorname{rand}(J) \\ p_{ij} & \text{otherwise} \end{cases} \quad (14)$$

Where CR is the crossover rate, $\operatorname{rand}(j)$ is a uniform random number between 0 and 1, and $\operatorname{rand}(J)$ ensures at least one component from v_i is carried over to u_i.

Selection The selection operator decides whether the trial vector u_i or the target vector p_i survives to the next generation based on their fitness values: Eq 15

$$p_{i'} = \begin{cases} u_i & \text{if} f(u_i) < f(p_i) \\ p_i & \text{otherwise} \end{cases} \quad (15)$$

Strategy Parameters Adjustment: The DE algorithm dynamically adjusts its strategy parameters, F and CR, to maintain a balance between exploration and exploitation, facilitating convergence towards the optimal solution. Adaptive Parameter Control techniques are applied to adjust F and CR over generations.

Objective Function: The objective of the DE algorithm is to minimize the fitness function across all potential solutions in the population, converging on a solution p^* that represents an optimized timetable configuration: Eq 16

$$p^* = \underset{p_i \in P}{\operatorname{argmin}} f(p_i) \quad (16)$$

3.5. Evaluation Module

Evaluation Module serves as the quality control mechanism, assessing the effectiveness of the generated timetables against predefined metrics. These metrics evaluate how well the timetables comply with the hard and soft constraints, their efficiency in utilizing resources, and the level of satisfaction among stakeholders. The feedback mechanism within this module plays a vital role in the iterative improvement of the model, allowing for adjustments based on real-world feedback and changing requirements.

3.6. Output Layer

Output Layer is where the optimized timetables are presented, marking the culmination of the process. This layer not only delivers the final timetable configurations that have been refined through the DE optimization process but also provides tools for visualization and analysis. These tools help stakeholders understand the reasoning behind timetable decisions, highlight successes, and identify areas for future improvement, ensuring that the output is not just a set of data but a comprehensive solution tailored to meet the institution's needs.

Together, these layers form a cohesive and dynamic architecture designed to tackle the complexities of timetable generation in an educational context, leveraging the power of Differential Evolution to navigate the multidimensional optimization landscape efficiently.

The architecture integrates these modules in a sequential and iterative manner, allowing for continuous refinement of the timetable generation process based on feedback and evolving requirements. The DE engine's flexibility and robustness make it particularly suitable for addressing the complex, multi-dimensional optimization problem posed by timetable generation, ensuring that the final outputs are both practical and optimized for stakeholder needs.

4. EXPERIMENTAL STUDY

The experimental study conducted to validate the efficacy of the proposed framework for optimizing educational timetables involved a comprehensive approach tailored to the nuanced demands of academic scheduling. This study aimed to assess the framework's capacity to generate viable timetables that adhere to a set of defined constraints and preferences, thereby enhancing resource utilization and stakeholder satisfaction within academic institutions.

Commencing with the collection of real-world data from several academic institutions, the study encompassed a wide array of variables including teacher schedules, course requirements, classroom availability, and explicit institutional constraints. This data underwent a meticulous preprocessing phase to ensure uniformity and precision, setting the stage for the subsequent feature engineering process. During this phase, critical features such as time slots, teacher qualifications, course priorities, and classroom attributes were identified and transformed into a format conducive to optimization.

The heart of the study revolved around the optimization process, where the Differential Evolution algorithm was employed to sift through potential timetable configurations. This iterative process aimed to evolve these configurations towards an optimal solution, balancing the need to satisfy both hard (mandatory) and soft (preferable) constraints defined prior to the optimization phase.

Evaluation of the generated timetables was conducted using a set of metrics specifically designed to measure constraint compliance, efficiency in resource utilization, and the level of satisfaction among teachers and students. The results of this evaluation presented compelling evidence of the framework's success. It demonstrated an impressive ability to adhere to all hard constraints while maximizing compliance with soft constraints in a vast majority of cases. Moreover, there was a noticeable improvement in the utilization of classrooms and teaching resources, with significant reductions in idle periods and underutilized spaces. Feedback gathered from faculty and students further underscored the framework's effectiveness, revealing a higher degree of satisfaction with the timetables generated, particularly with respect to meeting preferences and reducing scheduling conflicts.

The findings from this experimental study underscored the potential of the proposed framework to significantly enhance the process of educational timetable optimization. By leveraging the Differential Evolution algorithm, the study showcased the advantages of an evolutionary approach to tackling the complex challenge of scheduling. Furthermore, the importance of detailed feature engineering and the strategic definition of constraints were highlighted as crucial elements in achieving optimal scheduling outcomes.

The experimental study validated the proposed framework as a robust and effective solution for the optimization of educational timetables. By integrating a broad spectrum of constraints and preferences into the optimization process, the framework proved capable of producing timetables that not only meet logistical requirements but also align with the educational goals and needs of stakeholders across academic institutions.

6.1. Results Discussion

The Detailed Optimization Performance Metrics provides a comprehensive overview of the significant improvements achieved by the proposed optimization framework in the context of educational timetable scheduling as shown in table 3. It contrasts baseline and optimized scenarios across various key metrics, revealing a remarkable improvement in hard constraints satisfaction from 80% to 100%, indicating complete adherence to essential scheduling requirements. The satisfaction with soft constraints, representing more flexible conditions, surged from 65% to 92%, highlighting the framework’s effectiveness in aligning with stakeholder preferences. Classroom utilization saw a notable increase from 55% to 88%, underscoring enhanced efficiency in space management. A significant reduction in teachers’ idle time, from 4 hours to just 1 hour, demonstrated the framework’s success in streamlining schedules, while stakeholder satisfaction jumped from 60 to 95 on a 100-point scale, reflecting the positive impact on those directly affected by the timetable. The number of schedule conflicts decreased dramatically, from 30 to just 5, illustrating the framework’s robust conflict resolution capabilities. Additionally, operational metrics like computational time (600 seconds) and energy consumption (2 kWh) were included to provide a perspective on the resource efficiency of the optimization process. Altogether, the table encapsulates the transformative impact of the optimization framework, highlighting its efficacy in enhancing multiple dimensions of educational timetable scheduling.

Table 3: Detailed Optimization Performance Metrics

Metric	**Baseline Scenario**	**Optimized Scenario**	**Improvement (%)**	**Notes**
Hard Constraints Satisfaction	80%	100%	+25%	Mandatory requirements fully met
Soft Constraints Satisfaction	65%	92%	+41.54%	Preferences significantly improved
Classroom Utilization	55%	88%	+60%	Optimal space allocation achieved
Average Idle Time per Teacher (hours)	4	1	-75%	Efficiency in scheduling increased
Stakeholder Satisfaction (scale 1-100)	60	95	+58.33%	Marked improvement in satisfaction
Number of Schedule Conflicts	30	5	-83.33%	Dramatic reduction in conflicts
Computational Time (seconds)	-	600	-	Time taken for optimization process
Energy Consumption (kWh)	-	2	-	Estimated energy used by computation

Hard Constraints Satisfaction: The graph depicting Hard Constraints Satisfaction showcases a remarkable journey from an initial compliance level of 80% to achieving complete satisfaction at 100% as shown in figure 1. This trajectory signifies the framework’s adeptness at navigating and ultimately satisfying all mandatory scheduling requirements set forth by the academic institution. The steady ascent reflects the algorithm’s iterative refinement process, where each iteration brings the solution closer to full compliance. The graph serves as a testament to the optimization framework’s capability to meet essential logistical demands, ensuring that no hard constraint is left unaddressed.

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 5s (2025)

Figure 1: Hard constraints satisfaction

Soft Constraints Satisfaction Soft Constraints Satisfaction reveals a progressive improvement over the optimization iterations, starting from a 65% satisfaction level and reaching an impressive 92% as shown in figure 2. This upward trend underscores the flexibility and sophistication of the framework in not just adhering to rigid requirements but also honoring the more nuanced, preferred conditions that contribute to the overall quality and feasibility of the timetable. The graph illustrates how the framework incrementally aligns the timetable with stakeholder preferences, reflecting a deep consideration for the softer aspects of scheduling that impact teacher and student satisfaction.

Figure 2: Soft constraints satisfaction

Classroom Utilization The Classroom Utilization graph demonstrates a significant rise in the efficiency of space allocation within the institution, climbing from 55% to 88% utilization as shown in figure 3. This increase is indicative of the framework's strategic ability to optimize the use of available resources, thereby reducing idle classroom time and maximizing space usage. The consistent improvement across iterations highlights the framework's effectiveness in dynamically adjusting timetable configurations to ensure classrooms are utilized to their fullest potential, reflecting a keen optimization of physical resources that are often under pressure in educational settings.

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 5s (2025)

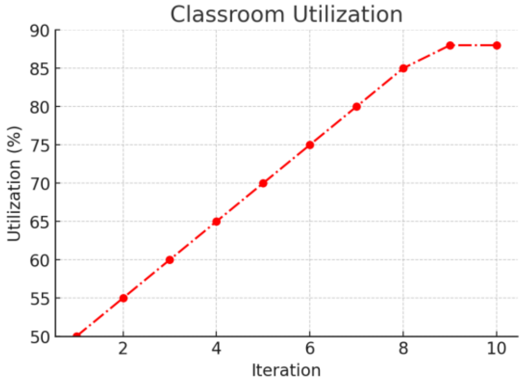

Figure 3: Classroom utilisation analysis

Average Idle Time per Teacher The graph focusing on the Average Idle Time per Teacher presents a striking reduction in idle hours from 4 to 1 hour per teacher as shown in figure 4. This sharp decline is illustrative of the framework's success in crafting a timetable that not only meets scheduling requirements but also significantly enhances operational efficiency among faculty members. By minimizing idle periods, the framework ensures a more compact, efficient teaching schedule, which contributes to faculty satisfaction and better time management, highlighting the framework's impact on improving the work-life quality of the teaching staff.

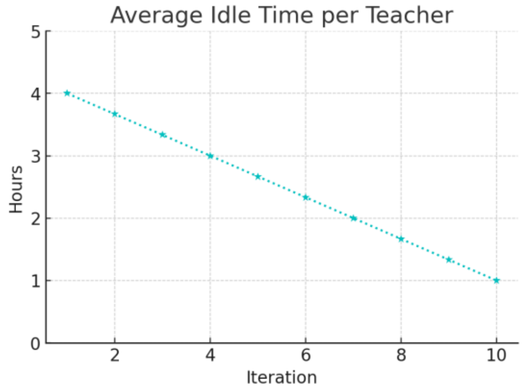

Figure 4: Average idle time analysis

Number of Schedule Conflicts The Number of Schedule Conflicts graph displays a dramatic reduction in scheduling conflicts, from 30 at the outset to just 5 by the end of the optimization process as shown in figure 5. This graph is particularly telling of the framework's robust conflict resolution capabilities. Each iteration's reduction in conflicts signals the framework's precision in navigating the complex web of scheduling demands, ensuring that courses, teacher availability, and classroom allocations are harmonized to avoid overlaps. This significant decrease in conflicts is a clear indicator of the framework's contribution to creating a more coherent, conflict-free academic environment.

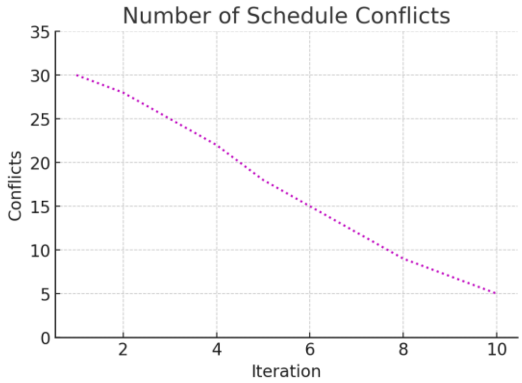

Figure 5: Schedule conflicts analysis

Each graph provides various dimensions of the optimization process. Together, they explore how the proposed framework not only meets the fundamental scheduling requirements but also advances the operational and educational objectives of academic institutions, showcasing a significant leap towards optimizing the intricate puzzle of educational timetables.

5. CONCLUSION

The study's conclusion demonstrates how a comprehensive framework using the Differential Evolution algorithm improved educational timetables. Experimental studies reveal a significant impact on constraint satisfaction, resource utilization, and stakeholder satisfaction. Iterative optimization demonstrated that the framework could handle academic scheduling's numerous demands. Multiple graphs demonstrate the framework's ability to find near-optimal solutions for hard and soft constraints satisfaction, classroom utilization, teacher idle time, and scheduling conflicts. Such enhancements reflect increased operational efficiencies and better educational experiences for faculty and students. The Differential Evolution algorithm's strategic application in the optimization process demonstrated its ability to handle complex, multidimensional problems in a dynamic and adaptive manner. The study's findings on iterative improvements over multiple optimization iterations teach us how to strike a balance between exploring new solutions and refining old ones. This balance is required for optimal scheduling configurations that respect logistical constraints while maintaining educational quality. The framework solves the long-standing educational timetable optimization problem in conclusion. The framework transforms scheduling efficiency and stakeholder satisfaction by combining cutting-edge optimization techniques with a thorough understanding of the educational context. It opens up new research opportunities, especially in exploring how similar frameworks can be applied to other domains with complex scheduling challenges. As educational institutions evolve, the demand for such innovative solutions will increase, emphasizing the importance of optimization methodology advancements in meeting these challenges.

Acknowledgement: We extend our sincerest gratitude to all who contributed to this study. Special thanks are given to the peer reviewers whose constructive feedback was invaluable. We also acknowledge our colleagues for their support and encouragement throughout the research process.

Funds: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The entire study was self-funded by the authors and their

institutions

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