

Evaluating the computational and organizational complexity of university course timetabling using multi-semester operational data

Dorota Borkowska¹, Anna Gładysz^{1*}

¹ Department of Computer Engineering in Management, Rzeszow University of Technology, Al. Powstańców Warszawy 12, 35-029 Rzeszów, Poland

* Corresponding author's e-mail: anna.gladysz@prz.edu.pl

ABSTRACT

Creating course schedules at a university is a complex combinatorial optimization problem in which teaching activities must be assigned to available time slots and resources while satisfying organizational, spatial, and instructional constraints. This study presented an empirical analysis of a periodically conducted department-level timetabling process supported by an integrated environment developed by the authors. The environment covers the full planning cycle: automatic acquisition and standardization of data from dean's office systems, preparation of input data and constraints, timetable generation using dedicated software, publication of final schedules, and analysis of process data. The empirical material covered eight consecutive semesters and thirty repeated generation runs for each semester instance. Normalized indicators were used to compare instances of different scale, including constraint density, generation time per constraint, generation efficiency, and post-generation adjustment effort. Across the analyzed period, 39,977 constraint records were processed, of which 75.74% were time constraints. Manual adjustments decreased from 154 to 52, while the adjustment rate fell from 9.90% to 3.04%. The results indicate that instance size alone does not explain the practical difficulty of timetable generation. Constraint structure, generation-time stability, and post-generation correction effort provide complementary information for assessing academic timetabling complexity under real organizational conditions. The observed reduction in manual adjustments is consistent with the improved process control, although the available data do not allow the observed trend to be attributed solely to the integrated environment.

Keywords: university course timetabling, academic scheduling, constraint density, timetable generation, manual adjustments, information systems.

INTRODUCTION

Course scheduling at universities is a classical educational timetabling problem and belongs to the class of complex combinatorial optimization problems. It involves assigning teaching activities to available time slots and resources, such as instructors, student groups, and classrooms, while satisfying the organizational, infrastructural, and pedagogical constraints [1]. A feasible timetable must avoid conflicts between instructors, student groups, and rooms. However, a practically acceptable timetable should also take into account soft

constraints, including instructor preferences, the distribution of classes throughout the week, the reduction of gaps, and the avoidance of undesirable time slots [2,3].

University course timetabling has been widely studied using heuristic, metaheuristic, exact, and mathematical optimization approaches. Heuristic and metaheuristic methods are commonly applied to generate feasible and high-quality timetables under complex constraint conditions [4,5]. Exact approaches, including post-enrollment course timetabling models and mixed-integer programming formulations, constitute another important

research direction, offering effective representations of complex institutional constraints and resource allocation problems [6,9]. Recent studies have further extended these formulations to accommodate the emerging organizational requirements, demonstrating the continuing evolution of university timetabling models toward increasingly realistic planning environments [10].

While heuristic and metaheuristic methods primarily aim to generate high-quality feasible timetables within acceptable computational time, exact and mathematical programming approaches emphasize optimality and rigorous constraint representation, although their applicability may become limited for highly constrained real-world instances. In contrast, the studies addressing practical university timetabling focus on organizational aspects, data preparation, institutional requirements, and user acceptance, thereby extending the problem beyond algorithmic optimization alone.

Despite these methodological developments, real-world university timetabling problems remain highly institution-specific. Their difficulty depends not only on the number of activities, instructors, student groups, or classrooms, but also on the structure of study programs, the organization of the academic week, local scheduling rules, as well as the availability and quality of input data [10]. Practical timetabling also differs from simplified benchmark settings because the final timetable must be accepted by multiple users and may require adjustments resulting from local organizational conditions, user preferences, and changes occurring during timetable preparation [11]. Recent research also highlights that university timetabling models continue to evolve in response to changing institutional requirements, emphasizing the need to represent practical organizational constraints within optimization models [10].

For this reason, the practical difficulty of academic timetabling should not be evaluated only as an algorithmic problem of generating a feasible schedule. Under real university conditions, timetable generation is one stage of a broader operational process that includes data acquisition, constraint preparation, automatic generation, verification, manual adjustments, and publication. Consequently, generation time alone may be insufficient to assess the effectiveness of the scheduling process. Additional indicators are needed to describe constraint structure, generation-time stability, and the amount of

post-generation intervention required before the timetable can be used in practice.

This study analyzed a recurring department-level course timetabling process supported by an integrated environment developed by the authors. The empirical material covered eight consecutive semesters and included the data describing the scale of the teaching process, the structure of time and spatial constraints, repeated timetable generation times, and the number of manual adjustments made after automatic generation. The study focused on the operational evaluation of the timetabling process, rather than on comparing optimization algorithms.

The methodology used to prepare scheduling data, standardize the information obtained from administrative systems, and transform institution-specific organizational rules into the scheduling model was described in previous studies [13,15]. Differences in organizational structures, study regulations, curricula, and scheduling policies were addressed during the data preparation and constraint-definition stages preceding timetable generation. In contrast, the framework proposed in this study focused on evaluating the scheduling process itself through normalized indicators derived from generic process characteristics. Consequently, the proposed measures are independent of a specific organizational structure and may be applied in different higher education institutions, provided that local organizational requirements are appropriately represented during the preparation of scheduling data. Nevertheless, additional validation across multiple universities remains an important direction for future research.

The aim of the article was to assess whether the practical difficulty of university course timetabling can be explained by instance size alone or whether it requires additional indicators describing constraint concentration, generation efficiency, generation-time stability, and post-generation adjustment effort. The study addressed the following research questions:

- RQ1: To what extent do basic scale indicators, such as the number of teaching hours, class units, instructors, and student groups, explain timetable generation time?
- RQ2: Does constraint density provide useful diagnostic information about post-generation adjustment effort?
- RQ3: How do winter and summer semester instances differ in terms of computational and organizational indicators?

The scientific contribution of this study lies in the empirical assessment of university course timetabling as a real-world socio-technical process, rather than solely as an algorithmic optimization task. The article combined computational indicators, such as generation time, generation efficiency, and time cost per constraint, with organizational indicators, such as the number and rate of manual adjustments required after automatic timetable generation. This process-oriented perspective provided a framework for monitoring academic timetabling complexity across semester instances of different scales.

MATERIALS AND METHODS

This section describes the organization of the scheduling process under study, the scope of the empirical data, and the method used to calculate the indicators employed in the analysis. The study is a case study and focuses on the actual process of preparing semester-long course schedules at the level of a single college department.

The subject of this study is the real-world problem of scheduling classes, which is addressed on a recurring basis at the level of a single college department. This process involves preparing a semester-long course schedule for full-time undergraduate and graduate programs, taking into account several fields of study, student groups, instructors, course units, as well as organizational and spatial constraints. In terms of terminology, the issue under analysis falls within the field of university course timetabling, i.e., the problems related to assigning classes to available time slots and resources while adhering to a specific set of constraints [12].

The process under analysis involves preparing class schedules for first- and second-cycle degree programs conducted in a full-time format. Scheduling takes place within a fixed structure of the academic week, divided into eight class blocks and taking into account classes held on a weekly and biweekly basis. Consequently, the scheduling process requires the simultaneous consideration of two overlapping time structures, which can affect both the feasibility of finding a valid solution and the quality of the final schedule.

The constraints considered in the analyzed scheduling process are classified according to their functional role as either hard or soft constraints. Hard constraints define the conditions that must

always be satisfied for a timetable to be feasible and therefore cannot be violated during schedule generation. Soft constraints represent organizational preferences and quality requirements that improve timetable usability but may be relaxed if necessary to obtain a feasible solution. This distinction was introduced to describe the scheduling model used in the analyzed process. Since the objective of this study was the evaluation of the scheduling process rather than the computational impact of individual constraint types, no weighting scheme is assigned to particular constraints and all recorded constraint instances are treated uniformly in the proposed indicators. The most important ones include:

- a prohibition on the same instructor teaching multiple classes simultaneously,
- the prohibition against assigning a single group of students to multiple classes at the same time,
- the prohibition against booking the same classroom multiple times,
- classroom capacity limits and restrictions resulting from specialized classroom equipment.

Soft constraints relate to the quality of the schedule and the convenience of its users. In the process under study, they include, among others:

- instructors' preferences regarding the days and times of classes,
- limiting the number of time slots for students and instructors,
- an even distribution of classes throughout the week,
- minimizing the number of classes held in the evening,
- the ability to provide days off from classes for student groups or instructors.

The examples listed above illustrate the principal categories of hard and soft constraints considered in the analyzed scheduling process. They are intended to explain the operational characteristics of the scheduling model, rather than to provide an exhaustive taxonomy of constraint types. Since the objective of this work was the evaluation of the scheduling process, all constraint records were treated equally in the subsequent analyses, without differentiating their relative computational importance.

The distinction between generic benchmark constraints and institution-specific operational

requirements is consistent with the recent developments in university course timetabling, where optimization models increasingly incorporate practical organizational features to better reflect real-world scheduling processes [7,8].

In actual university practice, course scheduling is rarely a one-time computational task. It is an iterative process that involves preparing input data, defining constraints, generating a schedule, evaluating the resulting solution, and making adjustments based on organizational considerations. The literature emphasizes that practical course timetabling problems differ from simplified test models, because they require consideration of local scheduling rules, resource availability, user preferences, and the changes that arise during the timetable preparation process [11,12].

For this reason, in the case under analysis, particular importance was attached not only to the very fact that a schedule was generated, but also to the subsequent corrective effort. The number of manual adjustments was treated as an indicator of the practical difficulty of the scheduling process, as it reflects the extent of intervention required after the automatic generation was completed. A manual adjustment was defined as a single recorded change affecting one activity unit after the schedule was automatically generated. This approach allows scheduling to be analyzed as a combination of a computational problem and an organizational process, rather than solely as an optimization task reduced to finding a feasible solution.

For the purposes of the empirical analysis, the recorded constraint instances were additionally classified according to the scheduling aspect to which they refer, namely time constraints and spatial constraints. This classification is independent of the distinction between hard and soft constraints described above. Time constraints refer to the conditions related to scheduling activities within specific time slots, whereas spatial constraints concern the assignment of activities to appropriate rooms and locations. Consequently, the reported numbers of time and spatial constraints represent aggregated counts of all recorded constraint instances, irrespective of whether they correspond to hard or soft scheduling requirements.

The collected dataset does not include complete information on room types, room capacities, class types, or all individual preferences of instructors. Therefore, the study does not aim to develop a complete optimization model of the timetabling problem, but rather to provide an

empirical evaluation of the scheduling process based on comparable semester-level indicators.

The FET program was used to generate schedules as part of an integrated process for preparing class schedules [13,14]. During the practical use of the FET program in the course planning process, it was observed that one of its greatest strengths is its ability to adapt to unusual and complex planning situations that frequently arise in the day-to-day operations of a university [15]. The integrated timetable creation process consists of six stages: data collection, data entry, creation of course units, schedule generation, manual adjustments, and timetable publication (Figure 1).

A key element of the system was the development of dedicated tools to automate the extraction of data from dean's office systems and its conversion to the XML format used by FET [13,15]. This allowed for the automatic generation of class structures, student groups, classroom resources, and scheduling constraints without the need for manual data entry. This solution significantly reduced the risk of organizational errors and enabled the standardization of the input data preparation process. The actual scheduling process was carried out by the FET calculation engine, which uses heuristic algorithms and constraint programming mechanisms.

The system made it possible to account for both hard and soft constraints resulting from the organizational specifics of the department under analysis. The next stage of the process was the automation of the post-processing phase and the publication of schedules. The scripts developed enabled the immediate conversion of the results generated by FET into the formats compatible with the department's web platforms and systems for sharing schedules with students and staff. Despite the high degree of process automation, the specific nature of the analyzed department—which includes a large number of class groups along with a significant number of scheduling constraints—means that manual adjustments to the generated schedule are required. These adjustments constitute a validation step that takes place after the schedule is automatically generated and before it is published. If inconsistencies are detected or organizational adjustments are needed, the adjustment may require updating the input data or regenerating the schedule. The data sources were input files and the schedule generation results obtained from the FET program. The

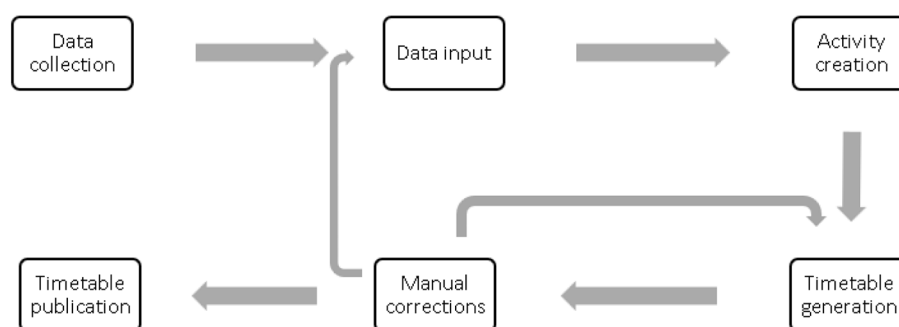


Figure 1. The diagram of the integrated process for creating course schedules

empirical data covered eight consecutive semesters (Table 1).

For each semester, the following data were recorded: the number of hours in the schedule, the number of student groups, the number of instructors, the number of class units, the number of time constraints, the number of space constraints, the minimum, maximum, and average generation times, and the number of manual adjustments.

Based on the source data, indicators describing the scale of the problem, the structure of the

constraints, the generation time, and the adjustment effort were calculated (Table 2). The variables presented in Table 2 were not assigned equal weights and were not aggregated into a single composite complexity index. Instead, they represented complementary dimensions of the timetabling process. Teaching hours, class units, student groups, and instructors described the organizational scale of the semester instance; time and spatial constraints characterized its constraint structure; generation-time variables

Table 1. The division of the analyzed academic cycles into semesters

Semester code	Academic year	Semester	Designation
S1	2022–2023	Winter (W)	2022/2023 W
S2	2022–2023	Summer (S)	2022/2023 S
S3	2023–2024	Winter (W)	2023/2024 W
S4	2023–2024	Summer (S)	2023/2024 S
S5	2024–2025	Winter (W)	2024/2025 W
S6	2024–2025	Summer (S)	2024/2025 S
S7	2025–2026	Winter (W)	2025/2026 W
S8	2025–2026	Summer (S)	2025/2026 S

Table 2. Source variables and their interpretation

Symbol	Indicator name	Interpretation
H	Number of teaching hours	Volume of the teaching process
N	Number of classes (scheduling units)	Number of units requiring scheduling
G	Number of groups	Scale of student group organization in a given semester
L	Number of instructors	Scale of staff resources
C	Scheduling constraints	Total number of time and space constraints
C_T	Time constraints	Number of time-related conditions
C_S	Space constraints	Number of conditions related to the location of classes
M	Number of manual adjustments	Number of interventions after the schedule is generated
T_{min} [s]	Minimum generation time	Shortest recorded generation time
T_{max} [s]	Maximum generation time	Longest recorded generation time
T_{avg} [s]	Average generation time	Typical generation time

described computational performance and stability; and manual adjustments represented post-generation organizational effort. For each analyzed semester, thirty repeated generation runs were performed using the same set of input data and the same time and space constraints. All thirty generation attempts for each semester resulted in a valid schedule. Due to the heuristic nature of the FET program's algorithm, the time required to generate a schedule may vary between attempts, which is why multiple measurements were necessary. The research was conducted using a computer equipped with an 11th Gen Intel® Core™ i7-1165G7 processor with a clock speed of 2.80 GHz, 40.0 GB of RAM, and a 64-bit operating system for the x64 architecture. For each semester, the following were determined:

- T_{min} – minimum time required to generate a plan,
- T_{max} – maximum time to generate a plan,
- T_{avg} – average time to generate a plan,

The median generation time and the standard deviation were additionally calculated to describe the stability of the timetable generation process across repeated runs. The median was used as a measure less sensitive to single extreme values than the arithmetic mean, while the standard deviation provided information on the variability of generation time for the same semester-level scheduling instance. These descriptive statistics were not used for formal hypothesis testing, but they supplemented the assessment of generation-time stability under comparable input-data and constraint conditions.

In addition, the number of time constraints (C_T) and space constraints (C_S) introduced in each semester was compiled. The results obtained made it possible to assess the relationship between the complexity of the scheduling problem and the efficiency of the schedule generation process.

The analyzed set of constraints consisted of a basic set of initial conditions developed by the authors based on many years of experience in organizing and scheduling classes. The defined set of constraints was implemented each time prior to the first schedule generation process for each of the analyzed semesters, ensuring consistency in the research conditions and comparability of the results obtained. The basic constraints taken into account in the planning process included:

Time constraints:

- A teacher's not available times
- Max days per week for a teacher
- Max gaps per day for a teacher

- Max gaps per week for a teacher
- Max hours daily for a teacher
- A students set's not available times
- An activity has a preferred starting time
- An activity has a set of preferred starting times
- Min days between a set of activities
- Max days between a set of activities
- A set of activities has the same starting hour.

Two activities are ordered

- space constraints:
- A subject has a set of preferred rooms
- A subject has a set of preferred rooms
- A subject has a preferred room.

The list includes the types of constraints used in the FET system, and their specific number varied from semester to semester. The introduction of these constraints was intended to ensure that basic organizational conditions were met as early as the initialization stage of the scheduling process, thereby improving the quality of the generated schedules, enhancing the working conditions of faculty members, and reducing the excessive number of breaks between classes.

To evaluate the efficiency of the scheduling process, an analysis was conducted of the time required to generate class schedules for a basic set of initial constraints. Adopting a uniform set of initial conditions for all analyzed semesters ensured that the results obtained were comparable.

For the purposes of this analysis, a single scheduling constraint was defined as a single constraint record stored in the input data of the FET program. This means that the number of constraints does not refer solely to the number of constraint types, but to the number of their specific instances assigned to instructors, groups, classes, rooms, or time slots in a given semester.

To describe the complexity of an instance, a constraint density index, denoted as D_C , was used. This index expresses the ratio of the total number of temporal and spatial constraints to the number of class units in a given semester:

$$C = C_T + C_S \quad (1)$$

$$D_C = \frac{C_T + C_S}{N} \quad (2)$$

where: C denotes the total number of scheduling constraints, C_T denotes the number of time constraints, C_S denotes the number of spatial constraints, and N denotes the number of class units.

The value of the D_c index indicates the average number of constraints per class. In practical terms, higher values indicate that each scheduled activity is subject to a greater number of organizational restrictions, which generally reflects a more constrained scheduling environment, although not necessarily a more computationally difficult instance.

The manual adjustment rate is denoted as MR . It represents the proportion of class units that required manual intervention after the schedule was automatically generated. The indicator is calculated as the ratio of the number of manual adjustments, M , to the number of class units, N :

$$MR = \frac{M}{N} \quad (3)$$

The MR value allows for a comparison of the adjustment workload between semesters with different numbers of classes.

The average generation efficiency is denoted as E_{avg} . This metric defines the average number of class units generated per unit of time. If the average generation time T_{avg} is expressed in seconds, the metric is calculated using the following formula:

$$E_{avg} = \frac{N}{T_{avg}} \quad (4)$$

where: N denotes the number of course units, and T_{avg} denotes the average schedule generation time expressed in seconds.

The E_{avg} metric allows for a comparison of the efficiency of the generation process between

semesters of different scales. Intuitively, this indicator represents the throughput of the scheduling process, that is, the average number of activity units generated per second. Higher values correspond to greater generation efficiency.

To conduct an in-depth assessment of the effectiveness of the implemented solution, an algorithmic cost indicator E_a was introduced, defined as the average schedule generation time per individual planning constraint:

$$E_a = \frac{T_{avg}}{C} \times 1000 \quad (5)$$

where: T_{avg} denotes the average time required to generate a schedule, and C denotes the total number of temporal and spatial constraints.

The result is expressed in ms/constraint. This metric allows for a comparative assessment of the normalized time cost of generating a schedule relative to the number of scheduling constraints in the analyzed semester instances. From an operational perspective, E_a can be interpreted as the average computational effort associated with processing a single recorded constraint.

Lower values indicate that schedules are generated more efficiently relative to the number of constraints considered. In this study, the E_a indicator was adopted as an auxiliary measure of the normalized time cost of generating a schedule relative to the number of scheduling constraints. This approach allows for the comparison of instances

Table 3. Normalized ratios and formulas

Symbol	Indicator name	Formula	Interpretation
C	Total number of constraints	$C = C_T + C_S$	Total number of constraints
D_c	Constraint density	$D_c = \frac{C_T + C_S}{N}$	Average number of constraints per activity unit
S_T	Share of time constraints	$S_T = \frac{C_T}{C_T + C_S}$	Proportion of constraints related to time availability and scheduling
S_S	Share of spatial constraints	$S_S = \frac{C_S}{C_T + C_S}$	Proportion of constraints related to room assignment and spatial availability
E_a	Algorithmic cost per constraint	$E_a = \frac{T_{avg}}{C} \times 1000$	Average generation time per individual scheduling constraint
MR	Manual adjustment rate	$MR = \frac{M}{N}$	Proportion of activity units requiring post-generation adjustment
$M/1000H$	Adjustments per 1.000 teaching hours	$\frac{M}{H} \times 1000$	Normalized measure of post-generation adjustment effort
E_{avg}	Average generation efficiency	$\frac{N}{T_{avg}}$	Number of activity units generated per generation time
T_{1000}	Time per 1.000 activity units	$\frac{T_{avg}}{N} \times 1000$	Generation time normalized by the number of activity units

that differ in the number of constraints and complements the classical analysis of generation time. The normalized indices made it possible to compare semesters that differ in the number of courses and the volume of instructional hours (Table 3).

The proposed indicators were designed as normalized process measures and are not directly dependent on a specific university organizational structure. Institution-specific characteristics, including curricula, study regulations, organizational units, and scheduling policies, are incorporated during the data preparation and constraint-definition stages preceding timetable generation. Once these requirements are represented as scheduling activities and constraint records, the proposed indicators can be calculated using the same definitions. Their primary purpose is to support longitudinal monitoring within an institution and comparative analyses across institutions, provided that consistent definitions of scheduling activities, constraints, and manual adjustments are applied.

The D_C and MR indicators are unweighted diagnostic measures. In the calculation of D_C , each constraint is treated as a single recorded constraint, although different constraint types may influence timetable generation to different degrees. Given the complexity of the scheduling problem, all constraint records were treated uniformly, rather than assigned subjective weights. Similarly, MR measures the frequency of post-generation interventions without distinguishing their severity or organizational impact. The constant of 1.000 used in T_{1000} is solely a scaling factor selected to improve the readability of the results and has no influence on the comparisons or conclusions.

The schedule generation time was recorded for thirty runs of the FET program performed for each semester. For each semester instance, the minimum generation time T_{min} , the maximum generation time T_{max} , and the average generation time T_{avg} were calculated. Only the runs that resulted in a valid schedule were included in the analysis. All analyzed semesters were generated in a comparable software and hardware environment, using the same version of the FET program and the same method of preparing the input data.

The metrics T_{1000} and E_{avg} describe the same aspect of the generation process from two perspectives: T_{1000} indicates the time per 1.000 class units, while E_{avg} indicates the number of units generated per second.

A manual adjustment was defined as a single recorded change affecting a single class unit, made after the schedule was automatically generated. The adjustment could involve a change in the date, room, class size, or any other element requiring organizational adjustments. The number of manual adjustments (M) was used as an indicator of the workload following the completion of the automatic schedule generation.

Particular importance in the analysis was assigned to time and space constraints. Time constraints refer to the conditions related to the possibility of scheduling specific classes within particular time slots. These may result from instructor availability, the organization of student groups, the structure of the academic week, or other organizational rules adopted in the planning process. Spatial constraints, on the other hand, refer to the conditions related to the assignment of classes to the locations where they are held.

The analysis was exploratory in nature. It included a comparison of indicator values across consecutive semesters, a comparison of winter and summer semesters, as well as an assessment of selected linear relationships between variables. Pearson's linear correlation coefficient was used to assess selected relationships between variables. Due to the small number of observations, the correlation results should be treated as supplementary, and no causal conclusions should be drawn based on them.

In addition, for the relationship between constraint density and the number of manual adjustments, a simple sensitivity check was performed by recalculating the correlation coefficient after excluding the first semester, which clearly differed from the remaining instances in terms of both constraint density and adjustment effort.

The empirical material covers eight consecutive semesters, which should be interpreted as eight comparable organizational instances of the real-world course timetabling process. The limited number of semester-level observations results directly from the practical nature of the analyzed process. In university course timetabling, input data cannot be freely replicated or extended over long periods without losing comparability, because scheduling tools, interfaces with administrative systems, study programs, the structure of student groups, institutional rules, and the organization of the academic cycle are modified relatively often. Extending the observation period would therefore increase the nominal number of

semesters, but it would also introduce heterogeneous instances generated under different organizational and technical conditions. For this reason, the study deliberately focused on the most recent period in which data collection rules, the integrated FET-based workflow, and the definition of scheduling constraints remained sufficiently consistent. Consequently, the dataset is suitable for descriptive and exploratory process analysis, but it does not provide a sufficient basis for full inferential statistical analysis, robust hypothesis testing, or causal modeling.

Although thirty generation attempts were performed for each semester, these attempts were repeated measurements of the same scheduling instance and therefore cannot be treated as independent semester-level observations when analyzing the relationships between instance characteristics, constraint density, generation time, and manual adjustments. The actual number of independent organizational observations is eight semesters. With such a small number of semester-level cases, reliable estimation of multivariate models, formal hypothesis testing, and generalization to other departments or universities would not be methodologically justified. Therefore, Pearson correlation coefficients are used only as exploratory

indicators of possible relationships observed in the case study, not as evidence of causal dependence or statistically generalizable effects.

RESULTS

The analysis covered eight consecutive semesters, from 2022/2023 W to 2025/2026 S. The data were presented in tables showing the characteristics of the scheduling instances, normalized indicators, a comparison of winter and summer semesters, and correlations between selected variables.

The basic characteristics of the scheduling instances, broken down by the semesters analyzed, are presented in Table 4. These include the number of scheduled hours, the number of groups, the number of instructors, the number of classes, the minimum, maximum, and average generation times, the number of time and space constraints, and the number of manual adjustments. The analysis used the total number of adjustments recorded for a given semester.

The following tables present normalized indices (Table 5), a comparison of the winter and summer semesters (Table 6), and correlation

Table 4. Characteristics of scheduling instances in following semesters

Semester	H	G	L	N	T_{min} [s]	T_{max} [s]	T_{avg} [s]	C_T	C_S	M
S1	25095	223	206	1555	3	23	7.9	4932	1557	154
S2	22500	204	194	1275	5	18	11.03	2908	1007	103
S3	22500	244	193	1586	1	3	2.1	3605	1023	91
S4	22875	214	172	1429	2	5	3.07	3184	1013	69
S5	25845	254	187	1691	2	10	5.17	3805	1339	89
S6	25935	205	172	1608	2	11	6.47	3625	1323	81
S7	30915	241	220	1832	2	4	2.6	4150	1332	79
S8	28170	213	185	1710	8	18	12.73	4068	1106	52

Table 5. Normalized indicator values

Semester	D_C	S_T	S_S	E_a [ms/constraint]	MR	M/1000H	$\frac{T}{1000}$ [s/1000 activities]	E_{avg} [activity/s]
S1	4.17	0.76	0.24	1.22	9.90%	6.14	5.08	196.84
S2	3.07	0.74	0.26	2.82	8.08%	4.58	8.65	115.59
S3	2.92	0.78	0.22	0.45	5.74%	4.04	1.32	755.24
S4	2.94	0.76	0.24	0.73	4.83%	3.02	2.15	465.47
S5	3.04	0.74	0.26	1.01	5.26%	3.44	3.06	327.08
S6	3.08	0.73	0.27	1.31	5.04%	3.12	4.02	248.53
S7	2.99	0.76	0.24	0.47	4.31%	2.56	1.42	704.62
S8	3.03	0.79	0.21	2.46	3.04%	1.85	7.44	134.33

Table 6. Comparison of winter and summer semesters

Semester	G_{avg}	N_{avg}	L_{avg}	C_{avg}	$C_{T_{avg}}$	$C_{S_{avg}}$	T_{avg} [s]	M_{avg}	E_{avg} [ms/constraint]	E_{avg} [activity/s]
Summer	209	1505.5	180.75	4558.5	3446.25	1112.25	8.325	76.25	1.83	240.98
Winter	240.5	1666	201.5	5435.75	4123	1312.75	4.4425	103.25	0.79	495.94

coefficients describing selected relationships between variables (Table 7).

The values in Table 5 show that the analyzed semesters differed not only in problem scale, but also in constraint structure, normalized generation cost, and post-generation adjustment effort.

The proposed normalized indicators were not intended to be aggregated into a single weighted measure of scheduling complexity. Instead, each indicator describes a different dimension of the timetabling process, including structural, computational, or organizational characteristics. The overall assessment is therefore based on the complementary interpretation of these measures, rather than on their relative weighting.

The tables are supplemented by the charts showing the average schedule generation time, the time range for generation, the structure of constraints, the density of constraints, the number and rate of manual adjustments, the relationship between the number of classes and the average generation time, and a comparison of winter and summer semesters. These charts serve an interpretive function and help identify relationships that are less apparent in the tables alone.

The scale of the problem of creating class schedules

The first dimension analyzed was the scale of the scheduling problem in subsequent semesters. To describe this, the number of scheduled hours, the number of groups, the number of instructors, and the number of classes were used (Table 4). A comparison of these values indicates that the institutions studied were not homogeneous. The number of scheduled hours ranged from 22,500

to 30,915, the number of groups from 204 to 254, the number of instructors from 172 to 220, and the number of classes from 1.275 to 1.832.

The problem was most pronounced in semester S7, which had the highest number of scheduled hours, the highest number of class units, and the highest number of instructors. At the same time, the longest average generation time occurred in S8, indicating that the largest scale of an instance did not correspond to the highest generation cost. The individual scale parameters did not change in parallel. An increase in the number of scheduled hours did not always correspond to a proportional increase in the number of classes, groups, or instructors.

Constraint structure and density

The second key area of analysis was the structure of the constraints present in the scheduling process (Figure 2).

Throughout the analyzed period, 39,977 constraints were recorded, of which 30,277 were time constraints and 9,700 were spatial constraints. This means that time constraints accounted for 75.74% of all constraints, while spatial constraints accounted for 24.26%. This structure indicates that, in the case under analysis, the main source of scheduling complexity was temporal availability and the organization of classes over time, rather than solely the assignment of classes to classrooms. To compare semesters with different numbers of classes, the constraint density index D_c , the value of which indicates the average number of constraints per class unit. In the analyzed data, the value of the D_c index ranged from 2.92 to 4.17. The highest constraint density was recorded in semester S1, while the lowest was in semester S3 (Figure 3).

Table 7. Correlations between selected variables

Relationship	Correlation	Interpretation
H vs T_{avg}	0.037367607	Virtually no linear relationship
N vs T_{avg}	-0.259238102	Weak negative relationship
T_{avg} vs M	0.028378389	Virtually no linear relationship
D_c vs M	0.866074812	Strong association for all semesters, but sensitivity check without S1 reduced the correlation to 0.181; diagnostic interpretation only

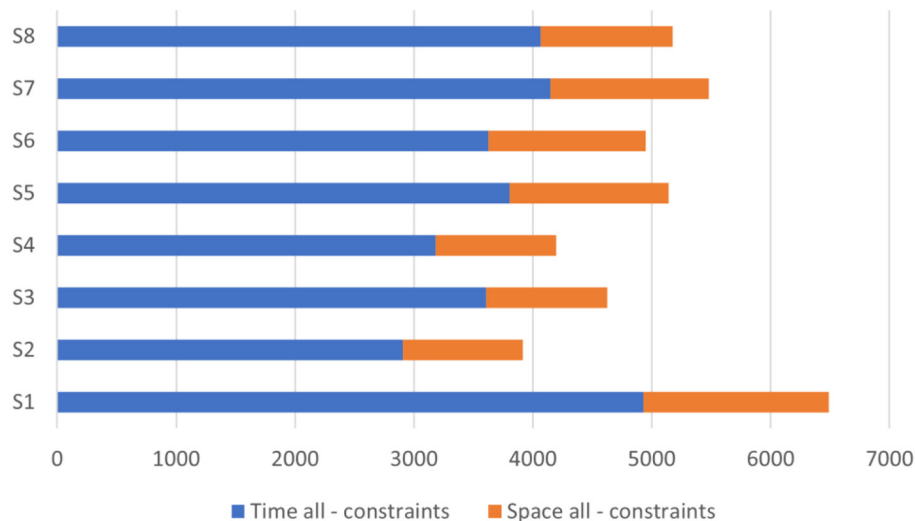


Figure 2. Structure of scheduling constraint

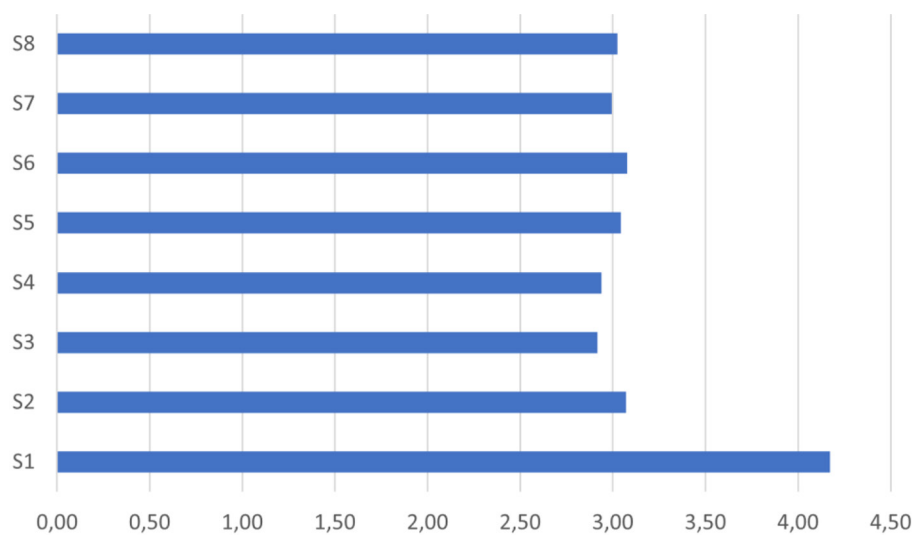


Figure 3. Constraint density

The restriction density chart helps identify the semesters in which the concentration of restrictions was particularly high. Semester S1 stands out the most, as it had the highest D_c value and the greatest number of manual adjustments. D_c values after semester S2 are relatively stable and range from approximately 2.92 to 3.08, while semester S1 clearly differs from the other instances.

Generation time

The data included the minimum, maximum, and average generation times. The article placed particular emphasis on the average generation time, as it better describes the typical course of the process than a single minimum or maximum value. In the analyzed data, the average generation

time ranged from 2.10 s to 12.73 s. Importantly, the largest instance in terms of the number of staff hours and the number of course units was not the instance with the highest average generation time.

Figure 4 shows that the highest values for the average generation time occurred in semesters S2 and S8, while the lowest occurred in S3 and S7. The longest generation time observed in Semester S8, despite a constraint density similar to that of the other semesters, indicates that D_c reflects only the number of constraints per activity unit. It does not account for the type or interaction of constraints, which may substantially influence the timetable generation process.

The distribution of generation times shown in Figure 5 confirms the stability of the scheduling process. In most of the semesters analyzed,

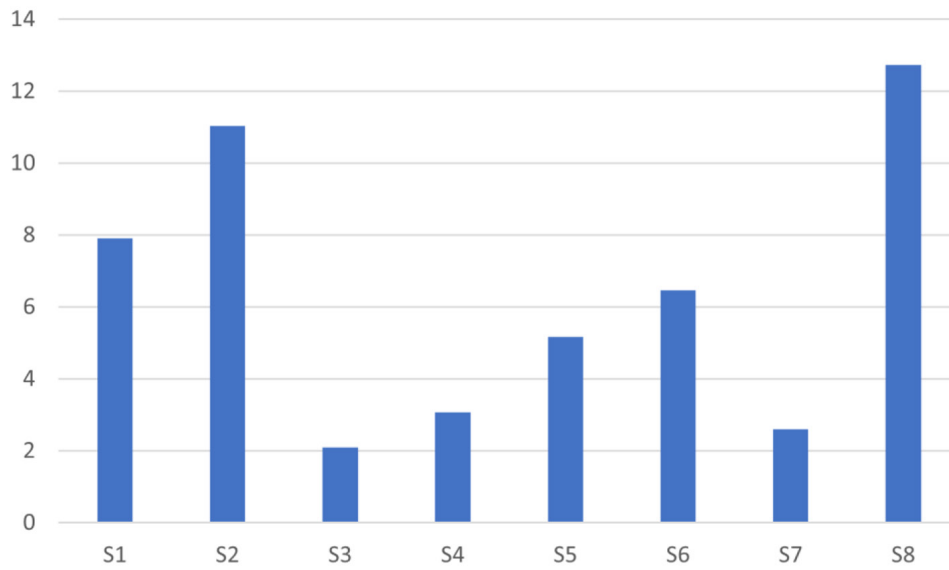


Figure 4. Average time to generate a schedule

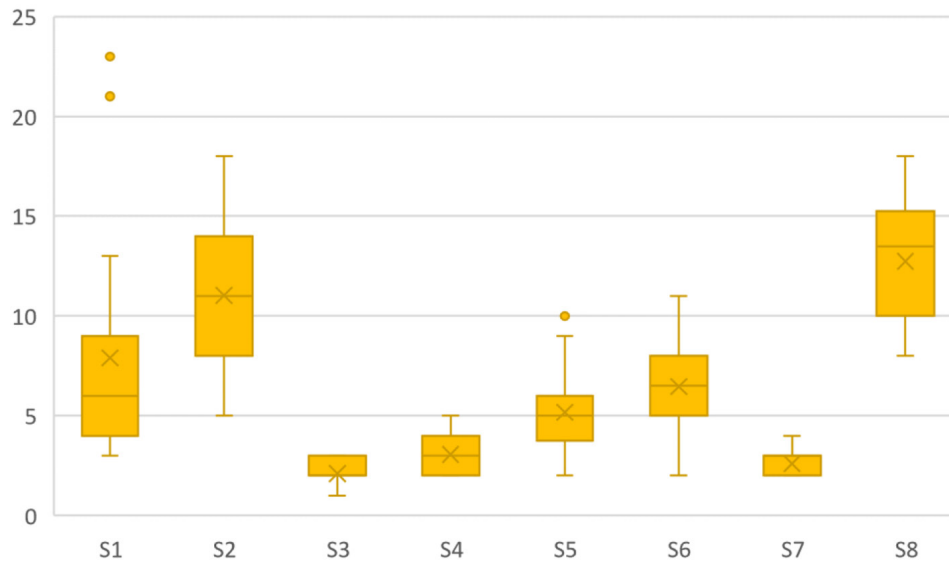


Figure 5. Distribution of schedule generation times in thirty repeated runs for each semester

the interquartile range was small, which means that the vast majority of runs completed in very similar time frames. The greatest variation in results was observed for semester S1. In this case, two outliers corresponding to the longest schedule generation times were also observed. For semesters S3 and S7, very little variation in results was observed, as evidenced by both low standard deviation values (Table 8) and a narrow interquartile range. Despite the highest average generation time in semester S8, the variation in results remained moderate.

The median and standard deviation values provide additional insight into the stability of the

Table 8. Median and standard deviation of schedule generation time across thirty runs

Semester	Me[s]	SD[s]
S1	6	5.42
S2	11	3.57
S3	2	0.66
S4	3	1.11
S5	5	2.05
S6	6.5	2.21
S7	3	0.62
S8	13.5	2.92

Note: $SD[s]$ – the standard deviation of generation time, $Me[s]$ – the median generation time.

schedule generation process. The lowest variability was observed in semesters S3 and S7, where the standard deviation was 0.66 s and 0.62 s, respectively. These semesters were also among those with the lowest average generation times, indicating a relatively stable and predictable generation process. In contrast, semester S1 was characterized by the highest standard deviation, equal to 5.42 s, which suggests greater variability between repeated runs. Semesters S2 and S8 also showed relatively high generation times, with median values of 11.00 s and 13.50 s, respectively. This confirms that these instances were not only slower on average, but also more demanding from the perspective of repeated timetable generation.

The generation time analysis is supplemented by the E_a metric, which defines the average generation time per scheduling constraint. In the analyzed data, the value of this metric ranged from 0.45 ms/constraint in semester S3 to 2.82 ms/constraint in semester S2. Low values of the indicator were also recorded in semester S7, even though it was the semester with the highest number of hours, classes, and instructors. This means that the largest scale of instances was not synonymous with the highest generation cost per constraint.

The E_{avg} metric, which represents the number of activity units generated per second, reached its highest values in semesters S3 and S7, at 755.24 activity/s and 704.62 activity/s, respectively. The lowest generation efficiency was recorded in semesters S2 and S8, where the E_{avg} values were 115.59 activity/s and 134.33 activity/s, respectively. These results confirm that the efficiency of schedule generation does not depend solely on

the number of classes, but also on the structure of the instances and the distribution of constraints.

Although T_{1000} and E_{avg} are mathematically reciprocal, they were retained because they provide two complementary perspectives on scheduling performance. T_{1000} expresses the normalized generation time required to process a fixed number of activity units, whereas E_{avg} represents the corresponding processing throughput. In contrast, E_a normalizes generation time with respect to the number of scheduling constraints and therefore reflects a different aspect of computational performance related to the constraint structure of the scheduling instance.

Manual adjustment effort

A key element of the analysis was the number of manual adjustments made after the schedule was generated (Figure 6). This variable was treated as a proxy measure of the quality of the planning process and the amount of work required on the organizational side after the automatic generation of the schedule was completed. It should not be interpreted as a direct measure of the algorithm's quality, as the number of adjustments may also depend on the quality of the input data, organizational changes, additional agreements, or the factors not accounted for in the collected dataset.

During the period under review, the number of manual adjustments decreased from 154 in the first semester to 52 in the last semester. At the same time, the adjustment rate—that is, the ratio of the number of manual adjustments to the number of classes—decreased. In the first semester, it

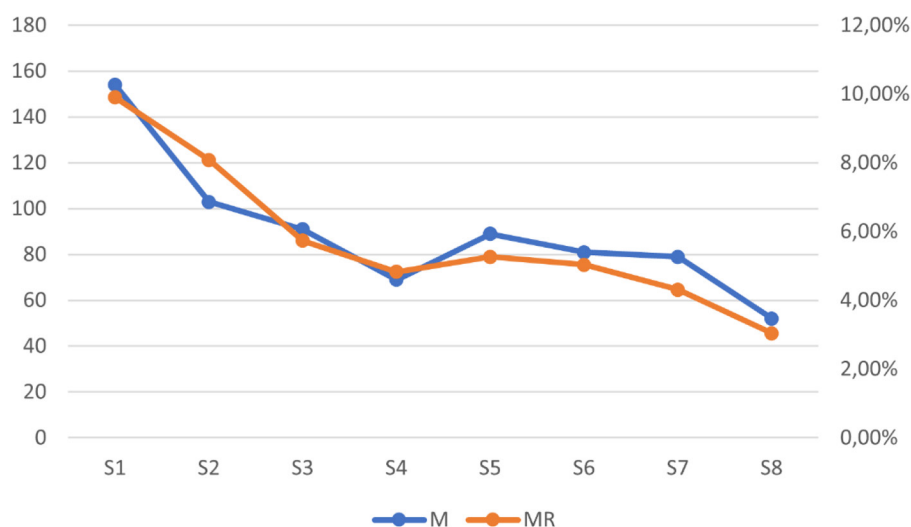


Figure 6. Number of manual adjustments and adjustment rate

was approximately 9.90%, while in the last semester it was approximately 3.04%. This trend may indicate an improvement in the planning process, understood as a reduction in the extent of manual intervention after the schedule has been generated.

The graph showing the number and rate of manual adjustments indicates that this decline was not entirely linear, but the overall trend is clear. It is particularly significant that the reduction in the number of adjustments occurred despite the continued large scale of the teaching process. This reduction can also be explained by the increasing organizational acceptance of the published timetable. As the integrated scheduling process matured over successive planning cycles, both academic staff and students increasingly recognized the generated timetable as the best feasible solution under the existing organizational constraints. Consequently, fewer requests for post-publication modifications were submitted, contributing to the observed decrease in manual adjustments.

Winter and summer semester comparison

The study also compares the scheduling characteristics between the analyzed winter and summer semester instances (Figure 7). A comparison of winter and summer semesters shows that winter semesters had, on average, a greater number of classes and a greater number of class units, while summer semesters were characterized by a longer average generation time. The average number of classes in winter semesters was 1.666, and in summer semesters, 1,505.5. At the same time, the average generation time was 4.4425 s for winter semesters and 8.325 s for summer semesters. This result provides an important basis for further analysis, as it indicates that a smaller number of classes does not necessarily mean a reduction in the complexity of the scheduling instance.

This observation should be interpreted as an exploratory finding rather than as evidence of a general observed winter–summer difference,



Figure 7. A compare of the summer and winter semesters

because it is based on only four winter and four summer semester instances. In the analyzed department, summer semesters typically include a higher proportion of laboratory classes conducted in specialized teaching rooms. These activities impose more restrictive room-allocation requirements and may reduce scheduling flexibility, thereby increasing generation time despite a comparable overall constraint density.

A comparison of the E_a and E_{avg} metrics further confirms the distinct nature of winter and summer semesters. Winter semesters, despite having a higher average number of groups and class units, were characterized by a lower average algorithmic cost per constraint and a higher average generation efficiency. The average value of E_a was 0.79 ms/constraint for winter semesters and 1.83 ms/constraint for summer semesters, while the average value of E_{avg} was 495.94 activity/s and 240.98 activity/s, respectively. This result indicates that summer semesters were less computationally favorable in terms of constraint structure, despite their smaller organizational scale.

Correlation analysis

An analysis of the correlation between selected variables indicates that the scale of the scheduling problem does not explain the average schedule generation time in a linear manner. The correlation between the number of hours in the H schedule and the average generation time T_{avg} was 0.037, which indicates a virtually non-existent linear relationship. Similarly, the correlation between the number of classes N and the average generation time T_{avg} was weak and negative, reaching a value of -0.259. These results indicate that a higher teaching volume or a greater number of class units did not directly translate into a longer schedule generation time.

A virtually non-existent linear relationship was also observed between the average generation time T_{avg} and the number of manual adjustments M , for which the correlation coefficient was 0.028. This means that the time required to generate a schedule and the number of subsequent manual adjustments describe different aspects of the planning process. The average generation time can be treated as an indicator of technical and computational cost, while the number of manual adjustments can be treated as an indirect measure of the organizational effort required after the schedule is generated.

The highest exploratory correlation was observed between constraint density and the number of manual adjustments. The correlation coefficient calculated for all eight semester-level observations was 0.866, which indicates a strong positive linear association within the analyzed dataset. However, this result should be interpreted with particular caution because Semester S1 clearly differed from the remaining instances by having both the highest constraint density and the highest number of manual adjustments. Semester S1 represents the first practical implementation of the integrated timetable preparation workflow in the analyzed department. During this initial planning cycle, additional refinement of input data, constraint definitions, and organizational requirements was required, whereas subsequent semesters benefited from the experience gained during earlier planning cycles. A sensitivity check showed that, after excluding S1, the correlation decreased substantially to 0.181, indicating that the observed association is driven primarily by this influential observation. Consequently, the relationship between constraint density and manual adjustment effort should be regarded as an exploratory diagnostic finding rather than statistically generalizable evidence. Constraint density may therefore be considered a useful process-monitoring indicator, but not a reliable standalone predictor of post-generation adjustment effort.

DISCUSSION

The present findings reinforce the previous observations that organizational and structural characteristics contribute more to practical timetabling complexity than the scale of a scheduling instance alone. This means that the number of classes, groups, or instructors describes only the size of the problem but does not fully capture its structural complexity. This finding is consistent with the previous studies emphasizing that real-world university timetabling complexity is strongly institution-specific and cannot be reduced to instance size alone [3,10–12]. Local study regulations, curriculum structure, instructor availability, room specialization, and the interaction of hard and soft constraints determine the shape of the feasible solution space. The present results extend this perspective by showing that computational performance should be interpreted together with generation-time stability

and post-generation organizational effort. This process-oriented perspective complements recent studies that have focused on extending optimization models to better capture practical institutional requirements, indicating that computational performance should be interpreted together with the organizational context in which timetables are generated and implemented [7,8].

The predominance of time constraints over spatial constraints suggests that scheduling flexibility is limited primarily by temporal resource coordination, rather than by room allocation alone. This observation is consistent with the previous studies emphasizing that instructor availability, student-group organization, and institutional scheduling rules often represent stronger limiting factors than classroom availability in real-world university timetabling [3,11,12]. From a practical perspective, this finding indicates that improving the coordination of temporal constraints may have a greater impact on the quality of generated timetables than focusing exclusively on room allocation.

This interpretation is further supported by the median and standard deviation of generation time calculated for thirty repeated runs of each semester instance. The standard deviation values show that the stability of the generation process differed substantially between semesters. In particular, S3 and S7 were characterized by very low variability, whereas S1 showed the highest dispersion of generation time. This indicates that the evaluation of timetable generation should not be based solely on average time, since two instances with comparable average values may differ in terms of repeatability and predictability of the generation process.

The introduction of the constraint density metric made it possible to compare semesters with different numbers of classes. The analysis showed that the semester with the highest constraint density also had the highest number of manual adjustments. The sensitivity analysis indicates that the apparent relationship between constraint density and manual adjustment effort is strongly influenced by Semester S1. Constraint density should therefore be treated as a descriptive process-monitoring indicator, rather than as a reliable predictor of post-generation workload. However, the relationship should not be interpreted as evidence of a stable statistical dependence, because the high correlation between constraint density and manual adjustments was strongly influenced by the first semester.

The results regarding manual adjustments show that the evaluation of the scheduling process should not be limited to the generation time alone. In practice, it is also important to consider how much intervention the schedule requires after the automatic process is complete. The number of manual adjustments can be treated as an indicator of the practical quality of the planning process, although it is not a direct measure of the algorithm's quality.

The algorithmic cost indicator E_a should not be interpreted as a direct measure of computational complexity because it does not account for the varying difficulty of individual constraint types. Constraint density should therefore not be interpreted as a direct measure of computational burden, because it assigns the same numerical contribution to each recorded constraint. In practice, however, various constraint types may differ substantially in their restrictiveness and computational impact. For example, instructor unavailability, ordered-activity relations, minimum-day constraints, and specialized room requirements may reduce the feasible solution space to different extents. A more precise assessment of their relative influence would require constraint-level analyses or weighted constraint models based on a substantially larger dataset.

The relatively long generation times observed for Semesters S2 and S8 illustrate this phenomenon. Although these semesters contained fewer activity units than some winter semesters, they typically included a higher proportion of laboratory classes that may require specialized laboratories with limited availability. Such requirements reduce room-allocation flexibility and strengthen the interaction between spatial and temporal constraints, which may increase the computational effort required to generate a feasible timetable despite a comparable overall constraint density. Since the available dataset does not include a detailed classification of course types or room requirements, this explanation should be regarded as a plausible organizational interpretation based on the authors' knowledge of the analyzed scheduling process, rather than as statistically verified causal evidence.

From a practical perspective, the differences in generation time are small in absolute terms and do not directly determine the operational usefulness of the scheduling system. Their main value is diagnostic, as they indicate differences in the computational behavior and stability of

semester instances. More important for university operations is whether the generated timetable requires substantial post-generation intervention and whether it is accepted by its users. Although all analyzed runs produced formally valid timetables, feasibility alone does not guarantee organizational quality. A practically satisfactory timetable should also limit undesirable gaps, respect user preferences, use specialized rooms appropriately, as well as be accepted by academic staff and students as the best feasible solution under the existing constraints. The decreasing number of requested adjustments therefore provides complementary information about timetable quality beyond formal validity. From an operational perspective, minimizing the number of post-publication modifications reduces the administrative workload associated with timetable maintenance and improves the stability of the published schedule.

The main limitation of the study was the small number of independent semester-level observations. The dataset reflected a real operational process rather than an experimental environment in which the number of instances can be freely increased. Moreover, the available data were aggregated and did not include complete information on room capacity, room equipment, class type, detailed instructor preferences, or the categories of manual adjustments. As a result, the study did not aim to build a complete predictive or causal model of timetable generation difficulty. Its purpose was instead to provide an exploratory, process-oriented assessment based on comparable real-world semesters and to identify the indicators that may support systematic monitoring of academic scheduling complexity.

Another limitation concerns the institutional specificity of the analyzed case study. The investigated scheduling process reflected the organizational structure, curricula, scheduling policies, and operational constraints of a single academic department. Other universities may differ substantially with respect to program organization, room resources, constraint composition, or the completeness and quality of scheduling data. Such differences may influence both the values of the proposed indicators and the observed scheduling performance. Consequently, the numerical results presented in this study should not be directly generalized to other institutions without appropriate validation under local organizational conditions.

An additional limitation is the lack of a detailed classification of time constraints and the absence of an analysis of the probability of generation failure, since all recorded attempts resulted in a valid schedule. For this reason, the analysis describes the practical course of the process but does not fully explain the sources of difficulty in individual instances.

The contribution of this study lies in shifting the focus from the mere generation of a schedule to the evaluation of the entire planning process. In university practice, a mathematically valid solution is not always organizationally acceptable. Therefore, combining computational metrics, such as generation time, with organizational metrics, such as the number of manual adjustments, allows for a more comprehensive assessment of the scheduling process effectiveness.

The proposed set of indicators can be used as a tool for monitoring subsequent course planning cycles. Combining measures of problem scale, constraint structure, generation time, and adjustment effort enables the comparison of semesters that differ in the organization of the teaching process. This approach can help identify the instances requiring greater organizational attention, better preparation of input data, or a more thorough analysis of constraints before launching the generation process.

CONCLUSIONS

The study confirmed that the practical complexity of university course timetabling is multidimensional and cannot be evaluated solely through the scale of a scheduling instance.

Regarding RQ1, the basic scale indicators did not explain average timetable generation time in a consistent linear manner. The correlation between the number of teaching hours and average generation time was 0.037, while the correlation between the number of activity units and average generation time was -0.259. The largest scheduling instance was therefore not the most computationally demanding one. This indicates that the structure and interaction of constraints are more informative than instance size alone.

Regarding RQ2, constraint density provided useful descriptive information about the concentration of scheduling restrictions, but its relationship with manual adjustment effort was not robust. The correlation between constraint

density and the number of manual adjustments decreased from 0.866 to 0.181 after Semester S1 was excluded. Consequently, constraint density should be treated as a diagnostic process-monitoring indicator rather than as a reliable stand-alone predictor of post-generation workload.

Regarding RQ3, the analyzed summer semester instances had a longer average generation time than the winter instances despite having fewer activity units. This difference may partly reflect the greater proportion of laboratory classes requiring specialized rooms in the analyzed summer semesters. However, because the comparison includes only four winter and four summer semesters and is influenced by Semesters S2 and S8, it should be interpreted as an exploratory case-specific pattern rather than as evidence of a general seasonal effect. Across the eight semesters, 39,977 constraint records were processed, of which 75.74% were time constraints. The number of manual adjustments decreased from 154 to 52, while the adjustment rate declined from 9.90% to 3.04%. This reduction is consistent with improved preparation of input data, more consistent constraint definition, accumulated organizational experience, and increasing acceptance of the published timetable by academic staff and students as the best feasible solution under the existing constraints.

For practical timetable monitoring, the most useful measures are the manual adjustment rate, generation-time stability, and normalized generation performance. The manual adjustment rate directly reflects post-generation organizational effort, while the median and standard deviation of generation time provide information about the repeatability and predictability of the generation process. Algorithmic cost and generation efficiency facilitate comparisons between semester instances of different sizes. Constraint density remains useful for identifying structurally unusual instances, but it should be interpreted together with the composition and interaction of constraint types.

Scheduling administrators should therefore monitor not only average generation time but also its variability, the number and type of post-generation adjustments, and atypical changes in normalized indicators. They should also standardize the definitions of scheduling activities, constraint records, and manual adjustments, verify input data before generation, and review the instances showing unusually high adjustment effort or unstable generation performance. Further research should validate the proposed framework

using larger datasets from other departments and universities. Particular attention should be given to the classification and weighting of individual constraint types, the development of a weighted adjustment index, and the analysis of course types, specialized room requirements, and constraint interactions. Such validation would help determine whether the proposed indicators can support broader cross-institutional comparisons and the development of a composite measure of practical timetabling complexity. Another promising direction for future research is the application of artificial intelligence techniques, including machine learning and AI-assisted optimization, to support constraint modeling, parameter tuning, and timetable generation. The normalized indicators proposed in this study may provide an objective framework for evaluating the practical performance of such methods under real organizational conditions and for comparing them with conventional scheduling approaches.

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