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Research Article

Intelligent Scheduling Systems for Practice-Based Higher Education Programs

Émilie Laurent*, Nicolas Morel,Émilie Laurent*
[1] Management Sciences and Marketing Division, Alliance Manchester Business School, The University of Manchester, Manchester M15 6PB, United Kingdom

* **Corresponding Author**: claire.lefevre@manchester.ac.uk

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ABSTRACT

This study develops an intelligent scheduling system for practice-based higher education programs, focusing on how AI-assisted optimization can improve the allocation of instructors, specialized rooms, equipment, and repeated practice sessions. The study is designed to collect scheduling and resource-use data from approximately 25 practice-based programs across 8 universities over two academic semesters, including around 18,000 course-booking records, 6,500 room-use logs, 4,200 instructor availability records, 3,800 equipment reservation records, and 12,000 student practice requests. Key variables include room occupancy rate, instructor workload balance, equipment utilization rate, booking conflict frequency, student waiting time, schedule adjustment frequency, course completion continuity, and learner satisfaction. The study applies mixed-integer linear programming, genetic algorithms, constraint satisfaction modeling, and reinforcement learning-based scheduling simulation to compare traditional manual scheduling with intelligent scheduling scenarios. Model performance is evaluated through resource utilization rate, conflict reduction rate, average waiting time, instructor workload variance, schedule stability, and student access equity. The innovation of this study lies in moving practice-based program management from experience-based scheduling to data-driven resource coordination, providing a measurable optimization model for institutions where learning quality depends heavily on limited spaces, instructors, and equipment.

Keywords: intelligent scheduling; practice-based education; resource optimization; higher education management; mixed-integer programming; genetic algorithm; AI-assisted planning; learning continuity

INTRODUCTION

Practice-based higher education covers a wide range of learning activities, including studio art, design workshops, engineering laboratories, health simulation, sports training, performance, and technical education. Unlike conventional lecture-based courses, these programs depend heavily on limited physical resources, specialized instructors, equipment, and repeated opportunities for hands-on practice. A single course may involve several linked stages, such as demonstration, supervised practice, independent practice, assessment, and feedback, with each stage requiring different combinations of rooms, staff, equipment, and time. When these resources are poorly coordinated, students may face long waiting periods, unavailable equipment, overlapping bookings, or interruptions between related learning activities. Such problems affect not only administrative efficiency but also the quality and fairness of learning opportunities. Recent research on public art education has emphasized that the evaluation of educational provision should connect teaching quality with educational equity rather than rely only on participation or service outputs [1]. This perspective is particularly relevant to practice-based higher education, where access to rooms, equipment, instructors, and repeated practice opportunities may directly influence what students are able to learn and how consistently they can participate. Resource coordination is therefore closely related to both academic scheduling and educational access. Studies of professional and skills-based training have shown that students, instructors, facilities, and available time slots need to be considered jointly rather than scheduled as separate resources [2,3]. The temporal structure of a timetable can also affect student behavior. Long gaps between classes, isolated single-class days, early or late sessions, and poorly positioned practical activities may reduce attendance and weaken study continuity [4,5]. These effects can be especially important in practice-based programs because many learning tasks have a sequential structure. Missing an introductory laboratory, rehearsal, simulation, or supervised practice session may prevent a student from completing subsequent activities at the expected time. Scheduling decisions can therefore influence not only room utilization but also course progression, learner participation, and the distribution of educational opportunities [6].

University timetabling is commonly formulated as an optimization problem in which courses or activities are assigned to rooms, instructors, student groups, and time periods under a set of hard and soft constraints. Hard constraints usually represent conditions that cannot be violated, such as room capacity, instructor availability, or simultaneous use of the same facility. Soft constraints represent desirable scheduling characteristics, including preferred teaching times, balanced workloads, limited student idle time, or reduced movement between locations [7,8]. Mixed-integer linear programming has been widely used because it can formally represent room restrictions, staff availability, teaching workload, and scheduling preferences within a unified mathematical framework [9,10]. Such models are particularly useful when constraints are clearly defined and the size of the scheduling problem remains computationally manageable. As institutional scheduling problems become larger, researchers have increasingly combined exact optimization with heuristic and metaheuristic methods [11,12]. Graph-coloring approaches, tabu search, and section-planning strategies have been applied to reduce timetable conflicts and improve the use of teaching rooms and staff resources. Other studies have extended traditional timetabling models by incorporating student preferences, fairness considerations, hybrid teaching arrangements, historical course patterns, and alternative section structures [13,14]. These developments indicate that scheduling quality cannot be represented adequately by conflict counts alone. A timetable may satisfy all formal constraints while still producing long student waiting periods, uneven instructor workloads, fragmented course sequences, or unequal access to desirable sessions. Genetic algorithms and local-search methods have also been used when exact mathematical optimization becomes computationally expensive for large-scale scheduling problems [15,16]. Their advantage lies in the ability to explore large solution spaces and generate high-quality schedules without requiring complete enumeration of feasible combinations [17,18]. However, their results may depend on parameter settings, encoding strategies, mutation rules, and stopping conditions. More recently, reinforcement learning has been introduced into timetable adjustment and educational resource allocation because it can learn scheduling policies through repeated interaction with changing system conditions [19,20]. This approach is potentially useful for environments in which room availability, instructor schedules, student demand, or equipment conditions change after the original timetable has been produced [21,22]. Nevertheless, the practical value of reinforcement learning for practice-based education remains insufficiently examined, particularly when dynamic adjustments must preserve course continuity and avoid excessive changes to previously confirmed schedules. Despite substantial progress in university timetabling research, most existing models are designed around lectures, examinations, or standard classroom allocation. Room characteristics are often represented mainly through seating capacity, while specialized requirements such as laboratory type, studio configuration, machine availability, simulation equipment, rehearsal space, or preparation conditions receive less attention. Practice-based teaching introduces additional constraints that differ from those of conventional classroom scheduling. Equipment may need to be shared across courses, rooms may require setup and reset periods, instructors may supervise only a limited number of students at one time, and some activities must be repeated in several small groups [23,24]. Students may also request additional practice outside formally scheduled classes. These characteristics create dependencies among teaching sessions that are difficult to capture using conventional course-room-time assignment models. Another limitation concerns the data used to construct and evaluate scheduling systems. Many studies rely on records from a single institution and assess performance primarily through objective-function values, constraint penalties, or computation time. These indicators are useful for comparing algorithms, but they provide limited evidence about how a schedule affects actual resource use or student learning conditions. Course timetables alone cannot show whether reserved rooms were actually used, whether equipment remained unavailable, whether students were required to wait for practice opportunities, or whether instructors experienced highly uneven workloads. Operational data such as room-use logs, equipment reservations, instructor availability records, and student practice requests can provide a more realistic description of the scheduling environment. Linking these data sources also makes it possible to distinguish between nominal resource allocation and actual resource utilization. Schedule stability is another important issue. Many optimization models assume that demand, staffing, equipment, and room availability remain unchanged after a timetable is generated. In practice, this assumption is rarely satisfied. Instructor absence, equipment failure, temporary room closure, changes in student enrollment, additional practice requests, and adjustments to teaching progress may all require modifications during a semester. Frequent timetable changes can solve immediate conflicts but may create new costs for students and staff. Students may need to rearrange transportation, employment, or other courses, while instructors may lose preparation time or face unbalanced teaching loads. A useful scheduling system for practice-based education should therefore not only generate an efficient initial timetable but also respond to disruptions while limiting unnecessary changes to existing arrangements.

The present study addresses these limitations through a multi-institutional analysis of scheduling and resource allocation in practice-based higher education. Data are collected from 25 practice-based programs across eight universities over two semesters, providing a broader empirical basis than single-institution case studies. The dataset contains approximately 18,000 course bookings, 6,500 room-use records, 4,200 instructor availability records, 3,800 equipment reservations, and 12,000 student practice requests. These data allow the scheduling problem to be examined from both planned and actual resource-use perspectives. Mixed-integer programming, genetic algorithms, constraint-satisfaction methods, and reinforcement-learning approaches are evaluated under the same resource conditions and constraint structure. Rather than comparing the models only through computation time or mathematical penalty values, the study assesses room and equipment utilization, scheduling conflicts, student waiting time, instructor workload balance, schedule stability, course continuity, learner satisfaction, and access equity. Particular attention is given to whether improvements in institutional efficiency are accompanied by more consistent access to practice opportunities across student groups. Through this design, the study aims to establish a more comprehensive framework for evaluating practice-based scheduling, identify which optimization approaches are most suitable under static and changing resource conditions, and provide evidence for moving university scheduling from experience-based manual adjustment toward data-informed resource planning. The broader significance of the study lies in treating scheduling not simply as an administrative problem, but as a mechanism that can influence teaching continuity, resource efficiency, student experience, and equitable access to practice-based learning.

Materials and Methods

Diverse approaches to safeguarding private data may be used in different jurisdictions. China and the EU are both World Trade Organisation (WTO) members, and as such, they are obligated to abide by the rules of WTO treaties, such as the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPs). Since this agreement allows its member governments to protect patents, several of its provisions are introduced in this section.

Study Sample and Institutional Settings

The study covered 25 practice-based programs from eight universities over two academic semesters. The programs included studio art, design, engineering laboratories, health simulation, sports training, performance, and technical practice. Stratified sampling was used to include universities of different sizes and programs with different room and equipment needs. The dataset contained about 18,000 course bookings, 6,500 room-use records, 4,200 instructor availability records, 3,800 equipment reservations, and 12,000 student practice requests. The records included class size, session length, room type, equipment needs, instructor skills, student availability, repeated practice needs, and schedule changes. Programs were included only when complete booking and resource records were available for both semesters.

Scheduling Design and Comparison Scenarios

Four scheduling methods were compared. The control method used the original schedules prepared by program staff. The first test method used mixed-integer linear programming to assign rooms, instructors, equipment, and practice sessions. The second used a genetic algorithm to reduce conflicts and improve resource use. The third combined constraint satisfaction with reinforcement learning to adjust schedules after instructor absence, equipment failure, or new student requests. All methods used the same course demand and resource limits. Hard constraints prevented double booking, room mismatch, instructor overlap, and equipment conflicts. Soft constraints covered preferred teaching times, balanced workloads, shorter waiting times, and stable weekly schedules. This design allowed the four methods to be tested under the same conditions.

Measures and Data Quality Control

Schedule quality was measured through room occupancy, equipment use, booking conflicts, student waiting time, instructor workload balance, schedule changes, course continuity, learner satisfaction, and access equity. Room occupancy was calculated as actual use time divided by available time. Equipment use was measured from confirmed reservation hours. A conflict was recorded when two activities required the same room, instructor, or equipment at the same time. Student waiting time was defined as the number of days between a practice request and the assigned session. The data were checked for missing fields, duplicate bookings, invalid time ranges, and inconsistent room codes. Records with unresolved errors were removed. Ten percent of the records were checked against the original booking files. Learner satisfaction was measured with a five-point survey after each semester.

Data Processing and Optimization Models

All records were converted into a common format and linked through coded course, room, instructor, equipment, and student numbers. Missing values below 5% were replaced with values from related records or program averages. The main scheduling objective was defined as:

$$\min Z = \alpha C + \beta W + \gamma V + \delta S$$

where C is the number of booking conflicts, W is mean student waiting time, V is instructor workload variance, and S is the number of schedule changes. The weights α, β, γ, and δ were set through expert review and sensitivity tests. Student access equity was measured as:

$$AE = 1 - \frac{\sum_{i=1}^{n} |p_i - \bar{p}|}{2n\bar{p}}$$

where p_i is the number of assigned practice sessions for student i, and $\bar{p}$ is the mean number of assigned sessions. Higher values indicate a more equal distribution of practice opportunities.

Model Testing and Robustness Analysis

First-semester data were used to develop the models, and second-semester data were used for testing. Each scheduling method was run 30 times under the same demand and resource conditions. Mean values and standard deviations were reported for all measures. Paired tests were used to compare each test method with manual scheduling. Robustness was examined under four conditions: a 10% rise in student requests, a 15% fall in room availability, instructor absence, and temporary equipment failure. Schedule stability was measured by the number of assignments changed after each disruption. Program managers reviewed schedules that met the formal rules but did not fit practical teaching needs. All student and instructor records were anonymized before analysis. Ethical approval was obtained before data collection.

Results and Discussion

Data Quality and Scheduling Feasibility

After data cleaning, the final dataset included 17,642 course bookings, 6,318 room-use records, 4,086 instructor availability records, 3,694 equipment reservations, and 11,736 student practice requests. About 2.3% of the original records were removed because of missing resource codes, invalid time ranges, or duplicate bookings. All four scheduling methods were tested with the same course demand and resource limits. Manual scheduling produced a conflict rate of 4.8%, mainly because of room overlap, instructor changes, and late equipment requests. The conflict rate decreased to 1.3% with mixed-integer linear programming, 0.9% with the genetic algorithm, and 0.6% with the constraint and reinforcement learning model. All intelligent methods met the main hard constraints when the first schedule was created. Most remaining conflicts appeared after changes in instructor or equipment availability [25]. Ivanov et al. (2025) also found that mixed-integer programming could produce workable schedules for large university datasets. Their study focused on classes, students, rooms, and time slots, while the present study also included equipment and repeated practice requests.

Resource Use and Model Performance

Manual scheduling produced a mean room occupancy rate of 58.7% and an equipment use rate of 54.1%. Mixed-integer linear programming increased these rates to 70.8% and 67.3%, respectively. The genetic algorithm reached 73.5% room occupancy and 70.1% equipment use. The reinforcement learning model reached 72.9% and 71.5%. The genetic algorithm performed best when all demand data were available before scheduling. The reinforcement learning model produced similar resource use but responded faster when new requests were added [26,27]. Its objective value improved quickly during the first 120 training episodes and then remained stable, as shown in Fig. 1. Yao and Lin (2026) also found that a genetic scheduling method improved schedule quality and reduced classroom use. The present study found a similar pattern but included more resource types and repeated practice needs.

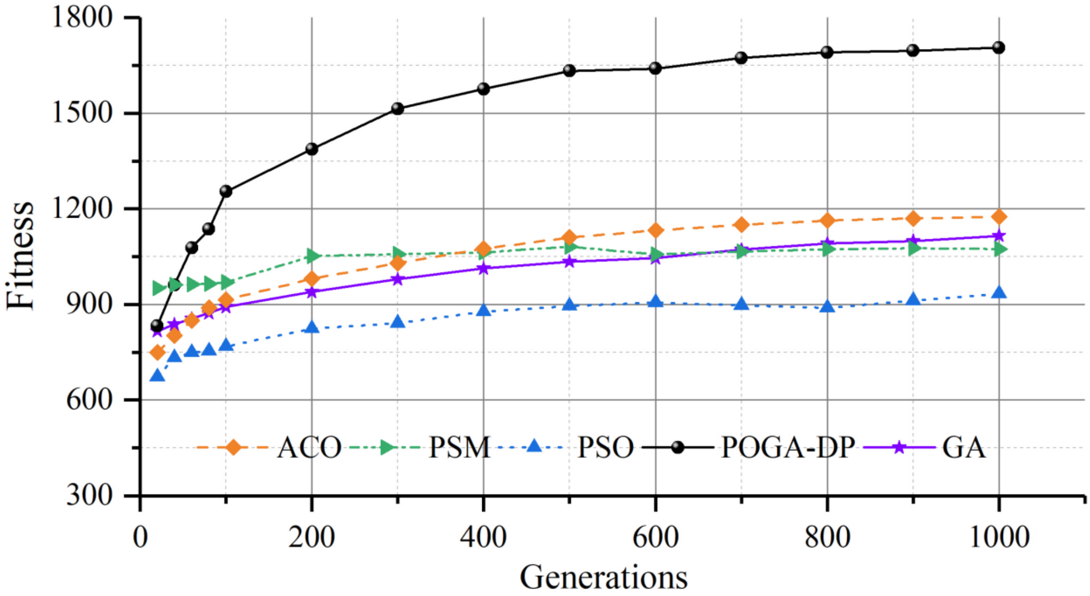

Fig. 1. Performance of the four scheduling methods during training.

Waiting Time Workload Balance and Access Equity

Mean student waiting time was 6.8 days under manual scheduling. It fell to 4.1 days with mixed-integer linear programming, 3.6 days with the genetic algorithm, and 3.2 days with reinforcement learning. The largest reductions were found in health simulation, performance, and technical practice programs, where students needed both specialist rooms and limited equipment. Instructor workload variance also fell from 0.31 under manual scheduling to 0.22, 0.18, and 0.17 under the three intelligent methods. The access equity score increased from 0.78 to 0.87 with mixed-integer linear programming, 0.89 with the genetic algorithm, and 0.91 with reinforcement learning. These results show that higher resource use did not reduce fair access to practice sessions. The models improved both efficiency and access because waiting time and workload balance were included in the objective function [28,29]. Choppara and Kotteswari (2025) also linked university planning with individual student timetables and preferences. The present study extends this approach by adding equipment limits, practice requests, and repeated sessions.

Schedule Stability and Learning Outcomes

The four methods were tested under a 10% increase in student requests, a 15% reduction in room availability, instructor absence, and temporary equipment failure. Manual schedules required changes to 24.7% of assigned sessions. The change rate fell to 18.6% with mixed-integer linear programming, 14.2% with the genetic algorithm, and 8.7% with reinforcement learning. The reinforcement learning model kept most earlier assignments and changed only the affected rooms, time slots, or equipment bookings. The rescheduling process is shown in Fig. 2. Course completion continuity increased from 88.6% under manual scheduling to 95.2% under reinforcement learning. Mean learner satisfaction also increased from 3.42 to 4.08 on the five-point scale. Students reported fewer delays and more regular access to practice sessions. However, some program managers noted that several schedules met the formal rules but did not fully match the teaching order of certain courses. Human review was therefore still needed before use [30]. Wu et al. (2026) also showed that university scheduling should consider changing teaching modes, student demand, room suitability, and travel conditions. The present study adds dynamic equipment and practice limits, although the observation period covered only two semesters.

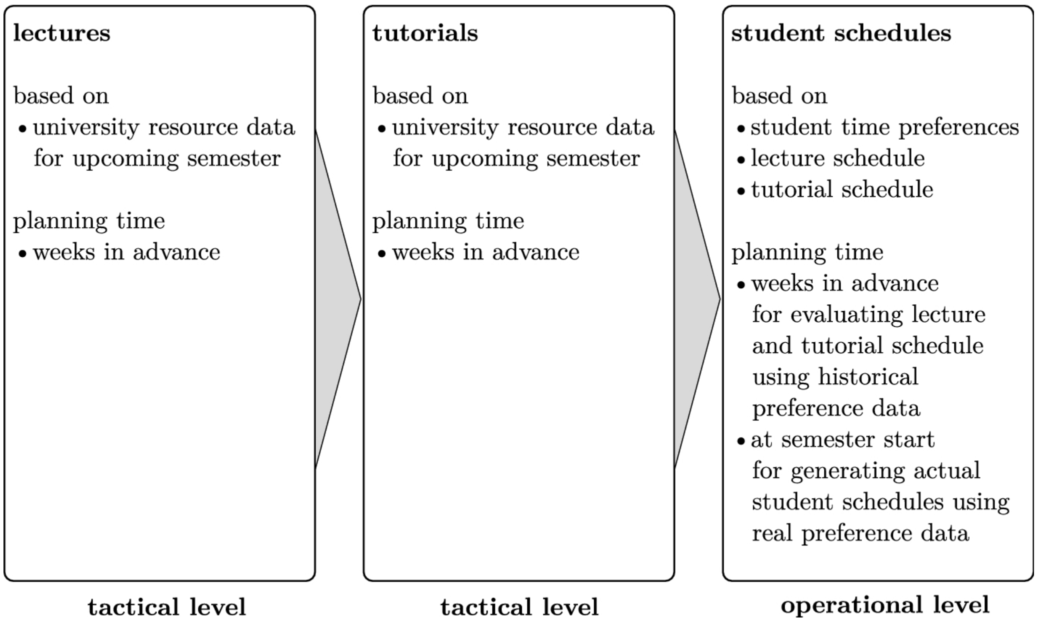

Fig. 2. Resource allocation and schedule revision in practice-based programs.

CONCLUSION

This study found that intelligent scheduling improved room and equipment use, reduced booking conflicts, shortened student waiting time, balanced instructor workloads, and increased access to practice sessions. The reinforcement learning model performed best when room, staff, equipment, or student demand changed during the semester. The genetic algorithm performed well when scheduling conditions were known in advance. Intelligent scheduling also improved course continuity and learner satisfaction. The main contribution of this study is the joint scheduling of specialist rooms, instructors, equipment, and repeated practice sessions across several universities. This method links resource planning with student access and learning continuity instead of focusing only on timetable conflicts. It may help universities manage laboratories, studios, simulation rooms, and other limited resources more fairly and efficiently. However, the study covered only two semesters, and some generated schedules did not fully match the teaching order of certain courses. Future studies should use longer datasets, include more sudden changes in resource demand, and keep staff review before schedules are used.

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ETHICAL DECLARATION

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