Automating School Timetabling: An Intelligent System Application Using Simulated Annealing

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***Abstract*—Dealing with scheduling difficulties remains a significant challenge for various organizations, especially educational institutions such as schools. Efficient scheduling is essential yet challenging, particularly because these scheduling tasks are categorized as NP-hard, requiring substantial computational resources. This is especially true when managing teachers' schedules manually, which can be time-consuming. To address these issues, there is a clear necessity for a system that can automate and streamline the scheduling process, speeding up schedule creation while ensuring that individual teacher needs are met. This study investigates school timetabling problem in SMPN 1 Jombang, with the goal of automating and optimizing the generation of teaching schedules. To solve the problem, Simulated Annealing (SA) with reheating algorithm is employed. The study also utilizes a Random Assignment approach for allocating teaching hours to specific time slots, constraint programming for generating feasible solutions, and Bin Packing approach for assigning teachers to time slots. The computational experiments show that With an initial temperature of 1000, a cooling rate of 0.7, and 20,000 iterations, the SA with reheating algorithm achieved a fitness value of 0.809. This result outperforms the benchmark algorithms, i.e., standard SA and the Hill Climbing algorithms.**

Keywords—Automation, Meta-heuristic, Optimization, School Timetabling Problem, Simulated Annealing

I. INTRODUCTION

Academic scheduling emerges as a significant challenge for every educational institution, driven by the need to address a broad spectrum of constraints and requirements [1]. These scheduling complexities involve four main elements: time constraints, resource limitations, meeting coordination, and various other restrictions [2], [3]. One key area within educational timetabling is the course scheduling issue, which entails assigning all relevant activities to specific timeslots and locations [4], [5]. This scheduling concern is notably intricate, placing it among the most complex of combinatorial optimization challenges and categorizing it as an NP-hard problem [6], [7]. The NP (Nondeterministic Polynomial) class encompasses a suite of problems that are solvable in polynomial time on a non-deterministic Turing machine, highlighting their complexity rather than an outright impossibility of polynomial-time resolution [8].

The selected case study for this research is SMPN 1 Jombang, an institution experiencing scheduling challenges directly pertinent to this research. At SMPN 1 Jombang, the task of constructing teaching schedules is undertaken semiannually, aligning with teacher availability each term. This scheduling process is recognized as intricate due to the school managing a roster of 61 teachers, 30 classes, and 14 subjects under the 2013 curriculum, compounded by numerous timeslot constraints.

Despite the utilization of a scheduling application at SMPN 1 Jombang, several significant shortcomings have been identified. The process for entering data into the system is particularly cumbersome and time-intensive. The automation provided by the application is limited, necessitating manual intervention for the initial assignment of class sessions to teachers. Following this, the application automatically slots these sessions into the overall schedule. However, this semi-automated approach results in a product that requires manual refinement to become fully functional. The system also falls short in accommodating all the less critical, but still important, scheduling preferences, often leaving out timeslots that cannot be seamlessly integrated and thus require manual assignment. This limitation leads to schedules that do not fully address the less stringent requirements, causing dissatisfaction among the faculty. For instance, some teachers are assigned schedules with inconveniently long gaps between classes, forcing them to endure lengthy waits. Furthermore, the schedule's presentation, which identifies teachers only by codes in their assigned timeslots, lacks clarity. This is particularly problematic for teachers responsible for multiple subjects, as they may find it difficult to determine which subject they are scheduled to teach during any given period.

Given the challenges outlined previously, this research aims to address the scheduling difficulties encountered by SMPN 1 Jombang. The strategy includes the creation of a specialized application designed to automate and refine the scheduling process, emphasizing the distribution of teaching duties. This initiative will incorporate the Simulated Annealing (SA) algorithm, a metaheuristic recognized for its robustness in tackling complex scheduling tasks [9], [10]. Evidence from prior applications of the SA method has consistently shown its ability to deliver commendable results in managing scheduling dilemmas [11]–[14]. An enhancement of the SA algorithm through the introduction of a Reheating phase (SAR) has the potential to further elevate its effectiveness, offering superior performance compared to the traditional SA approach [15], [16]. The effectiveness of the SAR algorithm is especially pronounced with an extended computation period, suggesting its substantial promise in

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improving the scheduling framework at SMPN 1 Jombang [17].

II. Related Work

The school timetabling problem (STP) is a well-known combinatorial optimization problem that has been extensively studied in the literature. Various methods have been proposed to address this problem, including heuristic, metaheuristic, and hybrid approaches. This section reviews recent works related to the application of simulated annealing (SA) and its variations in solving the STP. [18] provide a comprehensive survey on the use of metaheuristics in timetabling, including SA, genetic algorithms, and tabu search. They highlight the flexibility of SA in escaping local optima and its applicability to various types of timetabling problems.

In [19], a hybrid SA algorithm combined with a local search technique is proposed to solve the university course timetabling problem. The authors demonstrate that the hybrid approach significantly improves solution quality compared to traditional SA. The work by [20] explores a hybrid SA with a genetic algorithm to solve high school timetabling. The study shows that the integration of genetic operators enhances the exploration capabilities of SA, leading to better performance.

[21] introduce a hybrid simulated annealing and particle swarm optimization algorithm for university timetabling. The experimental results indicate that the proposed method outperforms standalone SA and other metaheuristics in terms of solution quality and computational efficiency. [22] present an adaptive SA algorithm for the high school timetabling problem. The proposed method adapts the cooling schedule dynamically based on the search progress, which helps in achieving better convergence rates.

In [23], the authors propose a multi-stage SA approach for the university course timetabling problem. The algorithm incorporates reheating mechanisms to avoid premature convergence and demonstrates effectiveness on benchmark datasets. [24] study the integration of constraint programming with SA for solving complex timetabling problems. Their approach leverages the strengths of both methods, resulting in high-quality solutions within reasonable computational time. [25] propose a multi-objective SA algorithm for solving the course timetabling problem. The algorithm simultaneously optimizes multiple objectives, such as minimizing the number of conflicts and balancing the timetable, showcasing superior performance over single-objective approaches.

The work by [26] explores a simulated annealing with reheating mechanism for the exam timetabling problem. The reheating mechanism helps in diversifying the search and escaping local optima, leading to improved solution quality. [27] present a novel hybrid algorithm combining simulated annealing with a heuristic initialization technique for the course timetabling problem. Their results indicate that the hybrid algorithm outperforms conventional SA in both solution quality and computational efficiency.

The reviewed studies underscore the versatility and effectiveness of SA and its hybrid variations in solving the STP. The integration of reheating mechanisms, hybrid approaches, and adaptive strategies have shown to enhance the performance of SA, making it a robust choice for addressing complex timetabling challenges. The novelty of this research compared to prior studies lies on the new dataset, which is firstly investigated in this study.

III. Methodology

A. Data Acquisition

In this study, the data comprises curriculum specifics and a comprehensive list of instructors, drawn from the designated case study at SMPN 1 Jombang. Initial steps include preprocessing to refine this data for subsequent analysis. Data collection is carried out through direct interactions, including surveys and interviews with the teaching staff, to grasp fully the constraints and requirements, ensuring the eventual schedule aligns with the educators' expectations.

B. Development of Automation and Optimization Model

The model for automation utilizes several methods, including Random Assignment, Constraint Programming, and Bin Packing.

- Random Assignment is used for scheduling each lesson hour to available timeslots.
- Constraint Programming ensures that the solutions generated in the scheduling automation only produce solutions that meet the predefined constraints.
- Bin Packing schedules teachers and will automatically add to the list of teachers if no available teachers can be scheduled.

For optimization, the model uses Low-Level Heuristic methods and the Simulated Annealing Algorithm.

- Low-Level Heuristic methods, such as the swap method, are used to generate new solutions in each iteration for optimization.
- Simulated Annealing Algorithm searches for the most optimal solution from the solutions created in each iteration.

C. Evaluation and Testing

This stage aims to evaluate the performance of the developed model. The first step in the evaluation is to ensure that the model has produced feasible results, meeting all the predefined hard constraints. This stage also includes a comparison between the classical SA algorithm and the SA algorithm with reheating to determine whether the SA algorithm with reheating provides better outcomes.

IV. Result and Discussion

A. Results of Data Acquisition

The dataset utilized in this study encompasses a comprehensive array of information necessary for timetable creation at SMPN 1 Jombang for the academic year 2022/2023. This includes detailed curriculum outlines, profiles on teaching staff, class information, and specific constraints that need to be addressed in the scheduling process. The assimilated data is concisely presented in Table I.

Following the acquisition of the necessary data, it undergoes a preprocessing phase to ensure its compatibility with the automation and optimization processes of the scheduling program. This preprocessing stage results in the formation of several key datasets, each tailored for specific aspects of

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TABLE I
SUMMARY OF DATA COLLECTION RESULTS

Parameter	Value
Number of Subjects	14
Number of Classes	30 (10 per level)
Hours per Week	48
Active Days per Week	6
Number of Teachers	61
Number of Hard Constraints	5
Number of Soft Constraints	3

the scheduling task. These datasets include information on the allocation of lesson hours (the meet dataset), details of available timeslots (the timeslot dataset), profiles of active teaching staff (the teacher dataset), and particulars related to the scheduling of Physical Education classes (the PE dataset). Collectively, these prepared datasets are pivotal in facilitating the automated scheduling and optimization functions of the developed application for SMPN 1 Jombang.

In the process of data collection for the program's automation and optimization, several key constraints were identified that are critical for constructing the lesson schedule at SMPN 1 Jombang. These constraints are divided into hard and soft categories, dictating the scheduling framework:

- Hard Constraints (HC):
    1) HC1: All teaching hours within the week must be fully scheduled.
    2) HC2: Physical Education (PE) subjects are to be scheduled only in the morning.
    3) HC3: A teacher cannot be assigned to two different classes at the same time, with an exception for PE teachers who may teach up to two classes concurrently.
    4) HC4: A single meeting must span at least 1 and no more than 3 continuous teaching hours. If sessions are divided, they should be allocated on different days.
    5) HC5: Subjects allocated more than 3 teaching hours per week, if divided, must be scheduled on different days.
- Soft Constraints (SC):
    1) SC1: Science subjects (MIPA) are preferred to be scheduled in the morning.
    2) SC2: Scheduling of teaching meetings for a teacher in two different classes back-to-back should be avoided.
    3) SC3: For subjects with sessions split across the week, scheduling them on consecutive days should be avoided.
    4) SC4: Addition of teacher-subject pairs to compensate for a lack of teacher availability is to be avoided.

B. Initial Solution Test Results

The primary aim of the initial solution test was to ascertain the capability of the automated scheduling solution to generate a feasible schedule adhering to all identified hard constraints. The outcome of this examination revealed that the schedule crafted by the application indeed meets the criteria for feasibility. To further evaluate the effectiveness of the created schedule, a series of five trials was conducted, focusing on the assessment of fitness values associated with the schedule's adherence to the constraints and overall optimization. The specific fitness values derived from these trials are detailed in Table II.

TABLE II
FITNESS VALUE PER TRIAL

Trial	Fitness Value
1	2,521
2	2,618
3	2,553
4	2,538
5	2,539
AVG	2,553

C. Parameter Test Results

Parameter testing aimed to pinpoint the optimal set of parameters for refining the scheduling solution tailored for SMPN 1 Jombang, utilizing the simulated annealing algorithm enhanced with a reheating process. The optimization parameters under consideration encompassed the total number of iterations, the initial temperature, the cooling rate, and the criteria for initiating the reheating phase, specifically the threshold of iterations without notable solution improvement. Four distinct scenarios were designed to explore the efficacy of various parameter configurations in optimizing the schedule. The details of these scenarios are methodically presented in Table III.

TABLE III
SCENARIO TEST PARAMETERS

Scenario	Iterations	Initial Temperature	Cooling Rate	Reheating Threshold
A	1000	100	0.7	10
B	1000	1000	0.7	10
C	1000	100	0.9	10
D	1000	1000	0.9	10

The execution of parameter testing involved conducting five trials for each identified scenario to evaluate their effectiveness in optimizing the SMPN 1 Jombang lesson schedule through the simulated annealing algorithm with reheating. The findings from these tests indicated that scenario B, characterized by an initial temperature setting of 1000 and a cooling rate of 0.7, outperformed the other scenarios. This specific configuration yielded the most favorable optimization results, achieving an average fitness value of 2.260. Detailed outcomes of these tests for all scenarios are systematically presented in Table IV, while Figure 1 offers a boxplot visualization, facilitating a comprehensive understanding and comparison of the results derived from the parameter testing.

D. Comparative Algorithm Test Results

This segment of the study focused on conducting comparative algorithm testing, aimed at evaluating the performance of

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TABLE IV
AVERAGE FITNESS VALUE FOR EACH SCENARIO

Scenario	Best Fitness	Delta Fitness
A	2,280	0,273
B	2,260	0,306
C	2,371	0,210
D	2,358	0,204

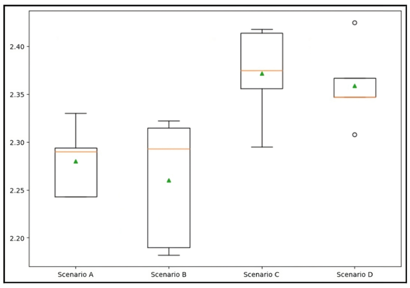

Fig. 1. Boxplot of Parameter Test Results

the simulated annealing algorithm with reheating in relation to other algorithmic approaches. Specifically, the study compared the enhanced simulated annealing algorithm against its unmodified counterpart and the hill climbing algorithm. The benchmarks for this comparative analysis were derived from the optimal parameters identified in scenario B of the previous testing phase, with the number of iterations specifically set at 5000 and 10000 for each comparative test. To ensure robustness in the findings, each set of parameters was subjected to five trials. The outcomes of this comparative evaluation are meticulously documented in Table V.

E. Discussion

The trial results and their corresponding visual representations in Figures 2 and 3 provide a multi-dimensional view of algorithmic performance in scheduling optimization. The unmodified simulated annealing algorithm appears to outperform its reheated counterpart within the 5000 to 10000 iteration range. Figure 2's boxplot clarifies that during the initial high-temperature phase, the unmodified algorithm is more likely to accept worse solutions, similar to the reheated version. However, as the temperature decreases, the acceptance of inferior solutions diminishes, and the algorithm's behavior gradually aligns with that of the hill climbing algorithm, ultimately refusing worse solutions entirely as it cools. This cooling phase can lead the unmodified algorithm to a standstill, often culminating in a local optimum without the capacity to surpass it.

In contrast, the simulated annealing algorithm with reheating intervenes in this stagnation by reheating after a set number of iterations without improvement, as showcased in the pattern of Figure 3. This reheating rejuvenates the algorithm's exploratory capabilities, allowing it to potentially bypass local optima by reconsidering previously rejected solutions. The prolonged iteration spectrum and the strategic use of reheating create a landscape where the reheated algorithm can potentially eclipse the unmodified version in reaching a more optimal solution.

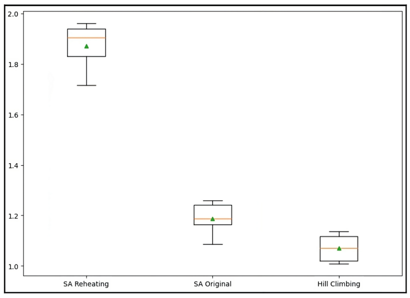

Fig. 2. Boxplot of Algorithm Comparison Trial Results 5000 Iterations

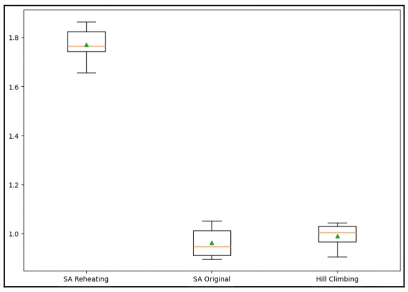

Fig. 3. Boxplot of Algorithm Comparison Trial Results 10000 Iterations

Confirming this, a deeper trial utilizing 20,000 iterations, an initial temperature of 1000, a cooling rate of 0.7, and a 25-iteration threshold for reheating has indeed shown that the reheated algorithm can achieve superior optimization. Starting with a pre-optimization fitness value of 2.585 and culminating in a post-optimization value of 0.809, the findings elucidate that increased iterations and a refined reheating condition enhance the reheated algorithm's outcomes. This progress is detailed in Figure 4, illustrating the solution development throughout the optimization process. These insights affirm that with appropriate parameter settings and a sufficient number of iterations, the simulated annealing algorithm with reheating not only has the potential to deliver better results than its unmodified counterpart but also surpasses the hill climbing algorithm, underlining the efficacy of strategic reheating in overcoming local optimization barriers.

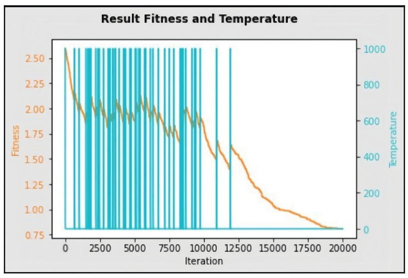

Fig. 4. SA Trial Results with Reheating over 20000 Iterations

F. Implementation of the Web-Based Scheduling Application

The next stage in this research entails the deployment of a web-based application, the design of which is predicated on the model that automates and optimizes the scheduling process. The application will facilitate the entry of dataset parameters and exhibit the outcomes of the scheduling algo-

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TABLE V
RESULTS OF ALGORITHM TESTING

Iteration	Trial	Initial Fitness	SA Reheating		SA Original		Hill Climbing	
			Best Fitness	Delta Fitness	Best Fitness	Delta Fitness	Best Fitness	Delta Fitness
5000	1	2,727	1,940	0,787	1,164	1,563	1,071	1,656
5000	2	2,643	1,831	0,812	1,241	1,402	1,118	1,525
5000	3	2,795	1,904	0,891	1,187	1,608	1,009	1,786
5000	4	2,474	1,961	0,513	1,259	1,215	1,136	1,338
5000	5	2,752	1,716	1,009	1,086	1,639	1,020	1,705
5000	AVG	2,672	1,870	0,802	1,187	1,485	1,070	1,602
10000	1	2,537	1,825	0,712	1,052	1,485	0,967	1,570
10000	2	2,688	1,864	0,824	0,946	1,742	1,043	1,645
10000	3	2,409	1,744	0,665	0,911	1,498	1,029	1,380
10000	4	2,498	1,765	0,733	0,896	1,602	0,906	1,592
10000	5	2,695	1,657	1,038	1,013	1,682	1,004	1,691
10000	AVG	2,565	1,771	0,794	0,964	1,601	0,989	1,575

rithm. It will be bifurcated into two main components: the back-end, which will handle the core web functionalities, including the automation and optimization algorithms for timetable generation, and the front-end, which will provide an intuitive user interface for data input and schedule visualization. The web application is engineered to showcase the schedules that have been automatically generated and fine-tuned through the application of a heuristic optimization algorithm. This is tailored to enhance the user experience by simplifying the process of feeding in the scheduling data and subsequently retrieving the optimized timetable.

V. CONCLUSION

In general, this study shows that our proposed algorithm is effective to solve the school timetabling problem in SMPN 1 Jombang. The proposed algorithm consists of random assignment, constraint programming, bin packing, and simulated annealing algorithm with re-heating. To evaluate its performance, the proposed algorithm is compared with two benchmark algorithms, i.e. standard SA and Hill Climbing algorithms. The computational experiments show that the proposed algorithm outperforms the benchmark algorithms with fitness function 0.809, 0.896, and 0.906 respectively. In addition to develop SA with reheating as a solver for the school timetabling problem. A web based application is also develop in order to make user generate school timetable much easier. As future work recommendation, tested over the same datasets, different algorithms may worth to investigate. It is also interesting to evaluate the performance of the proposed algorithm by testing it over different datasets.

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