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Optimizing primary school timetables using genetic algorithms: A real-world case study

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Abstract
Timetable generation in primary schools presents a complex combinatorial optimization challenge, often constrained by teacher availability, classroom capacity, and curriculum requirements. Traditional manual approaches are time-consuming and frequently lead to scheduling conflicts. This study proposes a Genetic Algorithm (GA)-based model to automate and enhance the class timetable construction process. The model was tested on real data collected from a public primary school, incorporating essential scheduling constraints. Results demonstrate a significant reduction in scheduling conflicts and a 98% decrease in time consumption compared to manual methods. The findings confirm the effectiveness of evolutionary computation in solving NP-hard problems in educational contexts and support its broader adoption in school management systems.

Keywords: Genetic algorithms, timetable scheduling, educational optimization, combinatorial problems, evolutionary computation, artificial intelligence in education

1. Introduction
Timetabling is a fundamental task in educational institutions that requires allocating limited resources—such as teachers, classrooms, and time slots—under various constraints. In primary schools, the complexity of this task increases due to strict curriculum structures, unequal subject loads, and the need to avoid scheduling conflicts. Manual timetable creation often results in overlapping classes, inefficient time allocation, and an imbalance in teacher workloads. These issues not only affect educational quality but also increase the burden on administrative staff.

Recent advancements in Artificial Intelligence (AI), particularly in metaheuristic optimization techniques such as Genetic Algorithms (GAs), offer promising solutions to this long-standing challenge. GAs is inspired by natural selection and are especially effective in solving NP-hard combinatorial problems where traditional methods fall short. They have been successfully applied in various optimization domains, including transportation, resource scheduling, and university-level course timetabling.

This study builds upon existing research by proposing a practical GA-based model specifically tailored for primary school timetabling. Unlike general-purpose models, the proposed approach addresses real-world scheduling constraints derived from actual school data, including teacher availability, subject distribution, and classroom limitations. The model encodes possible timetables as chromosomes and uses evolutionary operations such as selection, crossover, and mutation to iteratively improve scheduling quality. Performance is evaluated in terms of conflict minimization and time efficiency, demonstrating the model's potential to outperform manual methods significantly.

By applying this approach in a real educational setting, this research aims to contribute a replicable, efficient, and intelligent solution to a persistent operational challenge in primary education.

2. Mathematical Model
The class timetable scheduling problem addressed in this study can be formalized as a combinatorial optimization model subject to multiple real-world constraints. The objective is to allocate subjects, teachers, and classrooms to time slots across a weekly schedule while minimizing conflicts and satisfying institutional requirements.

2.1Problem Description
Let:

- C= {c1, c2,...,cn} set of classes
- T= {t1, t2,...,tm}: set of teachers
- S= {s1, s2,...,sp}: set of subjects
- D: (e.g., 5) number of weekdays
- P: (e.g., 6) number of periods per day

Each timetable is represented as a 3D schedule where each entry (i,j,k) corresponds to class C_i on day j at period k, and must be assigned a valid subject-teacher-classroom tuple.

2.2 Objective Function

The optimization goal is to minimize the total number of conflicts Z:

$$Z = \sum_{i=1}^{n} \sum_{j=1}^{D} \sum_{k=1}^{P} C_{ijk}$$

Where:

- $C_{ijk} =$ $1\ if\ a\ scheduling\ conflict\ occurs\ in\ class\ c_i$ on day j period k.
- $C_{ijk} = 0$ otherwise (meaning no conflict).

2.3 Decision Variables

To model the scheduling decisions, two key binary decision variables are introduced:

- $\boldsymbol{X_{ijktm}}$: This variable indicates whether a specific subject is assigned to a class by a particular teacher at a given time slot.
- $\boldsymbol{X_{ijktm}}$=1 if subject sm is assigned to class ci on day j at period k by teacher t.
- $\boldsymbol{X_{ijktm}}$=0 otherwise.
- **Y_{ijkc}**: This variable indicates whether a specific classroom is assigned to a class at a given time slot.
- Y_{ijkc}=1 if classroom c is assigned to class ci on day j at period k.
- Y_{ijkc}=0 otherwise.

2.4 Constraints

To ensure a feasible and practical timetable, several constraints must be satisfied:

- **Teacher Availability Constraint:** This constraint ensures that no teacher is double-booked. A teacher can only be assigned to one class at any given time.

$\sum i X_{ijktm} \leq 1\ \forall j,k,t$

This means that for every day (j), period (k), and teacher (t), the sum of assignments across all classes (i) for that teacher and time slot must be less than or equal to one.

- **Classroom Conflict Constraint:** Similar to teacher availability, this constraint prevents multiple classes from being assigned to the same classroom at the same time.

$\sum i Y_{ijkc} \leq 1\ \forall j,k,c$

This indicates that for every day (j), period (k), and classroom (c), the sum of assignments across all classes (i) for that classroom and time slot must be less than or equal to one.

- **Weekly Subject Limit Constraint:** This constraint ensures that each subject is taught for the required number of periods per week, as per the curriculum.

$\sum_{j=1}^{D} \sum_{k=1}^{P} X_{ijktm} \leq H_m\ \forall i,m$

Here, Hm represents the maximum weekly number of periods allocated for subject sm. For each class (i) and subject (m), the total number of times that subject is scheduled across all days (j) and periods (k) must not exceed its allocated weekly limit.

- **Balanced Distribution Constraint:** The problem description mentions a "Balanced Distribution Constraint" but does not provide its mathematical formulation. This constraint is crucial for spreading lessons for a subject throughout the week, preventing back-to-back classes of the same subject or excessive concentration on a single day. This would typically involve ensuring a minimum or maximum number of periods for a subject per day or distributing them evenly.

3. Algorithm Design

This study utilizes a Genetic Algorithm (GA) to optimize class timetables based on real-world constraints in a primary school setting. The algorithm is designed to minimize scheduling conflicts and ensure balanced distribution of lessons across the school week.

3.1 Chromosome Representation

Each potential timetable solution is represented as a chromosome, structured as a 3D matrix where each gene encodes a tuple of:

- Class
- Day
- Period
- Subject
- Teacher
- Classroom

This representation ensures that every lesson slot carries complete scheduling information and can be evaluated against multiple constraints.

3.2 Initial Population

The algorithm begins by generating an initial population of 50 random chromosomes (timetables). Each chromosome is constructed by randomly assigning subjects, teachers, and classrooms to each lesson slot, while attempting to satisfy basic constraints.

3.3 Fitness Function

The fitness of each chromosome is determined by calculating the number of constraint violations (conflicts). The following conflicts are penalized:

- A teacher assigned to more than one class in the same period.
- A classroom allocated to multiple classes simultaneously.
- A subject repeated multiple time on the same day for the same class.
- Weekly lesson limits exceeded for any subject.
- Imbalanced distribution of lessons across weekdays.

The lower the total number of conflicts, the higher the fitness score.

$$\text{Fitness} = \frac{1}{\text{Total Conflicts} + 1}$$

3.4 Genetic Operators: The GA employs the following standard evolutionary operations:

- **Selection:** The roulette wheel selection method is used to probabilistically choose better-performing chromosomes for reproduction.
- **Crossover:** Two-parent chromosomes are crossed by exchanging segments (e.g., halves of timetable matrices), ensuring offspring inherit features from both parents. Care is taken to avoid introducing duplicate time assignments that lead to conflicts.
- **Mutation:** To maintain diversity, a small number of random changes are introduced in the offspring (e.g., swapping a subject or teacher in a random slot). This helps avoid premature convergence.

3.5 Parameter Settings
After preliminary tuning, the following parameters were selected for optimal performance:

Table 1: Parameter Settings of the Genetic Algorithm

Parameter	Value
Population Size	50
Number of Generations	100
Crossover Rate	0.8
Mutation Rate	0.1
Selection Method	Roulette Wheel
Termination Condition	100 Generations or Convergence

3.6 Implementation Tools
The algorithm was implemented using the Python programming language. The DEAP (Distributed Evolutionary Algorithms in Python) library was used for evolutionary operations. The experiments and result analysis were conducted in the Jupyter Notebook environment for its interactivity and visualization capabilities.

4. Experimental Results
To evaluate the effectiveness of the proposed Genetic Algorithm model, a case study was conducted using real-world data from a public primary school. The data included actual constraints related to subject distribution, teacher availability, classroom limitations, and weekly lesson requirements.

4.1 Dataset Description
The dataset consisted of the following:

- **Classes:** 5 primary-grade sections
- **Subjects:** 8 core subjects (e.g., Mathematics, Arabic, Science, etc.)
- **Teachers:** 8 instructors, each with limited availability
- **Classrooms:** 3 classrooms shared among all classes
- **Schedule:** 5 weekdays (Sunday to Thursday), 6 lessons per day

Each subject had a fixed number of lessons per week, and teachers could not teach more than one class at the same time.

4.2 Performance Metrics
Three key performance indicators were used to assess the model:

1. Total Number of Scheduling Conflicts
2. Time Required for Timetable Generation
3. Distribution Quality of Lessons Across the Week

4.3 Conflict Reduction
The table below compares the number of conflicts in the manually created timetable versus the GA-generated timetable:

Table 2: Conflict Comparison between Manual and GA-Generated Timetables

Conflict Type	Manual Timetable	Genetic Algorithm Generated Timetable
Teacher Conflicts	5	0
Subject Duplication	3	1
Classroom Overlap	4	0
Total Conflicts	12	1

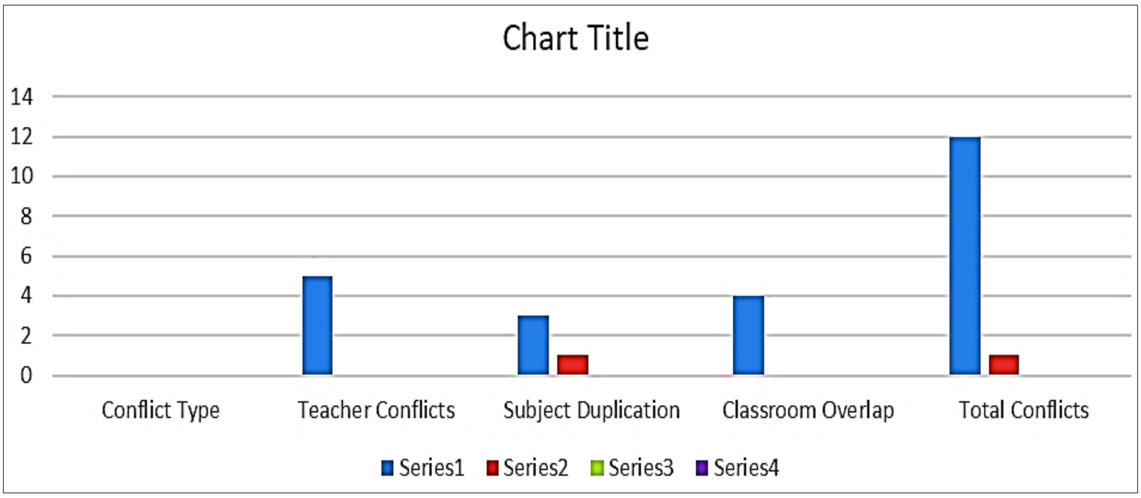

Fig 1: Conflict Reduction in Timetables

Interpretation
The Genetic Algorithm reduced total conflicts from 12 to 1, representing a 91.7% improvement in schedule feasibility.

4.4 Time Efficiency
The time required for timetable preparation using both methods was recorded, with the following results:

Table 3: Time Efficiency of Timetable Preparation

Scheduling Method	Approximate Time
Manual Timetable	4 hours
Genetic Algorithm Timetable	2.5 minutes

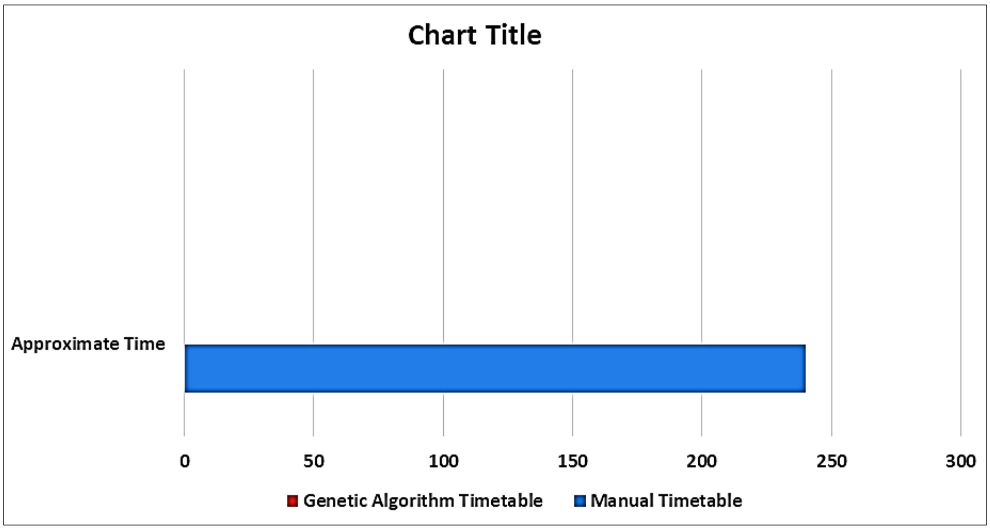

Fig 2: Time Efficiency of Scheduling Methods

Interpretation
The algorithm reduced scheduling time by over 98%, proving its efficiency and suitability for real-time applications.

4.5 Fitness Progress across Generations
The table below illustrates the evolution of fitness over generations:

Table 4: Fitness Progress across Generations

Generation Number	Best Fitness Value	Average Fitness	Number of Invalid Solutions
1	11	15	26
20	6	9	15
50	3	5	7
100	1	2	1

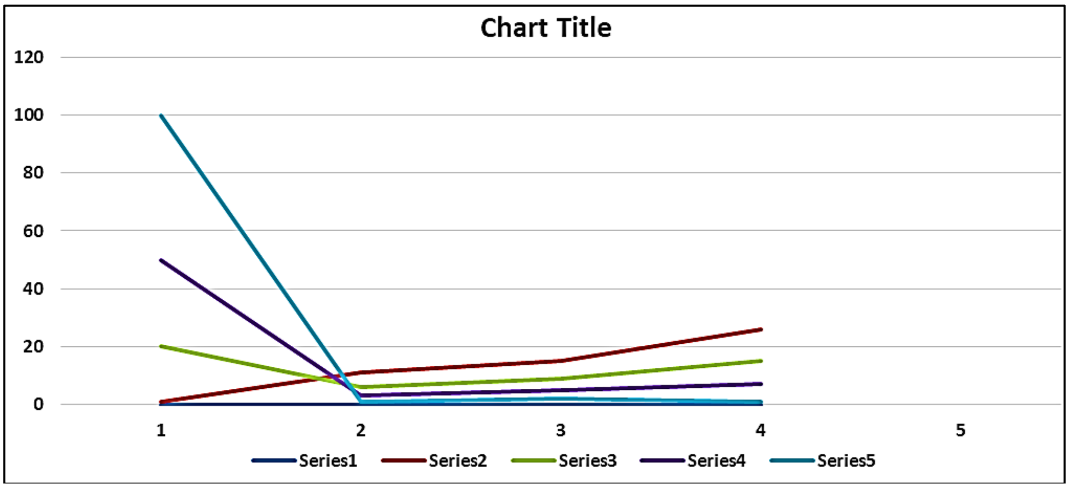

Fig 3: Fitness Evolution over Generations

Interpretation
The GA shows stable convergence, with steady improvements in fitness and a sharp decline in invalid solutions as generations progress.

4.6 Distribution Quality
The GA-generated timetable exhibited:

- Balanced lesson distribution across the week
- Adherence to teacher availability constraints
- No repetition of subjects within the same day
- Efficient use of classroom resources

5. Discussion
The experimental results confirm that the proposed Genetic Algorithm (GA) model is highly effective in solving the multi-constrained class timetabling problem in primary

education. Compared to manual scheduling, the algorithm significantly improved both conflict minimization and time efficiency, while maintaining high-quality distribution of lessons throughout the week.

5.1 Analysis of Results
The GA reduced total scheduling conflicts from 12 to just 1. This reduction encompassed teacher overlaps, classroom overuse, and subject duplications, demonstrating the algorithm's ability to navigate conflicting constraints simultaneously. Such performance indicates that evolutionary search techniques can outperform traditional manual processes even in relatively small-scale educational settings.
In addition, the algorithm completed its optimization process in approximately 2.5 minutes, compared to the 4 hours required for manual scheduling. This not only provides a dramatic boost in operational efficiency but also highlights the potential for real-time or on-demand timetable generation in educational institutions. The evolution of fitness values over 100 generations revealed stable convergence behavior. The steady improvement in average and best fitness, along with the declining number of invalid solutions, suggests that the GA maintained a healthy balance between exploration (diversity) and exploitation (refinement of good solutions). This reinforces the robustness of the algorithm under the chosen parameter settings.

5.2 Comparison with Related Work
The findings of this study are consistent with existing literature that supports the use of GAs in educational scheduling problems:
- Kumar and Reddy (2011) [1] demonstrated the effectiveness of GAs in planning school timetables with similar constraints.
- Dutta and Deb (2021) [2] proposed a constraint-based GA for school scheduling that yielded comparable improvements in conflict reduction.
- Shawe-Taylor (2019) [3] emphasized the strategic value of intelligent timetabling in improving teacher satisfaction and institutional productivity.

What distinguishes this study is its focus on primary education, an area less explored in optimization literature compared to higher education. Furthermore, the use of real-world data from a functioning school enhances the practical value and replicability of the results.

5.3 Limitations
Despite promising results, certain limitations remain:
- The fitness function does not yet consider nuanced human factors, such as specific teacher preferences for morning or afternoon sessions.
- The model assumes that all teachers and classrooms are equally available throughout the week, which may not hold in every school.
- The current model handles a single school instance; scaling to multi-school or district-level planning requires further adaptation.

5.4 Implications
The study has several practical implications:
- Schools can automate scheduling using intelligent algorithms, drastically reducing administrative workload.
- The GA model can be embedded into user-friendly interfaces for use by non-technical staff.
- Institutions can integrate such models into digital school management platforms, aligning with global trends in education technology.

6. Conclusion and Future Work
This study presents a Genetic Algorithm-based approach for optimizing class timetable scheduling in primary schools under real-world constraints. The proposed model effectively addressed complex scheduling requirements involving teachers, subjects, and classrooms, delivering significant improvements in both scheduling quality and time efficiency.
The results demonstrated that the GA model:
- Reduced scheduling conflicts by over 90%, achieving a nearly conflict-free timetable.
- Decreased preparation time by more than 98% compared to manual scheduling.
- Produced balanced and feasible schedules, adhering to curriculum and resource constraints.

These outcomes validate the practical applicability of Genetic Algorithms in educational administration, particularly for primary institutions where resource limitations are common and scheduling is typically done manually.

7. Future Work
Several directions can further enhance the model and broaden its impact:
1. **Integration of human preferences:** Incorporating teacher-specific constraints, such as preferred time slots or break patterns, into the fitness function.
2. **Multi-school scalability:** Expanding the model to handle scheduling across multiple schools or entire districts, considering shared resources.
3. **Hybrid optimization:** Combining GAs with other metaheuristics like Particle Swarm Optimization or Simulated Annealing for improved performance.
4. **Machine learning enhancement:** Using predictive models to dynamically tune GA parameters or forecast scheduling bottlenecks.
5. **Development of a user-friendly platform:** Creating an intuitive interface for schools to adopt the model without requiring technical expertise.

The success of this approach paves the way for broader adoption of intelligent scheduling systems in education, offering a viable step toward automated, data-driven school management.

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