

# Overview of Genetic Algorithms in Educational Timetabling: A Survey

Luca Quaer

luca@quaer.net

Wilhelm Büchner Hochschule

Darmstadt, Baden-Württemberg, Germany

## ABSTRACT

Educational timetabling is a complex optimization problem common to academic institutions such as schools, colleges and universities. It is a NP-complete combinatorial optimization problem, which requires efficient allocation of resources like classrooms and instructors to various activities within educational institutions. This paper examines the application of genetic algorithms addressing such timetabling problems, leveraging their ability to effectively explore large solution spaces.

The study provides a comprehensive analysis of the current state of research on genetic algorithms in educational timetabling, highlighting prevalent techniques and identifying underutilized strategies like parallelism and adaptive evolutionary strategies, emphasizing the potential for innovation in solving timetabling problems. Through a systematic literature review and discussion, the paper identifies trends and areas for future research, underscoring the importance of exploring innovative techniques to enhance the efficiency of genetic algorithms in addressing timetabling complexities. The findings contribute to advancing timetabling practices, exploring new methodologies and combinations of characteristics to ultimately push innovation in the field, increase the utilization of genetic algorithms and their effectiveness specifically in the domain of educational timetabling.

## KEYWORDS

Genetic Algorithms, Educational Timetabling, Metaheuristics

## 1 INTRODUCTION

Educational timetabling involves creating schedules for educational institutions such as schools, colleges, and universities. The problem domain can be divided into the following three main problems [19, 26]: High-School Timetabling (HSTP), University Course Timetabling (UCTP) and University Examination Timetabling (ETT). Although a clear distinction between these three problems is not always possible, they generally differ significantly from one another [7]. However, each of these problems essentially is a resource allocation problem with the goal of assigning classrooms, instructors, and students to specific time slots for various courses or activities, ensuring that all constraints and requirements are met. This includes avoiding conflicts (e.g. a student being scheduled for two classes at the same time), adhering to institutional policies, and maximizing the efficient use of resources.

The difficulty in finding a valid and effective solution to such a problem lies in meeting the diverse requirements of different stakeholders (e.g. students, teachers, administration), multiple constraints and resolving resource conflicts in a combinatorial complex solution space caused by the numerous constraints. Timetabling problems

like these are therefore known to be NP-complete in their general form, meaning that the difficulty of finding a solution increases exponentially with the problem size, which in turn makes it impossible to find a deterministic algorithm providing an acceptable solution in polynomial time [7]. One popular approach to addressing the complexity of timetabling problems is the use of metaheuristic algorithms [7]. This class of algorithms leverages a non-deterministic search approach which compromises on finding an optimal solution in favor of better runtime performance. Consequently, such algorithms are not guaranteed to find the best solution for a given problem, but a near optimal one [1]. Despite this limitation, metaheuristic algorithms are widely used in educational timetabling due to their ability to provide high-quality solutions within a reasonable timeframe. These algorithms can be broadly classified into two categories: single-solution and population-based metaheuristics [18]. Single-solution based algorithms use a single candidate solution and iteratively improve it by using local search, but are prone to get stuck in local maxima [18]. Population-based metaheuristics on the other hand work on multiple candidate solutions during the search process, avoiding the risk of getting stuck in a local maximum by maintaining diversity among the solution candidates [18]. Popular single-solution based algorithms in the timetabling domain are simulated annealing, local search and Tabu search [9, 18]. Well-known population based metaheuristics are genetic algorithms, particle swarm optimization and ant colony systems [7, 18].

Among these methods, genetic algorithms are known for their versatility and application in a variety of use cases with the need of searching for solutions of a combinatorial problem in a large solution space. Therefore, this paper specifically focuses on genetic algorithms and how they are used in the domain of educational timetabling.

Genetic algorithms (GAs) are a heuristic search method inspired by the process of natural selection in biological evolution and thus belong to the group of evolutionary algorithms [18]. As mentioned previously, genetic algorithms utilize a population based approach, meaning multiple solution candidates are iteratively evolved through numerous generations imitating the Darwinian theory of survival of the fittest [18].

This paper is structured as follows: First, the methods and details about how the research was conducted are explained. Then, the fundamentals of genetic algorithms and selected advanced concepts are presented. Introducing some basic concepts serves to better understand the properties of the algorithms, which are presented in the research results section of the paper. The selected concepts which are part of the introduction give a good overview of genetic search, but cannot be an exhaustive coverage of all developments and research in this field. After the introduction, the algorithms

identified in the literature research are presented in a morphological box including their most important characteristics. This provides an overview of the current state of research on genetic algorithms for educational timetabling, which is followed by a breakdown of the research results and a discussion highlighting research gaps that have the potential for further investigation providing opportunities for future work. Finally, the overarching findings from the literature research and the discussion are used to assess the potential success of genetic algorithms in future research.

## 2 METHODS

Publications in the past, especially survey papers, in the field of educational timetabling, showed a shift from metaheuristic methods like genetic algorithms towards mathematical optimization methods in the recent years [27]. Consequently, a research gap in the field of educational timetabling with regard to genetic algorithms opened up. This trend might suggest that genetic algorithms are not suitable in this domain, but research shows, that genetic algorithms have proven their effectiveness in solving timetabling problems [10, 25]. The decreasing utilization of genetic algorithms could be the result of researchers not using the best algorithm to solve a problem but rather methodologies they are already familiar with [9].

This paper analyzes the current use of genetic algorithms with focus on approaches to solve educational timetabling problems. The basis for this is a comprehensive systematic literature research that was carried out in order to identify as many relevant applications of genetic algorithms in the domain of educational timetabling as possible and present their most crucial characteristics. Several scientific databases such as IEEE Xplore, ACM Digital Library, SpringerLink and Google Scholar were searched with prominent keywords such as “educational timetabling”, “timetabling”, “scheduling”, “heuristic” and “metaheuristic”. In order to provide a comprehensive overview of the development and use of genetic algorithms in the field, preference was given to recent publications. However, older, established studies and papers were also taken into account to ensure that no previously researched methods were excluded only due to their age. Nevertheless, the primary objective was to provide a comprehensive and detailed description of the algorithms, with the aim of documenting its properties. Unfortunately, this objective is not consistently met in the researched publications, meaning some algorithms presented in this paper lack details about certain characteristics. In particular, this is the case when an algorithm was deliberately not published. In such instances, papers only disclose rough details and focus on discussing results only.

The research results are presented in form of a morphological box, which provides a clear overview of each algorithm and its most important characteristics. Included in the overview are properties such as the utilized encoding method, the type of fitness function and the genetic operators *selection*, *crossover* and *mutation*. Using a morphological box for presenting the results was a deliberate choice to not only offer a structured overview of the current state of research, but also to highlight the popularity of certain concepts throughout the presented algorithms. The table-like structure clearly shows prevalent and less utilized techniques of genetic search, as well as allowing to easily find combinations of algorithm properties, which

have not been used in this constellation before. The systematic analysis and presentation in form of a morphological box is intended to inspire practitioners and researchers to develop innovative and effective approaches and to further develop existing methods.

## 3 BASIC CONCEPTS

Genetic algorithms are a type of search and optimization algorithm inspired by the biological process of reproduction and natural selection and represent one branch in the field of evolutionary computing [8, 14].

In the search for a solution to an optimization problem, the set of possible solutions – the so-called solution space – must first be determined and made comprehensible for an algorithm in form of a data structure, which is suitable for representing a solution [1]. This representation of the solution is also called *encoding* and contains the data of a possible solution to the problem to be solved. In nature, this data is encoded on chromosomes. Similarly, in genetic algorithms the possible solution in coded form is also called *chromosome* or *individual* [1].

In addition, genetic algorithms employ a population based search approach, whereby instead of a single solution candidate a whole set of solutions is iteratively improved. Such a set of solutions is called *population* and consists of multiple chromosomes. The stages of iterative improvements are called *generations* [1].

In order for the algorithm to optimize towards a desired solution, it is necessary to have a measure in place to evaluate and compare the chromosomes. This value is referred to as *fitness* and is provided by the *fitness function* (also called *objective function*) [1].

With these basic terms defined, the general process of genetic algorithms can now be described as follows: First, an *initial population* must be created and the fitness of its chromosomes must be evaluated [1]. Pairs (or triples, quadruples, etc.) are then selected (*selection* phase) from this population in order to reproduce (known as *crossover*) [1]. The resulting offspring may undergo one or more mutations (*mutation* phase) with a defined probability before the fitness of these new chromosomes is determined (*evaluation* phase) [1]. Based on certain criteria, chromosomes from the current generation and their offspring are now selected, to replace the current population (*replacement* phase) [1]. The result of this step is a new generation of chromosomes forming a new (usually fitter) population [1]. From this population, chromosomes are once again selected for reproduction, starting the process all over again [1]. The genetic algorithm could theoretically continue indefinitely according to this pattern, with termination conditions serving as the only means of halting the process [7]. The forementioned phases of genetic algorithms will be explained in the following chapters.

### 3.1 Encoding

Genetic algorithms require two essential components: an encoding and a fitness function [1]. The encoding plays a pivotal role in the design of a genetic algorithm [18]. Its most significant property is that it fully represents the solution space of the problem at hand, thereby deriving the potential solution of the problem from a given chromosome [1]. Moreover, the encoding must be designed in consideration of the data processing of other algorithm components, such as the fitness function and the crossover operator [1]. The

fitness function must calculate the fitness value based on this representation of a solution candidate, and the crossover operator should generate offspring which represent valid solutions [1]. In particular, the latter aspect can often only be fulfilled by an adapted, domain-specific representation [1]. The following paragraphs present some well-known encodings.

**3.1.1 Binary Encoding.** Binary encoding is a method in which chromosomes are represented as strings of binary digits, i.e. an array of 0s and 1s [18]. Each unit of information (also called a *gene*) corresponds to one binary digit (*bit*). The main advantage of binary encoding is the ability to use common and well-researched crossover and mutation operators [18]. However, these strategies may lead to representations of invalid solution candidates, which would need to be repaired [7]. Such repair strategies are used in practice but pose the risk of introducing too much genetic information which is from neither of the parents [1, 7]. Furthermore, utilizing this encoding requires converting solution candidates into binary form [18]. Depending on the complexity of the problem this might not be feasible and thus require a different encoding. Other well-known encoding schemes are *decimal* and *hexadecimal* encoding. They work analogous to binary encoding except for using decimal and hexadecimal digits respectively [18].

**3.1.2 Value Encoding.** Value encoding is similar to binary encoding, as it also represents chromosomes as strings of values. In contrast to binary encoding, these values can be floating point numbers, integers or characters [18]. This encoding scheme is mainly used for finding the optimal weights in a neural network [18].

**3.1.3 Permutation Encoding.** The permutation encoding method is commonly used in ordering problems [18]. Similar to the encodings mentioned before, a chromosome is made up of an array of values, but as the name suggests, the position in the array encodes the order of the values in the context of an ordering problem [1, 18]. Given that the objects of the ordering problem are unique, this implies that the values in the array are unique too [1].

**3.1.4 Matrix Encoding.** Matrix encoding is a technique used in genetic algorithms where solutions are represented as matrices (two-dimensional arrays) rather than one-dimensional arrays. This encoding is particularly useful for problems that naturally map to a two-dimensional structure, such as scheduling, graphs (as adjacency matrix) layout design, or certain combinatorial problems [1].

## 3.2 Fitness Function

“In genetic algorithms a fitness function assigns a score to each individual in a population; this fitness value indicates the quality of the solution represented by the individual” [1]. “Evaluating the fitness function for each individual should be relatively fast due to the number of times it will be invoked” [1]. Consequently, it is arguably the most crucial component of a genetic algorithm, and it is the only chance to steer the process of genetic evolution in accordance with the desired optimization intentions [7, 20]. Especially in the context of constrained optimization problems with multiple objectives (e.g. hard and soft constraints), the fitness function must be carefully designed to convey the correct optimization target for solving the problem at hand [7, 8]. Timetabling problems usually

pose multiple objectives in form of hard and soft constraints [7]. These differ in their severity: hard constraints must be satisfied in order for the solution to represent a valid timetable, soft constraints on the other hand must not be satisfied and only contribute to the quality of the solution [7].

As previously stated, the design of the fitness function heavily depends on the employed encoding scheme. The encoded data of a solution candidate serves as the input value utilized by the fitness function to calculate the fitness of a chromosome [1]. Although there is no universal recipe for designing fitness functions, because they are highly domain-specific, there are some methods that can be used as a starting point. A prevalent method is to utilize a weighted sum as the foundation of a multi-objective fitness function. Furthermore, such a function can be enhanced through the incorporation of a penalty function, which accounts for constraint violations at a specific weight per constraint [7].

## 3.3 Initial Population

Once an appropriate encoding and a fitness function have been established, the initial step in the actual execution of the algorithm is to generate an initial population [1]. The initial population can be generated in two ways: randomly or heuristically. If the problem’s difficulty lies not in finding valid solutions, but in finding the optimal solution, then heuristic initialization may be a beneficial approach, as it could facilitate the evolution of the population. However, in cases where finding a valid solution is already a significant challenge, heuristics are not a viable option. In such instances, the initial population must be created randomly [1].

## 3.4 Selection

In the selection phase of a genetic algorithm, chromosomes are selected for mating (*crossover*) [1]. The prerequisite for this phase of the genetic algorithm is, that the fitness of each chromosome in the population has been evaluated [1]. At present, the most commonly employed selection techniques are roulette wheel, rank, tournament, Boltzmann, and stochastic universal sampling [18]. The following sections present a brief overview of selected methods.

**3.4.1 Roulette Wheel.** The roulette wheel selection method is also called proportional selection and works by assigning each individual a probability for reproduction according to its fitness relative to the whole population [1]. The expected value of the  $i$ -th chromosome to be selected for reproduction is therefore  $p_i = \frac{f_i}{\bar{f}}$  with  $f_i$  denoting the fitness of the  $i$ -th chromosome and  $\bar{f}$  representing the average fitness of all individuals in the population [1]. “Therefore, each individual of the population is represented by a space proportional to its fitness” [1] on an imaginary roulette wheel. “This wheel is then rotated randomly to select specific solutions that will participate in formation of the next generation.” [18]

**3.4.2 Rank Selection.** “Rank selection is the modified form of Roulette Wheel selection. It utilizes the ranks instead of fitness value” [18]. A possible approach of realizing this selection method is by ordering the individuals according to their fitness and add copies of individuals in a way that the best individual receives a predetermined multiple number of copies the worst one receives [1].

Using this selection strategy reduces the dominating effect of outstanding fit individual, but in turn distorts the difference between similarly fit individuals, which increases the selection pressure in stagnant populations [1]. Compared to Roulette Wheel selection it reduces the chances of premature convergence towards a local optimum [18].

**3.4.3 Tournament Selection.** There are numerous variants of this selection method [1]. The most common one is  $k$ -tournament selection where  $k$  individuals are randomly selected from a population and the fittest individual of the selected ones is considered for reproduction [1]. By choosing the tournament size  $k$  appropriately, the selection pressure can be easily scaled [1].

### 3.5 Crossover

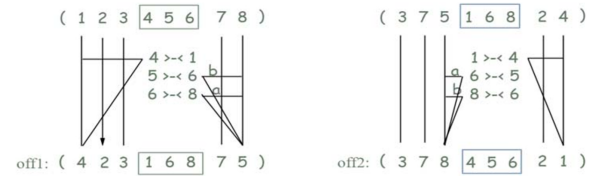
Crossover is the genetic operator which performs the actual mating of individuals selected during the selection phase [7]. Given the close relation between the encoding scheme and the crossover operator, certain crossover operators may not be compatible with some encodings in context of the problem at hand [1].

**3.5.1 Single-Point Crossover.** The single-point crossover method cuts each parent chromosomes into a head and tail section. For this a random position is chosen at which both chromosomes are cut [1]. For a chromosome using binary encoding for example, this translates to splitting the array used to represent the chromosome into two sections. The tail sections are then swapped producing two new individuals [1].

**3.5.2 Multi-Point Crossover.** Similar to the single-point crossover method, the multipoint crossover cuts the parent chromosomes into sections. In contrast to the single point crossover, and as the name suggests, the multipoint crossover method uses multiple random cuts instead of a single one [1, 18].

**3.5.3 Uniform Crossover.** Uniform crossover uses a randomly generated crossover mask, which contains information about what parent chromosome provides certain genes to the offspring [1]. This information could for example be: “the first and second gene (e.g. first and second value in the array) are taken from the first parent, the third gene is taken from the second parent”. To yield two children from the crossover operation, the mask can be inverted. This process is equal to randomly swapping genes (at the same position) between the parents and taking the resulting chromosomes as offspring [18].

**3.5.4 Partially Matched Crossover.** Partially matched crossover is the most commonly used crossover operator, as it performs better than most of the other operators [18]. This crossover technique works by randomly choosing a continuous part of genes from one parent, and swapping it with the corresponding genes (at the same position) from the other parent chromosome [18]. The left out genes are simply copied to the offspring chromosomes, except of genes with values which are contained in the parts that were swapped between the parents. The swapped section of genes denotes a mapping which is used to map these values to the offspring chromosomes instead of simply copying them [18].



**Figure 1: Partially matched crossover visualization [18]**

**3.5.5 Order Crossover.** Order crossover copies one (or more) parts of the parent to the offspring and fills the remaining space with genes from the respective parent, which are not present in the copied section [18].

### 3.6 Mutation

The mutation operator is used on the offspring created by the crossover operation, to allow undirected jumps to slightly different areas of the search space [1]. This procedure maintains genetic diversity throughout generations and helps in efficiently exploring the search space [1, 18].

The actual implementation of the mutation operator greatly depends on the chosen encoding, because mutating a chromosome could potentially lead to an invalid solution candidate depending on how the encoding is designed.

Well-known mutation operators are displacement, simple inversion and scramble mutation.

**3.6.1 Displacement Mutation (DM).** The displacement mutation operator selects a random section from a chromosome and moves it to another position on the chromosome [18]. This operation does not change the sequence of the genes not included in the moved section.

**3.6.2 Simple Inversion Mutation (SIM).** For simple inversion mutation a random section is selected from a chromosome. The order of the genes in this section is then reversed [18]. This mutation can be further enhanced by also moving the section to another position within the chromosome (similar to displacement mutation) [18].

**3.6.3 Scramble Mutation (SM).** The scramble mutation is very similar to the simple inversion mutation with the single difference of not inverting but shuffling the genes in the randomly selected part of the chromosome [18].

### 3.7 Evaluation

For the sake of completeness, the evaluation is listed here as separate phase, even though this is not common in the researched literature. The evaluation phase serves as the final step after successful application of the crossover and mutation operations, in which the fitness of the new individuals must be calculated in order to continue with the genetic algorithm.

### 3.8 Replacement

After the current generation has reproduced in the selection, crossover and mutation phase, which created new offspring, the question arises as to which of the new solution candidates should become members of the next generation [1]. In context of evolution the

replacement strategy determines the life span of the individuals and substantially influences the convergence behavior of the algorithm [1]. The following schemes are possible replacement strategies for genetic algorithms:

**3.8.1 Generational Replacement.** [1] As the name already suggests, the generational replacement strategy simply replaces the current population with the newly created offspring. This process may result in a decrease of the fitness of the best individual in the population at some stages of evolution [1].

**3.8.2 Elitism.** With an elitism method of generation replacement, the best individual (or the  $n$  best individuals) of the previous generation are retained for the next generation [1, 18]. This theoretically allows individuals to be immortal and might lead to premature convergence [1]. The special case of only retaining the best individual is also called “golden cage model” ( $n$ -elitism with  $n = 1$ ) [1]. In case the mutation operator is applied to the elite individuals to prevent premature convergence, the replacement strategy is called “weak elitism” [1].

**3.8.3 Delete- $n$ -last.** The  $n$  weakest individuals are replaced by  $n$  descendants [1]. If  $n$  is much smaller than the population size, this strategy is known as steady-state replacement scheme [1]. For  $n = 1$ , the changes between the old and new generations are minimal, while choosing  $n$  equal to the size of the population represents the previously discussed generational replacement strategy [1].

**3.8.4 Delete- $n$ .** In contrast to the delete- $n$ -last replacement strategy, this approach replaces  $n$  arbitrarily chosen individuals from the old generation rather than the weakest ones [1]. While this reduces the convergence speed of the algorithm, it also helps to avoid premature convergence, balancing between elitism and weak elitism [1].

**3.8.5 Tournament Replacement.** Tournament replacement is similar to the equally named selection strategy. In this replacement scheme competitions are run between sets of individuals from the old population and their offspring [1]. The winners of these tournaments become part of the new population [1].

### 3.9 Termination

As previously stated, the evolutionary process in genetic algorithms is an infinite loop that requires a termination criterion to halt. The desired termination constraint may vary depending on the problem and the context in which the algorithm is used in. One straightforward approach is to simply stop the genetic algorithm after a certain number of generations has been reached [7]. Another widely used method is to terminate the algorithm when the fitness value of the best individual has not changed over a predefined number of generations [8].

## 4 ADVANCED TECHNIQUES

In the field of genetic programming, it is common practice to adapt existing methods to fit one’s own use case. This has led to a steady development of new approaches to improve genetic search in general. While it is beyond the scope of this paper to provide an exhaustive overview of the many branches of advanced genetic search,

the following sections present a selection of important techniques in regard to solving timetabling problems.

### 4.1 Direct and Indirect Encoding

Genetic algorithms can be classified into two primary categories based on the employed encoding scheme: *direct* and *indirect* [28]. In a direct encoding, the chromosome encodes all features of a solution candidate, meaning that the whole search space is encoded [15, 28]. Depending on the problem domain, this means, that chromosomes may also represent invalid solution candidates. Therefore, direct encodings are prone to hard constraint violations on crossover and mutation operations, which requires applying additional mechanisms to find feasible solutions [15]. One possible solution is to repair these invalid chromosomes by applying a repair function that uses domain-specific heuristics to transform the chromosome to a valid state, with the downside of introducing genetic information not related to either of the parents [1, 7].

In contrast to a direct representation, an indirect (or *implicit*) encoding only *partially* encodes a solution candidate [28]. One advantage of not encoding all information of a solution is, that this restricts the search space the algorithm has to explore [15]. Furthermore, by using an indirect encoding, compliance with hard (and even soft) constraints can be guaranteed, if the encoding is designed to only represent valid solutions [15].

School timetabling problems are highly constrained, hence indirect encodings have been successfully applied to such problems [15].

### 4.2 Custom genetic operators

Especially for solving more complex solutions, like creating the forementioned school timetable with many constraints, customized variants of genetic operators may be necessary [3, 7]. An example for such a custom operator is presented in [7]. Their crossover operator is derived from a typical uniform crossover, but it is adapted to the problem domain to not cause problems with a teacher’s schedule [7]. Another potential application of such custom genetic operators could also be the prevention of producing infeasible solutions, when using encoding schemes that do not rule such invalid chromosomes out by design [11]. Similarly to the custom crossover operator mentioned above, mutation operators must also be adapted according to the chosen encoding scheme [3].

### 4.3 Selection Pressure

In the context of genetic algorithms, selection pressure refers to the intensity with which the algorithm favors the fittest individuals during the selection process for reproduction [1, 5]. When selection pressure is high, the algorithm strongly favors the best individuals in the population. These individuals are more likely to be selected for reproduction, leading to a quicker convergence towards optimal or near-optimal solutions. However, if the pressure is too high, it might cause premature convergence, where the population loses diversity and gets stuck in local maxima [5].

Conversely, when selection pressure is low, the algorithm less strongly favors the fittest individuals. This allows for a more diverse set of individuals to be selected for crossover. This helps to maintain genetic diversity within the population and can avoid premature convergence. However, if the pressure is too low, the

algorithm may converge very slowly or struggle to find optimal solutions efficiently [5].

Consequently, the selection pressure generated by the utilized selection method is always a compromise between convergence speed and avoiding premature convergence. It appears, that a dynamic intervention in the evolutionary process to adapt the selection process and the associated selection pressure would result in an improvement of the algorithm. This is exactly the approach taken by the offspring selection method explained in the following paragraph.

#### 4.4 Offspring Selection

Offspring selection (OS) is a self-adaptive selection pressure steering method [1]. Contrary to what the name suggests, this method does not replace previously presented selection methods, such as roulette-wheel or linear-rank schemes. Instead, a second selection step is introduced [1]. After the first selection step has been executed (for example roulette-wheel selection) and the crossover operation has been applied to the selected chromosomes, a further selection – the offspring selection – is applied [1].

The offspring selection considers the fitness of the individuals resulting from crossover. To assure the genetic search mainly progresses with successful offspring, the newly introduced selection step guarantees that a sufficient number of children surpass their parents' fitness [1]. The success ratio ( $SuccRatio \in [0, 1]$ ) controls the proportion of individuals in the next generation, with better fitness than their parents [1].

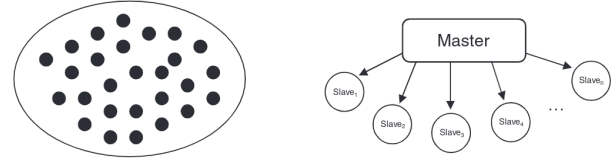
This inevitably leads to the following question: “Is a child better than its parents, if it surpasses the fitness of the weaker parent, the better parent, or some kind of weighted average of both?” [1]. To answer this question the offspring selection method introduces a comparison factor ( $CompFactor \in [0, 1]$ ), inspired by simulated annealing. This factor sets a fitness threshold between the worse and better parent. Early in the process, offspring only need to surpass the fitness of the weaker parent to be considered *better*. As the algorithm progresses, this threshold increases towards the fitness of the better parent, facilitating a broader search initially and a more focused search later [1]. The gradual increase of the comparison factor adjusts the selection pressure throughout the genetic search process, starting with a low selection pressure to prevent premature convergence and steadily increasing the pressure to not suffer from long runtimes until the search converges [1].

#### 4.5 Parallel Genetic Algorithms

Genetic algorithms are well suited for parallelization. There are various methods of implementing these, some of which require fundamental changes to the algorithm and others do not [1]. Concepts for parallel genetic algorithms fall into three categories: global parallelization, coarse-grained parallel GAs and fine-grained parallel GAs. The most popular for practical applications is the coarse-grained model, also known as the island model [1].

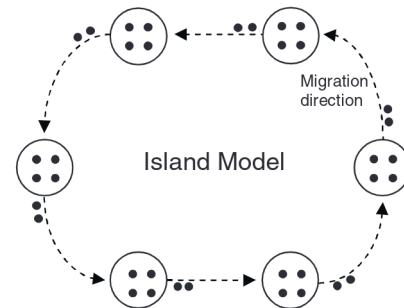
**4.5.1 Global Parallelization.** In global parallelization, a single population is used, and selection involves all individuals. This method retains the same qualitative properties as a sequential genetic algorithm, with the primary parallelized operation being the evaluation

of individual fitness. A master node distributes and collects workloads from slave processors, making this model efficient when fitness evaluation is the primary runtime bottleneck (see Figure 2)[1].



**Figure 2: Global parallelization: Single population (left) and the corresponding master-slave model (right) [1].**

**4.5.2 Coarse-grained parallel genetic algorithms.** Coarse-grained parallel genetic algorithms divide the population into subpopulations (called *islands* or *demes*) that evolve mostly in isolation, occasionally exchanging individuals during migration phases. This model introduces significant changes to the algorithm structure, differing from sequential genetic algorithms [1]. The main idea is that isolated demes will converge to different regions of the solution space, with migration and recombination combining relevant solution parts (see Figure 3)[1]. Coarse-grained parallel genetic algorithms are widely used due to their ease of implementation and therefore the most popular method of parallelizing genetic algorithms [1].



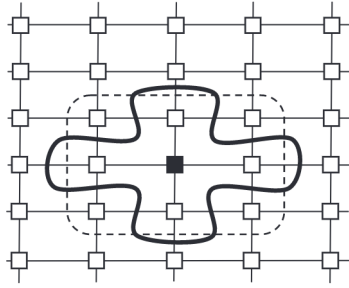
**Figure 3: Population structure of a coarse-grained parallel genetic algorithm [1].**

**4.5.3 Fine-grained parallel genetic algorithms.** Fine-grained parallel genetic algorithms involve many small demes which are part of one spatially distributed population [1]. The idea behind this is that individuals are spread throughout the global population like molecules in a diffusion process, with recombination restricted to local neighborhoods (see Figure 4) [1].

### 5 RESEARCH RESULTS

This chapter presents and discusses the results of the conducted literature analysis. It focuses on presenting the genetic algorithms found in literature and their properties in a morphological box, which was chosen to easily examine which combinations of traits have been used successfully to date, which have received lesser





**Figure 4: Population structure of a fine-grained parallel genetic algorithm with a cellular model [1].**

attention, and which new combinations offer potential for future research.

Table 1 shows the forementioned overview of genetic algorithms found in the literature research, and their main characteristics.

The application of genetic algorithms in the field of educational timetabling has demonstrated significant potential in addressing complex optimization problems. The following paragraphs discuss the various methodologies and strategies employed in the studies reviewed, highlighting both the prevalent and less commonly used techniques. The aim is to provide a comprehensive understanding of the current landscape, identify trends, and suggest potential areas for future research.

## 5.1 Prevalent Techniques

Several methods and strategies have emerged as popular choices among researchers working on educational timetabling problems. Direct encoding, multi-objective fitness functions, and the use of roulette wheel selection are some of the most frequently utilized techniques.

**5.1.1 Encodings.** Direct encoding methods are widely adopted across many studies. This approach involves representing the timetable directly in a matrix form, which simplifies the application of genetic operators and allows for straightforward interpretation and manipulation of solutions. Examples include the studies by Thanh (2007, [28]), Almeida (2015, [3]), and Akkan (2018, [2]). This prevalence suggests that direct encoding is effective in handling the constraints and requirements of timetabling problems.

**5.1.2 Fitness Functions.** The use of multi-objective fitness functions is another common strategy. Researchers often employ a weighted sum approach to balance various objectives, such as minimizing the number of constraint violations and maximizing robustness. This method is evident in the works of Liu (2011, [21]), Badoni (2015, [6]), and Matias (2018, [23]). Multi-objective functions provide a more holistic evaluation of solutions, aligning well with the complex nature of educational timetabling, which typically involves multiple competing goals.

**5.1.3 Selection Mechanisms.** Roulette wheel selection is frequently used to guide the evolution of solutions, as seen in Goos (2002, [15]), Beligiannis (2009, [7]), and Gozali (2020, [17]). This method mimics

natural selection by giving higher probabilities of selection to better-performing solutions, thus ensuring that high-quality timetables are more likely to propagate through successive generations.

**5.1.4 Crossover and Mutation Operations.** Crossover and mutation operators are rarely used as “defined in textbooks”. A popular choice among the reviewed algorithms is  $n$ -point crossover, although it has mostly been customized to suit the utilized encoding. For example, Thanh (2007, [28]) and Gozali (2020, [17]) employ two-point and multi-point crossover methods, respectively, while Goos (2002, [15]) integrates repair functions to handle infeasible offspring. Similarly, mutation strategies often involve domain-specific heuristics to prevent infeasible solutions. Swapping-based mutations, as utilized by Liu (2011, [21]) and Raghavjee (2015, [24]), are common, as they can oftentimes be utilized to explore the solution space without violating hard constraints.

## 5.2 Less Utilized Techniques

Despite the success of the aforementioned methods, several techniques are notably underutilized in the reviewed literature. These include parallelism, adaptive steering of the evolutionary process, and more sophisticated population initialization strategies.

**5.2.1 Parallelism.** Parallel genetic algorithms offer substantial advantages in terms of computational efficiency and solution quality by distributing the workload across multiple processors. However, only a few studies, such as those by Yousef (2016, [29]) and Gozali (2020, [17]), have explored this approach. Given the increasing availability of parallel computing resources, there is significant potential for further research in this area to enhance the scalability and performance of GAs in timetabling.

**5.2.2 Adaptive Evolutionary Strategies.** Adaptive and dynamic evolutionary strategies, which adjust parameters such as mutation rates or selection pressures based on the current state of the population, can improve convergence rates and solution quality. Despite their promise, these methods are rarely implemented in the reviewed studies. The lack of adaptive mechanisms suggests an area for future exploration, where more responsive algorithms could lead to more efficient search processes and better handling of diverse problem instances.

**5.2.3 Integration of Hybrid Methods.** Hybrid methods that combine genetic algorithms with other optimization techniques, such as local search or constraint programming, have shown promise in several studies, including those by Feng (2017, [13]) and Matias (2018, [23]). These approaches leverage the strengths of multiple algorithms to address different aspects of the problem more effectively. The success of hybrid methods suggests that further integration of complementary techniques could enhance the performance of genetic algorithms in timetabling.

## 6 DISCUSSION

The application of genetic algorithms in educational timetabling has yielded promising results, but it also highlights several areas for further exploration and improvement. This chapter evaluates the research results and identifies research gaps that could guide future studies.

Problem	Encoding	Fitness Function	Selection	Crossover	Mutation	Population Initialization	Elitism	Note	Source
ETT	Direct	?	?	Custom heuristic (ensuring valid solutions)	Custom (prevents infeasible results)	Heuristic (only feasible solutions)	?	Hybrid	[11] (1995)
HSTP	Direct (array)	Penalty points	Roulette wheel	One-, two-point and uniform (with repair)	Hybrid with repair function	Random	Yes	Uses domain knowledge	[15] (2002)
UCTP	Permutation (indirect) (2D matrix)	Custom (encoding-based metric)	?	Two-point	Random swap	Random (with heuristic)	?	Genetic and heuristic algorithm	[28] (2007)
HSTP	Enumeration (direct; 2D matrix)	Multi objective (weighted sum)	Roulette wheel	Dynamic, cost based operators	Custom	Random	Yes		[7] (2009)
HSTP	Decimal (direct)	Multi objective (weighted sum)	?	Custom	Custom	Random	?		[21] (2011)
HSTP	Matrix (variable length)	Two-step cost function	$t$ -Tournament	Multi-point (cut and splice)	Swapping (based on heuristics)	Random (fixed length)	?	Hyper-heuristic	[24] (2015)
UCTP	Direct	Multi-objective (weighted sum)	Tournament	Uniform	Random move in neighborhood	Random (uniform distribution)	?	Hybrid = GA + local search	[6] (2015)
UCTP	Direct (3D matrix)	Multi objective (weighted sum)	?	Custom	Repair function as mutation	Random	?		[3] (2015)
UCTP	Permutation	Weighted penalty func.	Roulette wheel	Cycle cross-over	Swap	Random	?		[30] (2016)
UCTP	Direct	Multi-objective (weighted sum)	Custom (gender based)	Single-point	Custom (local search)	?	?	Parallel; GPU accelerated	[29] (2016)
UCTP	Indirect (2D matrix)	MILP objective function	2-Tournament	Two-point	Two-step: random swap; then heuristic	Random and directed	Yes	Hybrid = GA + local search	[13] (2017)
UCTP	Direct (2D matrix)	Multi-objective (soft-constraints and robustness)	Roulette wheel and random (both used)	Partially matched with repair func. and hill climb	Hill climb operators (swap and move)	Heuristic (constraint programming based)	Yes (rank)		[2] (2018)
UCTP	Direct (3 matrices)	Multi-objective (weighted and squared sum)	?	Multi-point	Guided mutation with repair func.	Random	?	Hybrid = GA + guided search	[23] (2018)
UCTP	Enumeration (direct)	Dynamic multi-level	Roulette wheel	Customized multi-point	Custom multi-level	Greedy (minimizes hard constraint violations)	Yes (1 + $m$ )		[16] (2020)
UCTP	Enumeration (direct; 3D matrix)	Penalty points (for hard constraint violations)	Roulette wheel	Multi-point (directed by constraint violation)	Three-step: move, swap, compare	Greedy	Yes	Parallel (island model)	[17] (2020)
?	Binary (direct)	Custom	?	?	?	Random	Yes (best 10%)		[12] (2020)
UCTP	Dynamic length (direct)	Amount of constraint violations	Roulette wheel (with fitness threshold)	Single-point	?	?	Yes (during select.)		[4] (2021)
UCTP	Binary (direct)	Multi-objective (weighted sum)	Tournament	Multi-point	Custom (class mutation)	Heuristic (only feasible solutions)	Yes	Uses repair function	[22] (2023)

Table 1: Morphological box presenting genetic algorithms with their main characteristics



## 6.1 Encodings

The prevalence of direct encodings in the research results suggests a potential research gap regarding indirect encodings. The utilization of direct encoding schemes often leads to large search spaces, potentially making the algorithm less efficient. Indirect encodings, on the other hand, could significantly reduce the size of the search space, leading to faster solution discovery. Thanh (2007, [28]) provides a compelling example of an indirect encoding used for educational timetabling, demonstrating its potential to streamline the search process and improve performance. Further exploration of indirect encoding methods could yield substantial improvements in both efficiency and solution quality.

## 6.2 Parallelism and Hardware Acceleration

Parallelism in genetic algorithms offers significant advantages in terms of computational efficiency. However, it is underutilized in the context of educational timetabling. Studies by Yousef (2016, [29]) and Gozali (2020, [17]) are among the few that have explored parallel genetic algorithms, particularly through leveraging GPU acceleration. This suggests a substantial research gap in the broader utilization of parallelism.

Moreover, modern CPUs equipped with SIMD (Single Instruction, Multiple Data) capabilities present an additional opportunity for hardware acceleration. SIMD is a type of parallel processing that for example enables performing operations on large matrices efficiently, making it suitable for handling genetic operations on encoded matrices. Investigating the use of SIMD instructions for genetic algorithms could lead to significant performance gains on more widely available hardware, as opposed to relying on dedicated GPUs. This approach could democratize access to high-performance timetabling solutions, making them feasible on standard computational setups.

## 6.3 Adaptive Strategies and Parameter Tuning

One of the most significant challenges associated with genetic algorithms is the necessity for extensive parameter tuning [18]. Parameter tuning refers to the process of modifying input variables of the algorithm, such as crossover and mutation probabilities or the degree of elitism. This tuning process is not only labor-intensive and depending on the algorithm may require deep domain knowledge, it also tailors the genetic algorithm to a specific problem instance, making the algorithm impractical for software products distributed to end users.

Adaptive evolutionary strategies, which dynamically adjust the algorithm's behavior based on metrics like the selection pressure, are promising but rarely implemented in the reviewed studies. These strategies offer dual benefits: being based on crucial metrics of the genetic process they provide insights into the search process by monitoring such metrics, and furthermore they provide a certain degree of automatic parameter tuning.

An algorithm leveraging adaptive evolutionary strategies extensively and therefore needing less (or no) parameter tuning, would be more robust and versatile, capable of performing well across a variety of problem instances without manual intervention. This

capability could make genetic algorithms more accessible and practical for a wider range of timetabling instances, reducing the barrier to their adoption especially in smaller educational institutions.

## 6.4 Hybrid Methods

The integration of hybrid methods, which combine genetic algorithms with other optimization techniques like local search or constraint programming, has shown considerable promise. Studies by Feng (2017, [13]) and Matias (2018, [23]) demonstrate the effectiveness of hybrid approaches in addressing the multifaceted nature of educational timetabling problems. Hybrid methods can capitalize on the strengths of different algorithms, addressing various problem aspects more comprehensively. The success of these approaches suggests that further exploration of hybrid methods could further enhance the performance of genetic algorithms. Researchers may investigate novel combinations of optimization techniques, aiming to develop more robust and efficient solutions for educational timetabling.

## 7 CONCLUSION

The review of genetic algorithms applied to educational timetabling reveals a landscape dominated by well-established techniques such as direct encoding, multi-objective fitness functions, and roulette wheel selection. While these methods have proven effective, there is considerable potential for innovation through the adoption of less common strategies, including parallelism and adaptive evolutionary processes. Future research should focus on these underexplored areas to further enhance the capability and efficiency of genetic algorithms in solving complex timetabling problems. Especially the topics highlighted in the discussion – hardware acceleration, adaptive parameter steering and the continued integration of hybrid methods – present a promising direction for achieving superior results.

## 8 FUTURE WORK

The findings from this work will serve as the foundation for the author's master's thesis, in which a genetic algorithm for a school timetabling problem will be developed. The examinations conducted in this paper provide valuable information about the most frequently used techniques of genetic search within the timetabling domain as well as promising research gaps, which will serve as a reference point for selecting the most appropriate genetic methods for the algorithm to be developed.

## REFERENCES

- [1] Michael Affenzeller, Stephan Winkler, Stefan Wagner, and Andreas Beham. 2009. Genetic Algorithms and Genetic Programming: Modern Concepts and Practical Applications.
- [2] Can Akkan and Ayla Gülcü. 2018. A bi-criteria hybrid Genetic Algorithm with robustness objective for the course timetabling problem. *Computers and Operations Research* 90 (2 2018), 22–32. <https://doi.org/10.1016/j.cor.2017.09.007>
- [3] Maria Weslane Sousa Almeida, Joao Paulo Souza Medeiros, and Patricia Rufino Oliveira. 2015. Solving the academic timetable problem thinking on student needs. *Proceedings - 2015 IEEE 14th International Conference on Machine Learning and Applications, ICMLA 2015*, 673–676. <https://doi.org/10.1109/ICMLA.2015.184>
- [4] Ghazi Alnowaini and Amjad Abdullah Aljomai. 2021. Genetic Algorithm for Solving University Course Timetabling Problem Using Dynamic Chromosomes. *2021 International Conference of Technology, Science and Administration, ICTSA 2021*. <https://doi.org/10.1109/ICTSA52017.2021.9406539>

- [5] Thomas Back. 1994. Selective pressure in evolutionary algorithms: A characterization of selection mechanisms. In *Proceedings of the first IEEE conference on evolutionary computation. IEEE World Congress on Computational Intelligence*. IEEE, 57–62.
- [6] Rakesh P Badoni and D K Gupta. 2015. A hybrid algorithm for university course timetabling problem. 6 (2015). Issue 2. [www.iiste.org](http://www.iiste.org)
- [7] G. N. Beligiannis, C. Moschopoulos, and S. D. Likothanassis. 2009. A genetic algorithm approach to school timetabling. *Journal of the Operational Research Society* 60, 23–42. Issue 1. <https://doi.org/10.1057/palgrave.jors.2602525>
- [8] Jenna Carr. 2014. An Introduction to Genetic Algorithms.
- [9] Sara Ceschia, Luca Di Gaspero, and Andrea Schaerf. 2023. Educational timetabling: Problems, benchmarks, and state-of-the-art results. , 18 pages. Issue 1. <https://doi.org/10.1016/j.ejor.2022.07.011>
- [10] Mei Ching Chen, San Nah Sze, Say Leng Goh, Nasser R. Sabar, and Graham Kendall. 2021. A Survey of University Course Timetabling Problem: Perspectives, Trends and Opportunities. *IEEE Access* 9 (2021), 106515–106529. <https://doi.org/10.1109/ACCESS.2021.3100613>
- [11] David Graham Elliman. 1995. A Hybrid Genetic Algorithm for Highly Constrained Timetabling Problems. <http://www.yandy.com>
- [12] Mbunge Elliot, Fashoto Stephen Gbenga, and J Mnisi Emmanuel. 2020. Enhanced heuristic teaching timetabling algorithm using genetic algorithm. *International Journal of Scientific & Technology Research* 9, 4 (2020), 3804–3814.
- [13] Xuehao Feng, Yuna Lee, and Ilkyeong Moon. 2017. An integer program and a hybrid genetic algorithm for the university timetabling problem. *Optimization Methods and Software* 32 (5 2017), 625–649. Issue 3. <https://doi.org/10.1080/10556788.2016.1233970>
- [14] David E. Goldberg. 1989. *Genetic Algorithms in Search, Optimization & Machine Learning*. <https://doi.org/10.1023/A:1022602019183>
- [15] G Goos, J Hartmanis, and J Van Leeuwen. 2002. Lecture Notes in Artificial Intelligence Lecture Notes in Computer Science.
- [16] Alfian Akbar Gozali and Shigeru Fujimura. 2020. Solving University course timetabling problem using multi-depth genetic algorithm-solving UCTP using MDGA. In *SHS Web of Conferences*, Vol. 77. EDP Sciences, 01001.
- [17] Alfian A Gozali, Bobby Kurniawan, Wei Weng, and Shigeru Fujimura. 2020. Solving university course timetabling problem using localized island model genetic algorithm with dual dynamic migration policy. *IEEJ Transactions on Electrical and Electronic Engineering* 15, 3 (2020), 389–400.
- [18] Sourabh Katoch, Sumit Singh Chauhan, and Vijay Kumar. 2021. A review on genetic algorithm: past, present, and future. *Multimedia Tools and Applications* 80 (2 2021), 8091–8126. Issue 5. <https://doi.org/10.1007/s11042-020-10139-6>
- [19] Jeffrey H Kingston. 2013. Educational timetabling. In *Automated Scheduling and Planning: From Theory to Practice*. Springer, 91–108.
- [20] Kenneth E Kinnear Jr. 1994. A perspective on the work in this book. *Advances in genetic programming* (1994), 3–19.
- [21] Jun-Hui Liu and Na Li. 2011. Decimal encoding GA used to solve timetabling problem. *2011 6th IEEE Joint International Information Technology and Artificial Intelligence Conference*, 144–148.
- [22] Ahmed Redha Mahlous and Houssam Mahlous. 2023. Student timetabling genetic algorithm accounting for student preferences. *PeerJ Computer Science* 9 (2023). <https://doi.org/10.7717/peerj-cs.1200>
- [23] Junrie B. Matias, Arnel C. Fajardo, and Ruji M. Medina. 2018. A Fair Course Timetabling Using Genetic Algorithm with Guided Search Technique. *5th International Conference on Business and Industrial Research (ICBIR)*.
- [24] R Raghavjee and N Pillay. 2015. A genetic algorithm selection perturbative hyper-heuristic for solving the school timetabling problem. *ORiON* 31 (4 2015), 39. Issue 1. <https://doi.org/10.5784/31-1-158>
- [25] Amin Rezaeipannah, Zahra Abshirini, and Milad Boshkani Zade. 2019. Solving University Course Timetabling Problem Using Parallel Genetic Algorithm. *International Journal of Scientific Research in Computer Science and Engineering* 7 (10 2019), 5–13. Issue 5. <https://doi.org/10.26438/ijsrcse/v7i5.513>
- [26] Andrea Schaerf. 1999. A survey of automated timetabling. *Artificial intelligence review* 13 (1999), 87–127.
- [27] Joo Siang Tan, Say Leng Goh, Graham Kendall, and Nasser R. Sabar. 2021. A survey of the state-of-the-art of optimisation methodologies in school timetabling problems. *Expert Systems with Applications* 165 (3 2021). <https://doi.org/10.1016/j.eswa.2020.113943>
- [28] Nguyen Duc Thanh. 2007. Solving Timetabling Problem Using Genetic and Heuristic Algorithms. *Proceedings - SNPD 2007: Eighth ACIS International Conference on Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing* 1, 591–594. <https://doi.org/10.1109/SNPD.2007.464>
- [29] Ahmed H Yousef, Cherif Salama, Mohammad Y Jad, Tarek El-Gafy, Mona Matar, and Suzanne S Habashi. 2016. A GPU based genetic algorithm solution for the timetabling problem. In *2016 11th International Conference on Computer Engineering & Systems (ICCES)*. IEEE, 103–109.
- [30] Ítalo Gomes Gonçalves, Gomes Gonçalves, and Aline Lopes Balladares. 2016. Permutation encoding of the University Class Timetabling Problem: a case study in a Brazilian university Permutation encoding of the University Class Timetabling Problem: a case study in a Brazilian university 'Ítalo'. (2016). <https://doi.org/10.13140/RG.2.1.2352.5523>