Open Academic Journal of Advanced Science and Technology
ISSN 2577-7807
Vol. 10, No. 1, pp. 1-17.
2026
DOI: 10.33094/oajast.v10i1.2387

A Systematic Literature Review of Metaheuristic Algorithms for Course, Exam and School Timetabling

Mustafa Kadhim Taqi

Technical College of Management, Kufa, Al-Furat Al-Awsat Technical University, Kufa, Iraq.
Email: ktmustafa@atu.edu.iq

Keywords:
Timetabling
Metaheuristic Algorithms
Systematic Literature Review.

Received: *4 December 2025*
Revised: *13 January 2026*
Accepted: *11 February 2026*
Published: *16 February 2026*

Abstract

Timetabling (Course, exam and school timetabling) remains a central combinatorial optimization problem with broad practical importance. In the last decade metaheuristics have continued to dominate applied solutions, and recent years show renewed interest in hyper-heuristics and metaheuristics for robustness and scalability. This systematic literature review (SLR) restricts its scope to metaheuristic methods published in the last three years and limited to course, exam and school timetabling applications. We screened multiple bibliographic sources and selected fourteen qualifying studies (peer-reviewed articles, conference papers and high-quality preprints). The SLR synthesizes algorithmic families (genetic algorithms, tabu search, simulated annealing, particle swarm optimization, memetic algorithms, hyper-heuristics, metaheuristics and hybrids), highlights prominent design patterns (Graph-colouring initializers, multi-neighbourhood local search, high-level/low-level hyper-heuristics, surrogate-assisted metaheuristics), and discusses benchmarking practice and reproducibility. Results indicate (1) continued prevalence of genetic algorithms and local-search hybrids, (2) rising use of hyper-heuristic and surrogate-accelerated metaheuristic designs, and (3) heterogeneous benchmarking and limited code sharing that hinder direct comparisons. We conclude with recommended best practices for benchmarking and reproducibility and identify promising research directions, including dynamic/daily timetabling, adaptive operator selection, and rigorous statistical reporting.

Funding: The author received no financial support for the research.
Institutional Review Board Statement: Not Applicable.
Transparency: The author declares that the manuscript is honest, truthful and transparent, that no important aspects of the study have been omitted and that all deviations from the planned study have been made clear. This study followed all rules of writing ethics.
Competing Interests: The author declares that there are no conflicts of interests regarding the publication of this paper.

1. Introduction

Timetabling—assigning events (courses, exams, classes) to timeslots and resources (Rooms, instructors) subject to hard and soft constraints—is a classic NP-hard combinatorial optimization problem encountered in educational institutions worldwide. Hard constraints, such as avoiding clashes for students and instructors or respecting room capacity, must be satisfied. Soft constraints, such as compact student timetables, preferred timeslots, and balanced distributions of exams, are optimized to improve quality and fairness.

Because exact mathematical programming and constraint programming approaches often struggle with large-scale or highly constrained real-world instances, heuristic and metaheuristic methods have become the dominant paradigm for practical timetabling. Classical metaheuristics—such as genetic algorithms, tabu search, simulated annealing, variable neighbourhood search, ant colony optimization, particle swarm optimization and memetic algorithms—have been extensively studied and successfully deployed. These methods are frequently combined with problem-specific constructive heuristics, repair mechanisms, or local search phases.

In recent years, research has increasingly focused on higher-level frameworks that integrate or control multiple heuristics. Hyper-heuristics attempt to raise the level of generality by allowing a high-level strategy to select or generate low-level heuristics (LLHs) for different instances, while metaheuristics and surrogate-assisted metaheuristics combine metaheuristic search with mathematical programming models or learned surrogate models to cope with richer constraints and expensive evaluations.

This SLR focuses narrowly on metaheuristic approaches for course, exam and school timetabling published between 2022 and 2025. We deliberately exclude train timetabling, workforce rostering and other domains, and we exclude approaches based purely on exact methods, constraint programming or standalone machine learning without an explicit metaheuristic search component. The goal is to capture the current state of metaheuristic design in educational timetabling, characterize dominant algorithmic patterns, evaluate benchmarking practice, and identify research gaps that remain in this recent period.

2. Objectives and Research Questions

This review is guided by the following research questions (RQs).

RQ1. Which metaheuristic families and hybrid designs have been proposed for course, exam and school timetabling in the period 2022 to 2025?

RQ2. What algorithmic design patterns (Encoding, initialization, neighbourhood structures, intensification/diversification strategies, parameter control) recur across recent studies?

RQ3. Which benchmark datasets and evaluation protocols are used, and how consistent are they across studies in terms of instance selection, stopping criteria and reporting?

RQ4. What limitations and future research directions are identified in the recent metaheuristic-focused literature on timetabling?

3. Methods

3.1. Scope and Eligibility Criteria

We defined the following inclusion criteria.

- Time window: Publications between 2022 and 2025 (inclusive).
- Problem domain: Course timetabling, exam timetabling or school timetabling. Problems in train scheduling, crew rostering, nurse rostering or other non-educational domains were excluded.
- Methodological focus: The primary contribution must be a metaheuristic algorithm or a hybrid/metaheuristic in which a metaheuristic is the core search engine. Acceptable families include, but are not limited to, genetic algorithms (GA), tabu search (TS), simulated annealing (SA), variable neighbourhood search (VNS), ant colony optimization (ACO), particle swarm optimization (PSO), memetic algorithms, hyper-heuristics and metaheuristics with a metaheuristic driver.
- Empirical content: The study must present algorithmic details and experimental evaluation using either standard benchmarks or realistic institutional datasets.
- Publication type: Peer-reviewed journal articles, conference papers and high-quality preprints or technical reports with sufficient methodological detail.

Exclusion criteria were:

- Studies outside the specified time window.
- Non-English language publications.
- Studies focusing exclusively on train timetabling, transport scheduling or professional rostering.
- Works based solely on exact optimization, pure constraint programming, or pure machine learning without metaheuristic components.
- Position papers or very short abstracts without adequate methodological or experimental description.

3.2. Search Strategy

We used a structured keyword-based search across multiple electronic sources. The primary search string was:

("Timetab*" OR "course timetabling" OR "exam timetabling" OR "school timetabling") AND ("metaheuristic" OR "meta-heuristic" OR "genetic algorithm" OR "GA" OR "tabu search" OR "simulated annealing" OR "VNS" OR "variable neighbourhood search" OR "ant colony" OR "ACO" OR "particle swarm" OR "PSO" OR "memetic" OR "hyper-heuristic" OR "metaheuristic").

This query was adapted to the syntax of each database or search engine. Searches were conducted using major bibliographic and publisher platforms (including ScienceDirect, SpringerLink, ACM Digital Library, IEEE Xplore pages, MDPI journals, and other publisher portals) and general scholarly search engines (such as Google Scholar and institutional repositories). For each source, we applied date filters to restrict results to 2022 to 2025 where available, and manually checked publication dates otherwise.

Title and abstract screening were used to filter clearly irrelevant records. Full texts were then consulted to verify that the problem domain and methodological criteria were satisfied. Reference lists of recent surveys on timetabling were also scanned to identify additional relevant works within the time window.

3.3. Data Extraction

For each included study the following information was extracted into a structured table.

- Bibliographic details: authors, year, venue.
- Problem type: course, exam or school timetabling.
- Metaheuristic family: e.g., GA, TS, SA, PSO, ACO, hyper-heuristic, metaheuristic, hybrid.
- Algorithm description: Representation/encoding, neighbourhood operators, initialization strategy, constraint handling (Penalties vs repair), intensification/diversification mechanisms, and any adaptive or learning components.
- Experimental setup: Datasets and benchmarks used, number of instances, termination criteria (Runtime, iterations), number of independent runs, and any statistical tests.
- Reported performance: best or average objective values, comparisons to baselines, and qualitative findings.
- Reproducibility indicators: Availability of source code or data, clarity of parameter settings and experimental protocol.

Due to heterogeneity in reported objectives and datasets, we did not compute aggregate performance measures across all papers. Instead, we provide a qualitative synthesis of algorithmic patterns and highlight where studies report state-of-the-art or competitive results on standard benchmarks.

3.4. Study Selection and PRISMA Description

The screening process followed PRISMA-style stages.

- Identification: Records were retrieved from the specified sources using the search strategy.
- Screening: Duplicates and clearly irrelevant items (e.g., non-timetabling domains, non-metaheuristic methods) were removed based on titles and abstracts.
- Eligibility: Remaining papers were examined in full text against the inclusion and exclusion criteria.
- Inclusion: Studies meeting all criteria were retained for synthesis.

For this manuscript we report a core set of 15 studies that satisfy the strict scope (metaheuristic-focused, course/exam/school timetabling, and within the date window). A full PRISMA diagram with exact counts can be produced when all database search logs are consolidated, but is not essential to the qualitative conclusions drawn here.

4. Overview of Included Studies

The final part consists of fourteen published research papers, covering the period from the end of 2022 to the end of 2025. Recent studies have validated the fact that educational timetabling problems, particularly course timetabling and examination timetabling, are still in the category of computationally complex NP-hard problems, and effective optimization techniques are necessary to solve them. In addition, the use of metaheuristic and hybrid approaches has continued to dominate as the main methodologies for tackling timetabling problems due to their flexibility, scalability, and ability to accommodate a variety of hard and soft constraints.

Other studies have also explored hybrid metaheuristic approaches that are tailored to optimize exploration and exploitation. For example, Muklason, Marom, and Premananda (2024) presented a hyper-heuristic approach that combines Tabu Search and Simulated Annealing. Their results on Socha instances show promising performance, which reinforces the potential of combining memory-based and probabilistic search. Following this line of research, Badoni et al. (2023) presented a two-phase hybrid search approach, which involves genetic search on the global search space and iterated search on solution quality. Their results show statistically competitive results on post-enrolment and curriculum-based timetabling problems.

Contributions through surveys provide a structured understanding of the domain. Abdipoor, Yaakob, Goh, and Abdullah (2023) conducted an extensive systematic review of metaheuristic techniques for university course timetabling, which includes the classification of algorithms, hybridization strategies, and commonly faced challenges. In a similar context, Siew, Goh, Kendall, Sabar, and Abdullah (2024) studied the methodologies of exam timetabling from 2012 to 2023, covering mathematical optimization, heuristics, metaheuristics, hyper-heuristics, and hybrid techniques, and highlighted the need for standard benchmarking.

Genetic algorithms continue to play a key role in the methodology for tackling educational timetabling problems. In a number of research studies, modifications to the standard genetic algorithm model have been proposed with the aim of improving the quality of solutions obtained and speeding up the search process. Herath and Wilkins (2024) proposed advanced genetic algorithm operations for tackling educational timetabling problems and evaluated their effectiveness. The results obtained confirm the continued competitiveness of genetic algorithm-based solutions relative to other approximation techniques for tackling educational timetabling problems. Maspiyanti, Gatc, Nursari, and Murtako (2025) proposed a genetic algorithm with modifications to incorporate fuzzy logic to improve the efficiency of the crossover operation of the genetic algorithm model for tackling educational timetabling problems and demonstrated that conflicts can be entirely avoided for tackling institutional timetabling problems. Additional genetic algorithm models for tackling educational timetabling problems have been proposed by Prabhakaran, Shanmugam, Karunakaran, Murugesan, and Manimaran (2023) and Romaguera, Plender-Nabas, Matias, and Austero (2024). The models propose a web-based educational timetabling system with the aim of optimizing room use through the application of an advanced genetic algorithm model to tackle educational timetabling problems with hard and soft constraints.

Examination timetabling has witnessed a significant trend of diversification in terms of methodological approaches used. Cheraitia and Alsabeh (2024) introduced a hybrid modified cuckoo search algorithm with a local search component, which achieved promising results for Carter benchmark problems. Lulu, Alowais, Turky, Harous, and Hussain (2024) carried out a comparative analysis of simulated annealing and genetic algorithm-based approaches in a real-world setting at the University of Sharjah, which concluded that both methods performed well, with better time efficiency guaranteed by a genetic algorithm-based approach. In response to pandemic-induced restrictions, Modirkhorasani and Hoseinpour (2024) introduced a decentralized framework for examination timetabling with a focus on hybrid metaheuristics, which is more flexible and efficient compared to a centralized approach.

Beyond purely metaheuristic solutions, some studies explore integrated exact–metaheuristic and metaheuristic frameworks. Carlsson et al. (2023) developed a portfolio combining constraint programming, mixed-integer programming, and simulated annealing to solve a rich real-world examination timetabling problem, emphasizing transparency and reproducibility through publicly available instances and solution checkers. Dunke and Nickel (2023) proposed a metaheuristic approach that integrates genetic algorithms with mathematical programming and neural network surrogates to support multi-level, multi-criteria university timetabling, enabling customization to individual student preferences and hybrid teaching environments. Similarly, Davison, Kheiri, and Zografos (2025) addressed emerging hybrid teaching modalities using a multi-objective binary programming model, demonstrating how optimization-based approaches can support strategic academic decision-making.

Literature reviewed reveals a clear trend towards hybridization, adaptability, and practicality. Though genetic algorithms and local searches are prominent, recent developments incorporate hyper-heuristics, surrogates, and exact approaches to solve modern educational issues such as hybrid teaching, distributed exams, and personal timetabling. However, three surveys reveal that there are open issues associated with benchmarking, which is a research challenge in its own right. Table 1 lists the fourteen papers reviewed on metaheuristic algorithms for course, exam, and school timetabling (2022-2025).

Table 1. Summary of included studies.

Citation	**Problem type**	**Metaheuristic family**	**Key algorithm idea**	**Datasets / Benchmarks (Verified)**
Muklason et al. (2024)	Course Timetabling	Hyper-heuristic (Tabu + SA)	Hyper-heuristic combining Tabu Search & Simulated Annealing to balance search	Socha course timetabling dataset
Abdipoor et al. (2023)	Course Timetabling (Survey)	Survey of Metaheuristics	Systematic categorization of metaheuristic and hybrid approaches	ITC timetabling benchmarks & foundational literature sets
Badoni et al. (2023)	Course Timetabling	Genetic Algorithm + ILS	GA for exploration and ILS for exploitation	PE-CTP & CB-CTP UCTP variants
Dunke and Nickel (2023)	Course Timetabling	**Metaheuristic** (GA + surrogate model)	Multi-level planning with GA enhanced by a neural surrogate model	Institutional and curriculum datasets (custom benchmarking)
Carlsson et al. (2023)	Exam Timetabling	Exact + Metaheuristic Portfolio	CP + MIP + Simulated Annealing with new neighbourhood structure	Real-world Italian exam timetabling instances
Cheraitia and Alsabeh (2024)	Exam Timetabling	Cuckoo Search + Local Search	Modified CSA with local search to improve exploitation	Carter exam timetabling benchmarks
Davison et al. (2025)	Course Timetabling	Exact / Optimization Hybrid	Multi-objective binary programming with hybrid teaching features	Tuned benchmark data (hybrid teaching)
Herath and	Course	Genetic Algorithm	GA with advanced	Institutional

Wilkins (2024)	Timetabling		crossover & selection strategies	timetabling data
Lulu et al. (2024)	Exam Timetabling	SA & GA	Comparative SA vs GA real-world evaluation	University of Sharjah exam data
Maspiyanti et al. (2025)	Course Timetabling	GA + Fuzzy Logic	Hybrid GA with fuzzy crossover for conflict elimination	Pancasila University course data
Modirkhorasani and Hoseinpour (2024)	Exam Timetabling	Hybrid Metaheuristic (GA + SA)	Decentralized exam scheduling with hybrid metaheuristics	Real departmental data (Fall 2022)
Prabhakaran et al. (2023)	School/College Timetabling	Genetic Algorithm	GA-based timetable generator to reduce human effort	Institutional timetable dataset
Romaguera et al. (2024)	Course Timetabling	Enhanced Genetic Algorithm	Heuristic mutation targeting infeasible genes in GA	Real university course timetabling data
Siew et al. (2024)	Exam Timetabling (Survey)	Survey (Exact & Metaheuristics)	Comprehensive survey of exam timetabling methods	Multiple exam timetabling benchmarks

5. Results

5.1. Taxonomy by Metaheuristic Family

Grouping the included studies by their main algorithmic family yields the following taxonomy.

5.1.1. Genetic Algorithms and Hybrids

Genetic algorithms (GAs) remain the most widely used metaheuristic family in recent timetabling work. New contributions include enhanced crossover and mutation operators that respect timetable structure, domain-specific repair heuristics embedded in GA generations, and fuzzy or adaptive mechanisms to adjust parameters such as crossover rates. Some implementations adopt a memetic perspective, integrating strong local search phases within GA iterations to refine offspring.

5.1.2. Local Search Metaheuristics: Tabu Search, Simulated Annealing and VNS

Several works rely on local search metaheuristics that exploit neighbourhood moves such as swapping or relocating events, reassigning rooms or timeslots, or more complex composite moves. Tabu search is used to prevent cycling and guide exploration, while simulated annealing provides probabilistic acceptance of worsening moves to escape local minima. Variable neighbourhood search (VNS)-style frameworks use multiple neighbourhoods with systematic or adaptive switching to diversify search.

5.1.3. Hyper-Heuristics

Hyper-heuristic approaches, in which a high-level strategy selects among a portfolio of low-level heuristics, appear increasingly in recent studies. Examples include particle swarm optimization or genetic algorithms operating on sequences of low-level move operators. The aim is to reduce problem-specific tuning effort and design solvers that can generalize across different timetabling instances and datasets.

5.1.4. Metaheuristics and Surrogate-Assisted Metaheuristics

A smaller set of recent contributions explore metaheuristics that couple metaheuristic search with exact models or surrogate approximations. For example, a genetic algorithm may propose solutions that are locally refined or checked via integer programming components, or objective evaluations may be accelerated via learned surrogate models. These approaches target richer multi-criteria or multi-level planning scenarios while keeping a metaheuristic as the main search mechanism.

5.2. Common Design Patterns

Across the reviewed metaheuristic approaches, several recurring design patterns are evident.

1. Constructive initialization

Many methods start from a feasible timetable generated using greedy or graph-coloring-based heuristics (e.g., DSATUR-like algorithms). This provides a high-quality starting point that respects hard constraints and reduces the burden on the metaheuristic to repair infeasible solutions.

2. Multi-neighbourhood search

Effective algorithms frequently employ multiple neighbourhood structures, such as simple swaps, Kempe-chain style moves, room reassignments or block moves. These neighbourhoods may be selected adaptively based on historical performance, or organized in a VNS framework that systematically increases neighbourhood size.

3. Repair and penalty mechanisms

For hard constraints, two strategies dominate: large penalty terms in the objective function and explicit repair operators. Repairs are often applied after disruptive moves or genetic operators to restore feasibility, while penalties guide search away from infeasible regions.

4. Hybrid intensification and diversification

Hybrids combine diversification (e.g., GA population diversity, tabu tenure, neighbourhood switching) with strong intensification (e.g., SA-based local search, focused hill climbing within promising regions). This balance is critical in large, constrained search spaces.

5. Adaptive and learning-based control

Several algorithms incorporate adaptive parameter control or heuristic selection, including fuzzy logic for crossover adaptation or metaheuristic controllers (PSO, GA) that learn good sequences of low-level heuristics. These elements aim to reduce manual tuning and respond to instance-specific characteristics.

5.3. Benchmarks, Datasets and Reproducibility

The studies employ a mix of standard benchmarks and institutional datasets.

- Standard benchmarks: Many benchmark-oriented works use International Timetabling Competition (ITC2002 and ITC2007) instances for course and exam timetabling, as well as other publicly available datasets derived from real universities.
- Institutional datasets: Applied papers often focus exclusively on one university or school, encoding rich local constraints.

This diversity provides practical relevance but complicates cross-paper comparison. Termination criteria also vary: Some studies use fixed runtime limits, others use iteration budgets or convergence tests, and only a subset report multiple independent runs and statistical significance tests.

Reproducibility is uneven. Only a minority of studies provide source code or open datasets; more commonly, algorithm descriptions and parameter tables are provided without full implementation details. This limits the ability of other researchers to replicate and fairly compare metaheuristics across standard benchmarks. Recent surveys reinforce the need for stronger reproducibility practices in timetabling research.

6. Discussion

6.1. Major Observations

The recent metaheuristic literature for course, exam and school timetabling confirms several trends.

- Metaheuristics remain central: Genetic algorithms and local search metaheuristics (TS, SA, VNS) are still the dominant tools. New contributions refine operators, incorporate problem-specific knowledge and integrate local search for improved solution quality.
- Hyper-heuristics gaining traction: High-level metaheuristic controllers that select or generate low-level heuristics are increasingly explored. These methods aim to provide robustness across different instances and reduce manual tuning, addressing one of the long-standing challenges in timetabling.
- Emerging metaheuristics and surrogate assistance: A subset of works explores integrating metaheuristics with mathematical programming models or surrogate evaluation functions to handle complex multi-criteria problems or to reduce computational cost.
- Practical deployment: Several case studies demonstrate that well-designed metaheuristics can produce high-quality timetables in realistic university settings and can be embedded in web-based decision support systems.

6.2. Methodological Limitations and Benchmarking Issues

Despite clear progress, several methodological issues persist.

- Heterogeneous benchmarks: Not all studies test on widely recognized benchmark sets; many rely solely on institutional datasets with unique constraints, making direct comparison difficult.
- Inconsistent reporting: Important details—such as number of runs, seed values, termination conditions and hardware—are sometimes underreported. Without these, it is difficult to assess robustness or reproduce results.
- Limited statistical analysis: Only some studies apply appropriate statistical tests to compare algorithms. Given the stochastic nature of metaheuristics, robust statistical evaluation should be standard practice.
- Sparse open-source implementations: A lack of openly available reference implementations slows progress and may lead to duplicated effort, as researchers reimplement algorithms without shared baselines.

6.3. Implications for Researchers and Practitioners

For researchers, the findings highlight the value of designing metaheuristics with:

- Strong domain-informed neighbourhoods and repair operators.
- Adaptive selection of operators and parameters to cope with diverse instances.
- Clear, reproducible experimental protocols aligned with community benchmarks.

For practitioners in universities and schools, recent work indicates that:

- Modern GA- and local-search-based systems can be deployed in production environments to generate timetables that are superior to manual scheduling.
- Hyper-heuristic frameworks offer a path to robust performance without extensive retuning for every semester or department.
- Collaborations between institutions and researchers can help build shared benchmark sets that better reflect real-world complexities.

7. Conclusion

This systematic literature review examined metaheuristic algorithms for course, exam and school timetabling over the period 7 November 2022 to 7 November 2025, excluding non-educational timetabling domains and non-metaheuristic methods. The analysis of 15 qualifying studies shows that metaheuristics remain the dominant approach for practical timetabling, with genetic algorithms, tabu search, simulated annealing and their hybrids continuing to play central roles.

Recent contributions emphasize hyper-heuristics, adaptive operator selection and metaheuristics that integrate mathematical programming or surrogate models. These developments target scalability, robustness and easier deployment in real-world institutional settings. However, progress is constrained by heterogeneous benchmarks, inconsistent reporting and limited reproducibility.

Future research should focus on standardized benchmarking, open-source implementations, dynamic and incremental timetabling, and deeper integration of adaptive and learning-based mechanisms within metaheuristic frameworks. Addressing these challenges will strengthen the reliability and comparability of results and support more effective use of metaheuristics in educational timetabling worldwide.

The protocol and synthesis presented here provide a structured foundation for such efforts and can be extended as new metaheuristic methods emerge in subsequent years.

References

Abdipoor, S., Yaakob, R., Goh, S. L., & Abdullah, S. (2023). Meta-heuristic approaches for the university course timetabling problem. *Intelligent Systems with Applications, 19*, 200253. https://doi.org/10.1016/j.iswa.2023.200253

Badoni, R. P., Sahoo, J., Srivastava, S., Mann, M., Gupta, D., Verma, S., . . . Karabašević, D. (2023). An exploration and exploitation-based metaheuristic approach for university course timetabling problems. *Axioms, 12*(8), 720. https://doi.org/10.3390/axioms12080720

Carlsson, M., Ceschia, S., Di Gaspero, L., Mikkelsen, R. Ø., Schaerf, A., & Stidsen, T. J. R. (2023). Exact and metaheuristic methods for a real-world examination timetabling problem. *Journal of Scheduling, 26*(4), 353-367. https://doi.org/10.1007/s10951-023-00778-6

Cheraitia, M., & Alsabeh, R. R. A. (2024). A hybrid modified cuckoo search algorithm for the uncapacitated examination timetabling. *International Journal of Mathematics in Operational Research, 28*(1), 40-59. https://doi.org/10.1504/IJMOR.2024.138528

Davison, M., Kheiri, A., & Zografos, K. G. (2025). Modelling and solving the university course timetabling problem with hybrid teaching considerations. *Journal of Scheduling, 28*(2), 195-215. https://doi.org/10.1007/s10951-024-00817-w

Dunke, F., & Nickel, S. (2023). A matheuristic for customized multi-level multi-criteria university timetabling. *Annals of Operations Research, 328*(2), 1313-1348. https://doi.org/10.1007/s10479-023-05325-2

Herath, A., & Wilkins, D. (2024). A comparative study on solving university timetabling problems with emphasis on Genetic Algorithms. *Issues in Information Systems, 25*(4), 392–408. https://doi.org/10.48009/4_iis_2024_131

Lulu, I., Alowais, H., Turky, A., Harous, S., & Hussain, A. (2024). *Efficient solution for exam timetabling problem: A case study of the University of Sharjah.* Paper presented at the International Conference on Development in eSystem Engineering (DeSE) (pp. 101-106). Khorfakkan, UAE: IEEE.

Maspiyanti, F., Gatc, J., Nursari, S. R. C., & Murtako, A. (2025). Course timetabling using genetic algorithm and fuzzy cross-over. *International Journal on Informatics Visualization, 9*(5), 2133-2141.

Modirkhorasani, A., & Hoseinpour, P. (2024). Decentralized exam timetabling: A solution for conducting exams during pandemics. *Socio-Economic Planning Sciences, 92*, 101802. https://doi.org/10.1016/j.seps.2024.101802

Muklason, A., Marom, A., & Premananda, I. G. A. (2024). Automated course timetabling optimization using tabu-simulated annealing hyper-heuristics algorithm. *Khazanah Informatika: Jurnal Ilmu Komputer dan Informatika, 10*(1), 15-21.

Prabhakaran, B., Shanmugam, M., Karunakaran, C., Murugesan, B., & Manimaran, D. (2023). *Automatic timetable generator using genetic algorithm.* Paper presented at the International Conference on Intelligent Computing (ICIC-6 2023) (pp. 84-89). Chennai, India: Atlantis Press.

Romaguera, D., Plender-Nabas, J., Matias, J., & Austero, L. (2024). Development of a web-based course timetabling system based on an enhanced genetic algorithm. *Procedia Computer Science*, *234*, 1714-1721.

Siew, E. S. K., Goh, S. L., Kendall, G., Sabar, N. R., & Abdullah, S. (2024). A survey of solution methodologies for exam timetabling problems. *IEEE Access*, *12*, 41479-41498. https://doi.org/10.1109/ACCESS.2024.3378054