

Research Article

# A transdisciplinary approach to course timetabling an optimal comprehensive campus application

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## Abstract

Academic timetabling is a core process of higher education institutions (HEIs) with profound implications for stakeholder satisfaction and organizational efficiency. This process serves as the operational backbone of every HEI. It involves the allocation of professors to course-sections, schedules, and facilities such as classrooms and laboratories for a specific academic term. Given its mathematical complexity (NP-Hard) and despite the extensive literature on timetabling practices, real-world applications often present challenges that deviate from standard problem formulations, creating a gap between theory and practice. This research addresses these challenges by promoting knowledge integration and improving decision-making processes. The contribution of this article is twofold: Firstly, it introduces a transdisciplinary framework that considers stakeholder preferences and available organizational resources to optimize the expected academic performance of HEIs. At the core of this framework lies a quantitative decision support tool (based on a mixed integer optimization model) designed to bridge knowledge and resource gaps, thus aiding the decision-making team in achieving their objectives. Secondly, the article presents a practical demonstration of this framework using data from an entire HEI Campus, encompassing all schools and academic programs, to illustrate its efficiency and benefits.

**Keywords:** Academic timetabling, decision support tools and methods, mixed integer optimization, transdisciplinary approach.

## 1. Introduction

The academic timetabling problem (ATP), as defined by Wren (1995), is "The allocation of given resources to specific objects being placed in space and time page 47." This fundamental yet complex process forms the backbone of higher education institutions (HEIs) operations. It manifests in various forms, including subject, exam, and course scheduling. It occurs periodically across multiple parallel operational academic cycles within all HEIs (Nurmi & Kyngäs, 2008). Timetabling quality can profoundly impact a range of stakeholders, including professors, students, university operations executives, department and program chairs, and corporate governance (Sabin & Winter, 1986). This underlines the critical nature of academic timetabling and the pressing need to enhance its effectiveness and efficiency.

Despite its importance, tackling the complexities of academic timetabling is a significant challenge. These complexities have been highlighted in the academic literature (Burke et al., 2004), which is rich with practices, tools, and scheduling algorithms. Much of this research can generally be categorized into case study papers and solver papers (Kingston, 2022).

The implementation of current timetable solutions in HEIs faces several inherent obstacles. A key challenge is the rising demand for student-centric timetabling systems, necessitating the integration of individual student preferences into the scheduling process, a task not fully addressed by current literature or technological developments (Froese et al., 1998; Muklason et al., 2017). Additionally, the operational process of timetabling requires alignment with each HEI's unique structural preferences, governance trends, and educational ideologies (Clark, 1986), making adopting standardized solutions difficult. This disconnect hinders the application of the latest academic advancements in real-world settings.

However, the real-world complexities often outstrip standard problem formulations (Schaerf, 1999). This complexity can increase the difficulty of finding practical solutions (Qu and Burk 2009, Qu et al., 2009). These issues underpin the gap between theory and practice and indicate the need for a broader approach to solving real-world ATPs. Responding to this need, this paper introduces a transdisciplinary framework that considers stakeholders' preferences to tackle timetabling for HEIs. This paper represents a revised and extended version of Trigos & Coronel (2023).

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It's essential to note that the primary contribution of this article differs significantly from the traditional approach of introducing new mathematical models or algorithms for solving ATPs. Instead, the contribution revolves around introducing an innovative transdisciplinary framework to fill the literature gap concerning real-size instances. This framework, a practical decision support tool, considers a broad spectrum of stakeholders. The objective of this framework is to maximize the expected academic performance. This is achieved through the strategic assignment of professors to courses, sections, and time slots (schedules) that align with stakeholder preferences and profile affinity. This optimization process is underpinned by a quantitative model seamlessly integrated into a broader, transdisciplinary approach. To illustrate this framework further, this paper provides an example involving a real-size comprehensive HEI campus instance. This practical demonstration underscores how this transdisciplinary framework can prove advantageous to practitioners in higher education.

The rest of the article is structured as follows: Section 2 includes an overview of the ATP. Section 3 consists of the methodology, and it contains four subsections: problem definition, the definition of expected academic performance measurement, the mathematical model, and the transdisciplinary framework to solve the problem. Section 4 shows the numerical illustration where the framework is implemented. Finally, Section 5 presents the conclusions and directions for future research.

## 2. Academic timetabling: an overview

Academic timetabling is an evolving discipline that has attracted research attention from various sub-disciplines. An analysis of three pairs of PATAT-ITC (Practice and Theory of Automated Timetabling and International Timetabling Competition) conferences – 1995 and 1997; 2006 and 2008; and 2016 and 2018, Selimi et al. (2022) reveals the relative number of papers from each sub-discipline. Kingston (2022) delineates the developmental stages of academic sub-disciplines, which can be analogous to the evolution of academic timetabling. He characterizes these stages as follows:

Stage 1: An emergent area occasionally cited in the literature, yet its boundaries are nebulous and unclear.

Stage 2: A subject that one encounters more frequently within scholarly articles, with a scope that is starting to become clear.

Stage 3: A field with a well-delineated scope, evidenced by the standardization of datasets and frequent references in literature.

Stage 4: A domain considered mature where the pace of research might slow due to a perceived saturation or completion of its research agenda.

Kingston (2022) also remarks on the significance of progression through these developmental stages for academic sub-disciplines. He notes that substantial progress is often marked by a sub-discipline's advancement from one stage to the next. The transition from Stage 1 to Stage 2 can be achieved relatively quickly as it mainly requires increased interest in the field, prompting a series of case studies. However, the shift from Stage 2 to Stage 3 is more challenging. It demands a consensus on the precise scope of the sub-discipline, which must then be encapsulated in standard datasets. Historically, this difficult transition has often been facilitated by the organization of competitions that drive consensus and standardization.

Academic timetabling is currently at Stage 3 (Tan et al., 2021). This aligns with the findings presented in the context of the international timetabling competition ITC2021 by Van Bulck & Goossens (2023). At this stage, the emphasis shifts towards refining existing solutions and methodologies. Notably, case study papers within Stage 3 tend to offer fewer novel insights. This observation resonates with the state of research in academic timetabling, as exemplified by the ITC2021 competition.

Moreover, the authors of the ITC2021 papers acknowledge the pressing need to address the limited diversity in current problem instances, underscoring the field's maturity and the researchers' focus on improving established approaches. Instead, the emphasis is on solver papers introducing and applying optimization methods to existing data. While these papers are crucial for the progression of the discipline, they often experience diminishing returns as they primarily focus on refining solutions. As scheduling research progresses, debates regarding the "gap between theory and practice" intensify (Özcan et al., 2022). This growing concern is closely tied to the development and testing of benchmark examination timetabling problems in recent years, as discussed in the article by Ceschia et al. (2023). While the past decade has seen significant advancements in problem formulations and benchmark datasets, questions have arisen regarding these academic benchmarks' practical relevance and usability in real-world educational institutions (Burke & Petrovic, 2002). The ongoing discourse about bridging the gap between theoretical advancements and practical applicability underscores the need for timetabling solutions that excel in academic benchmarks and effectively address the complex scheduling challenges faced by educational institutions in practice (Pillay, 2014). Real-world problems introduce a range of research challenges due to their intrinsic complexities. A pivotal research avenue involves addressing these complexities. Researchers are prompted to combine techniques and ingeniously integrate diverse methodologies to ensure efficiency

and efficacy (Bettinelli et al., 2015). However, a significant disparity exists between the studied problems and real-life challenges. Factors like intricate course structures, scarce resources (time, faculty, and facilities), and the decentralized nature of information contribute to this difference. The actual complexity of university course timetabling often surpasses standard problem formulations. This increased complexity presents a two-fold challenge. First, developing an effective solution becomes arduous. Second, the derived solution may lack versatility, making it unsuitable for other universities, causing timetabling issues or creating diverse problems within the same institution (Mokhtari et al., 2021).

In summary, while academic timetabling has made substantial strides, bridging the gap between theoretical constructs and real-world challenges remains an ongoing endeavor. Researchers must continue innovating, ensuring that solutions are efficient and broadly applicable.

### 3. Methodology

This section is partitioned into four parts: firstly, the problem definition, where the timetabling model is explained; secondly, the definition of EAP is stated; the mathematical model is located in the third part; and, last, the description of the transdisciplinary framework is presented.

#### 3.1. Problem definition

HEIs represent complex organizations involving diverse stakeholders, including professors, students, management staff, academic authorities, and certification institutions. These institutions also manage critical resources (for a particular academic term, a semester, or a quarter), such as faculty members, schedules, and facilities (classrooms, laboratories, auditoriums, etc.). The central challenge in this context is course timetabling (CT), a special class of ATP. This crucial process entails allocating these resources effectively to the different course-sections within all the HEI academic programs.

Characteristics of CT are well-documented in existing research: Burke & Petrovic (2002), MirHassani & Habibi (2013), Chen et al. (2021), and Tan et al. (2021). This process entails resource allocation, involving physical facilities like classrooms and human resources, such as professors and support staff (Eleyan et al., 2018). The scheduling must be program-specific and tailored to each program's unique requirements. Additionally, it should maximize stakeholder preferences, considering professors' and students' scheduling needs and aligning courses with their availability and priorities (Özcan et al., 2013) while factoring in resource capacity constraints within HEIs (Abdullah et al., 2015). However, the complexities arise due to the combinatorial nature of exploring scheduling possibilities, resolving preference conflicts (Kheiri et al., 2018), and adapting to the dynamic nature of changing enrollment, faculty availability, and program offerings. These intricacies make CT a critical research and optimization challenge in educational management.

#### 3.2. Expected academic performance

The objective function at the heart of the transdisciplinary timetabling model centers on Expected Academic Performance (EAP). EAP emerges as a composite metric, reflecting the preferences and evaluations of multiple stakeholders involved in the educational process.

To construct the EAP metric, the following three parameters must be computed:

1. **Professor Preference ( $EAPP_{i,j}$ ):** This variable captures a professor's preference for teaching a specific course, measured on a scale from 0 to 1.
2. **Student Appreciation ( $EAPS_{i,j}$ ):** Representing the historical average of student satisfaction with a professor's instruction for a course, also gauged on a 0 to 1 scale.
3. **Institutional Validation ( $EAPI_{i,j}$ ):** A binary parameter (0 or 1) assessing whether a professor meets institutional and accreditation standards to teach a particular course.

In this framework, weights are allocated to professor preference ( $WP$ ) and student appreciation ( $WS$ ), with their sum equaling one ( $WP + WS = 1$ ). The EAP for a professor ( $i$ )-course-section ( $j$ ) assignment is calculated as  $EAP_{i,j} = (WP EAPP_{i,j} + WS EAPS_{i,j}) EAPI_{i,j}$ , effectively balancing the needs and feedback of both professors and students while adhering to institutional guidelines.

The objective function aims to maximize the EAP for all course assignments throughout the ATP. This optimization ensures educators' alignment with courses suited to their strengths and student preferences and conformity with institutional standards and accreditation bodies. Adaptability is a key feature of this model; it is designed to accommodate a variety of evaluation systems across different HEIs. The weighting and measurement criteria can be adjusted to tailor the model to any institution's specific requirements and stakeholder preferences. Despite the variability in implementation, the principle objective remains to enhance the overall educational experience by leveraging a multifaceted approach to course assignments that prioritizes expected academic outcomes.

### 3.3. The mathematical model

Table 1 shows the mathematical notation of the problem, and Figure 1 shows the mathematical model proposed in this research.

The objective function (1) to be maximized represents a weighted sum of elements, where the first sum computes the weighted average (by number of hours per course) of the HEI EAP. At the same time, the last four terms make a weighted sum of violations of the four soft constraints in the model (with weights  $W_f$ ,  $W_c$ ,  $W_j$ , and  $W_p$ ). Constraint set (2) seeks to get each full-time professor to make his/her/their academic load units. Constraint set (3) makes each part-time professor not to exceed his/her/their maximum academic units. Constraint set (4) makes each course meet its section demand. Constraint set (5) seeks to keep all assignments under classroom-type capacity. A dummy professor ( $i=0$ ) will be considered for flexibility purposes. This dummy professor can teach any course and is not limited by time or space. Its EAP will be regarded as negligible. Constraint set (6) ensures that all professors (except the dummy one) are not assigned more than once at a given time. Constraint set (7) provides that all sections of the same course do not overlap at any given time. Constraint set (8) seeks to avoid overlapping sections of the same program for each term at any given time. The upper bounds in the constraint set (9) seek to reduce model size before the pre-processing effort is made. This reduction is imperative because it directly influences the computational tractability of the problem. Pre-processing is essential to solving large problems, such as those encountered in educational timetabling (Trigos, 2002; Franco Sánchez, 2020; ILOG Cplex, 2023). The constraint set in (10) makes all decision variables  $X$ 's binary (the timetabling assignment). In contrast, constraint (11) makes all soft constraint sets (2,5,7 and 8) slack variables  $PNC_i$ ,  $OTCA_{tsdw,c}$ ,  $ONSSO_{j,t}$  and  $ONPTCO_{p,term,tsdw}$  non-negative.

The model in (1) through (11) is always mathematically feasible since excess classroom capacity is allowed at a penalty, and a dummy professor can teach any course-section with no space and time overlapping constraints. Thus, (3), (4) and (6) can always be met. Since the original number of binary variables is  $|I \times J \times T \times C|$ , then the constraint set (9) plays a significant role while writing the model (before pre-processing and calling a solver) to keep its size under a workable number for a comprehensive HEI campus (all schools, majors, and terms). However, it is important to note that while this model and notation serve as a robust starting point, they may not perfectly align with all evaluation systems or stakeholder preference measurement methods for every HEI. Therefore, adaptations may be required to fit particular modes of evaluation and stakeholder preference.

**Table 1.** Notation

Sets	Description
$I$	Set of professors, where $I = \{0, 1, \dots, i, \dots,  I  - 1\}$ , where professor 0 is a dummy member.
$IFTP$	A subset of $I$ representing full-time professors.
$IPTP$	A subset of $I$ representing part-time professors.
$J$	Set of courses, where $J = \{1, \dots, j, \dots,  J \}$ .
$T$	Set of course schedules, where $T = \{1, \dots, t, \dots,  T \}$ .
$C$	Set of classroom-types, where $C = \{1, \dots, c, \dots,  C \}$ .
$SType$	Set of subset courses type schedules, where $SType = \{1, \dots, st, \dots,  SType \}$ .
$TySS$	Set that defines course type schedules $SType$ , with schedules in $T$ . where $TySS = \{(st,t)   t \in T \text{ and } st \in SType\}$ .
$TSDW$	Set of time slots representing the academic period, where $TSDW = \{1, \dots, tswd, \dots,  TSDW \}$ .
$P$	Set of academic programs, where $P = \{1, \dots, p, \dots,  P \}$ .
$TERM$	Set of academic terms, where $TERM = \{0, 1, \dots, term, \dots,  TERM \}$ .
$CTerms$	Set that defines the courses for each term of each academic program, where $CTerm = \{(p, j, term)   p \in P, j \in J \text{ and } term \in TERM\}$ .
$CScT$	Set that relates courses and course schedules, where $CScT = \{(j, st)   j \in J, \text{ and } st \in SType\}$ .
Parameters	Description
$TSType_{st}$	Number of academic hours per period related to the $st$ course member of $SType$ .
$CA_{tsdw,c}$	Number of available units of the classroom-type $c$ at $tswd$ .
$Demand_{j,c}$	Number of sections required for course $j$ at classroom $c$ .
$EAPP_{ij}$	Professor $i$ preference of teaching course $j$ .
$EAPS_{ij}$	Student historical preference of professor $i$ teaching course $j$ .
$EAPI_{ij}$	Institutional preference of professor $i$ teaching course $j$ .
$Wp$	Institutional weight of professor preference.
$Ws$	Institutional weight of student preference.
$EAP_{ij}$	Expected academic performance of professor $i$ teaching course $j$ , where $EAP_{ij} = (Wp \cdot EAPP_{ij} + Ws \cdot EAPS_{ij})EAPI_{ij}$ if $j \neq 0$ , and $EAP_{0j} = 0.0001$ otherwise.

Table 1. Continued...

Parameters	Description
$FAL_i$	Academic load. It represents the upper limit of academic load units for part-time professors or the required amount for full-time professors. Each course taught by a professor counts as one academic unit.
$SSTSDW_{t,tsdw}$	Time coordination matrix, where $SSTSDW_{t,tsdw} = 1$ , if $tsdw$ is contained in $t$ , and 0 otherwise.
$NDH$	Number of demanded course hours, where $NDH = \sum_{vj \in I \text{ and } CScT_j,SType} Demand_{j,c} TSType_{SType}$ .
$Wc$	Penalty factor using overcapacity of classrooms.
$Wf$	Penalty factor for full-time professors not matching their academic load.
$Wj$	Penalty factor for courses with overlapping sections at the same time.
$Wp$	Penalty factor for overlaps of sections of the same program and term simultaneously.
Soft constraint slack variables	Description
$PNC_i$	The number of academic units below the academic load for full-time professor $i \in IFTP$ .
$OTCA_{tsdw,c}$	The number of units classroom-type $c$ is exceeded at $tsdw$ .
$ONSSO_{j,t}$	The number of sections of course $j$ overlapping beyond 1 at $t$ .
$ONPTCO_{p,term,tsdw}$	The number of sections of program $p$ of term overlapping beyond 1 at $tsdw$ .
Decision variable	Description
$X_{i,j,t,c}$	Equal one if professor $i$ is assigned to a section of course $j$ at schedule $t$ in classroom-type $c$ , zero otherwise.

$$\begin{aligned}
 \text{Maximize} \quad & \sum_{i,j,t,c,st} EAP_{i,j} \frac{TSType_{st} X_{i,j,t,c}}{NDH} \\
 & - Wf \sum_{vj \in IFTP} PNC_j \\
 & - Wc \sum_{tsdw,c} OTCA_{tsdw,c} \\
 & - Wj \sum_{j,t} ONSSO_{j,t} \\
 & - Wp \sum_{p,term,tsdw} ONPTCO_{p,term,tsdw} \tag{1}
 \end{aligned}$$

Subject to

$$\sum_{j,t,c} X_{i,j,t,c} = FAL_i - PNC_i \quad \forall i \in IFTP \wedge i \neq 0. \tag{2}$$

$$\sum_{j,t,c} X_{i,j,t,c} \leq FAL_i \quad \forall i \in IPTP. \tag{3}$$

$$\sum_{i,t} X_{i,j,t,c} = Demand_{j,c} \quad \forall j \in J \wedge c \in C. \tag{4}$$

$$\sum_{i,j,t} X_{i,j,t,c} \leq CA_{tsdw,c} + OTCA_{tsdw,c} \quad \forall SSTSDW_{t,tsdw} = 1 \wedge c \in C. \tag{5}$$

$$\sum_{j,t,c} X_{i,j,t,c} \leq 1 \quad \forall i > 0 \wedge tsdw \in TSDW, \text{ with } SSTSDW_{t,tsdw} = 1 \tag{6}$$

$$\sum_{i,c} X_{i,j,t,c} \leq 1 + ONSSO_{j,t} \tag{7}$$

$\forall j \in J, t \in T, tsdw \in TSDW, \text{ with } SSTSDW_{t,tsdw} = 1.$

$$\sum_{i,j,t,c} X_{i,j,t,c} \leq 1 + ONPTCO_{p,term,tsdw} \tag{8}$$

$\forall p \in P, term \in TERM, tsdw \in TSDW,$   
with  $SSTSDW_{t,tsdw} = 1.$

$$X_{i,j,t,c} \leq \begin{cases} 1 & \text{If } EAP_{i,j} > 0 \wedge Demand_{j,c} > 0 \wedge CScT_{j,st} \wedge TySS_{st,t} \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

$$X_{i,j,t,c} \in \mathbb{B}^{|I| \times |J| \times |T| \times |C|} \tag{10}$$

$$\begin{aligned}
 & PNC_i, \\
 & OTCA_{tsdw,c}, ONSSO_{j,t}, \\
 & ONPTCO_{p,term,tsdw} \geq 0 \quad \forall i \in I, tsdw \in TSDW, c \in C, j \in J, t \in T, \\
 & \quad p \in P, term \in TERM. \tag{11}
 \end{aligned}$$

Figure 1. Timetabling mathematical model.



### 3.4. The transdisciplinary framework

Table 2 outlines the transdisciplinary approach to addressing the CT problem. The framework comprises three phases: strategic planning, structural data building, and the procedures for resolving the periodic timetabling issue.

**Table 2.** Transdisciplinary academic timetabling framework

Phases	Steps and description
<b>Phase I: Strategic Planification</b>	Step 1: Identify the stakeholders (Professors, heads of departments, institution executives, etc.) Step 2: Assemble a representative transdisciplinarity team ( <i>TT</i> ).
<b>Phase II: Structural Data Building</b>	Step 3: Define the time planning horizon ( <i>TPH</i> ) and the scope of the endeavor (example a semester on a weekly basis) as the number of programs and terms ( <i>P, TERM</i> ) to be included. Step 4: Define the time minimum common multiple of time intervals ( <i>TW</i> ) during <i>TPH</i> . Step 5: Identify the time schedules ( <i>T</i> ) where each set member must be assembled as the union of the number of members of the set <i>TW</i> . Step 6: Identify the sets of feasible time schedules ( <i>SType</i> ) for courses, as well as the set TySS defining the possible schedules for each course <i>j</i> . Notice that <i>T</i> includes all possible course schedules. Step 7: Identify the institution's facility capacity per classroom-type <i>c</i> at any time <i>tsdw</i> ( $CA_{tsdw,c}$ ). Step 8: Build a data set of courses ( <i>J</i> ) and the classroom-types ( <i>C</i> ) that could be taught at <i>TPH</i> for all Terms ( <i>term</i> ). Step 9: Identify the set of full and part-time professors ( <i>IFT, IPT</i> ) along with their academic load <i>s(FA)</i> . Step 10: Define weights $W_p, W_s$ . Use historical data to compute $EAP_{i,j}$ for each professor <i>i</i> and course <i>j</i> .
<b>Phase III: Periodical Solution</b>	Step 11: Define/Update the number of sections per course required for the current academic term ( $Demand_{j,c}$ ), the related classroom-types ( <i>C</i> ), their available capacities and the subset of program terms (all of them unless told otherwise) to avoid overlapping. Step 12: Update the problem parameters using the latest available data. Step 13: Instance analytics: <ul style="list-style-type: none"> <li>13.1: Compute the classroom-types and facility utilization using available Classroom-type capacity during TPH (<math>CA_{tsdw,c}</math>) and course Demand (<math>Demand_{j,c}</math>).</li> <li>13.2: As a feasibility feature, for every course <i>j</i> compare the number of professors that can teach it (<math>\sum_{\forall i \in I \text{ and } EAP_{i,j} &gt; 0} 1</math>) with the number of sections demanded (<math>\sum_{\forall c \in C} Demand_{j,c}</math>).</li> <li>13.3: If either 13.1 or 13.2 are inconsistent, TT must consider adding professors, schedules and or facility capacity to promote problem feasibility.</li> </ul> Step 14: Build and solve the mathematical model described in Section 3.3. Step 15: If the solution is operationally infeasible: Identify any source of operational infeasibility regarding faculty, schedules, and classroom availability, and discuss it at the TT to act in consequence and go to Step 11 if necessary. Step 16: Implement the timetabling schedule.

## 4. Numerical illustration

This section will provide a detailed numerical demonstration of the transdisciplinary framework on an actual HEI campus, as outlined in Table 2. The first three subsections will follow closely the framework in Table 2. The fourth subsection will elaborate on the relevance of the TT decision-making power.

### 4.1. Phase I: Strategic Planification

During Phase I, the primary goal is to identify all stakeholders and assemble a representative transdisciplinarity team (TT) to work together on the problem to define the institutional parameters.

#### 4.1.1. Step 1, Step 2

In the framework context, **Step 1** and **Step 2** play pivotal roles by involving the identification of stakeholders and the assembly of the TT. The stakeholders in this exercise encompass a diverse group, including professors, students, heads of academic departments, university executives, and accrediting bodies. The motivated participation of the top leading campus HEI executive is paramount. This array of perspectives ensures a comprehensive approach to the timetabling challenge. On the other hand, the TT is meticulously curated and consists of key individuals, such as the head of physical facility administration, department heads, program heads, certification compliance officers, and analytics department officers. Notably, the strong backing of the top leadership in the HEI is a driving force behind this initiative, prompting their active participation within the TT. This collaboration fosters a holistic and practical approach to academic timetabling, aligning with the overarching framework's objectives.

## 4.2. Phase II: Structural Data Building

At this phase, the time planning horizon and the scope of the endeavor are defined, an entire semester (January-June in this case) at a week level (where the weekly schedules repeat every week of the semester), and all undergraduate programs of the campus HEI are included.

### 4.2.1. Step 3 to Step 10

The second phase of the academic timetabling framework involves a systematic approach to navigate the complexities of the campus HEI under analysis. Following the establishment of the conceptual framework (Table 2), the focus shifts to an in-depth analysis of the numerical data. This HEI campus boasts 90 ( $|P|= 90$ ) undergraduate majors, each extending across a spectrum of semester terms from 0 to 10 ( $|TERM|= 11$ ). It is worth noting that these 90 majors encompass a variety of program versions since HEI updates its program periodically, making several versions of the same major being taught in the same academic period for different student classes. This means that not all the 90 majors represent distinct fields of knowledge, and within each major, courses and students might be aggregated (**Step 3**). The challenge escalates with 41 distinct classroom-types ( $|C|= 41$ ), encompassing capacities ranging ( $CA_{tsdw,c}$ ) from 1 to 72 units over all the periods during the week ( $tsdw$ ), each presenting unique attributes such as seating arrangements and technology availability (**Step 4**). These classroom-types ( $c$ ) encompass a broad spectrum, including laboratories and auditoriums, necessitating an advanced approach to effective timetabling. Additionally, operational hours extend from 7:00 to 22:00 throughout the week (**Monday through Saturday**), comprising 180 ( $|TSDW|= 180$ ) potential half-hour slots, forming the foundation for scheduling (**Step 5**). Furthermore, classroom activities occurring within the 7:30 to 16:30 timeframe on weekdays and are built by the union of 30-minute subperiods, resulting in 274 time slots ( $|T|= 274$ ), composing 27 ( $|SType|= 27$ ) course time subsets, where each course  $j$  is assigned to a unique course type  $st$  (**Step 6**). Classroom-type utilization ranges from zero (nine classroom-types) to 62.96 percent (**Step 7**). Building a comprehensive data set suitable for timetabling during the designated planning horizon is essential.

The full instance data set and comprehensive solution report are available at Timetabling PMD 2023 (2023).

Classroom-type and HEI overall classroom utilization could be computed before solving the mathematical model in (1) through (11). The total classroom hours demanded by the HEI stands at 4,829 per week, while the total available classroom hours reach 11,609, yielding a comprehensive HEI classroom utilization of 41.6 percent (**Step 8**). With a faculty comprising 185 full-time ( $|IFTP|= 185$ ) and 440 part-time ( $|IPTP|= 440$ ) professors, 843 courses ( $|J|=843$ ) and 1,526 (sum of  $Demand_{i,c}$  for all  $i$  and  $c$ ) sections across all schools and majors (**Step 9**). This sets the stage for the subsequent steps in the framework, where both professor and student weights ( $W_p$  and  $W_s$ ) are set to 0.5. In addition, the objective function weights for the soft constraints were set to  $W_f = 10,000$  (related to full-time faculty meeting their academic load),  $W_j = 5,000$  (related to no sections of the same course to be overlapped),  $W_p = 3,000$  (related to no sections of the same program-term-time-of-the-week overlapping), and finally  $W_c = 1,000$  (related to classroom-type availability at any time-of-the-week). These decisions are pivotal in optimizing academic timetabling for enhanced educational outcomes (**Step 10**).

## 4.3. Phase III: Periodical Solution

In the final phase, the primary goal is to substitute the updated data set into the model (1) through (11) and solve it to optimality.

At this point, the TT works on the solution obtained by the model (the comprehensive output file is located in the link mentioned above) and checks for adjustments.

### 4.3.1. Steps 11 through 14

To address the CT problem, the mathematical model in (1) through (11) was built and ran in GAMS Studio 1.8.2 64-bit, under Cplex solver, on a MacBook Air with an M1 processor and 16 GB of RAM.

The resulting model size before pre-processing comprises 477,646 constraints and 38,802 binary variables. After pre-processing, the model was reduced to 23,218 constraints and 37,270 binary variables. One hundred percent optimality was achieved at 3,744.11 solver computer seconds (one hour, two minutes, and 24.11 seconds).

Optimal EAP was achieved at 88.92% (professors' and students' preference at 88.96 and 88.88 percent respectively). The complete solution file is included in the web link shown above.

### 4.3.2. Steps 15 and 16

In line with Step 15 of the framework, the TT now critically examines the distribution of faculty, schedules, and classroom allocations of the initial CT solution. The computer time required to achieve this first solution does not allow to execute the model again during the TT meetings but is short enough to be run between TT meetings. The TT analysis of this first solution follows.

Ten full-time professors (out of 195) did not make their full load {professor, underload courses} {35, 2} {59, 2}, {73, 2}, {93, 3}, {153, 1}, {310,2}, {328, 1}, {397, 1}, {455, 3}, and {549,1}. In addition, 85 sections (out of 1,526) were assigned to the dummy professor ( $i=0$ ). Therefore, faculty availability to teach these courses must be revised.

It is worth mentioning that the dummy professor has a negligible EAP where  $EAP_{0j} = 0.0001$  for all  $j$  in  $J$ ; thus, when assigning real faculty to substitute the dummy professor, the overall EAP of the CT solution will rise.

Even though nine classroom-types (1,5, 9, 13, 18 to 22, 25) have zero percent of utilization, the most utilized classroom-type is  $c=10$  with 62.96 percent of utilization, and some others (classroom-types 2, 29, 33, and 35) exhibit overutilization as shown in Table 3.

The first column of Table 3 shows the classroom-type, and the second one shows the conflicted periods. In contrast, columns three, four, and five show current capacity, exceeded units of capacity, and physical capacity (number of physical units in the facility). The difference between current and physical capacity units could have a number of causes, like cleaning time, for instance, where current capacity might be set to zero for classroom cleaning purposes. From Table 3, the TT now should check if one section scheduled from 17:00 to 19:00 on Monday and Tuesday at classroom-type two could be scheduled in other classroom-types with excess capacity (or the classroom-types that are not utilized at all). The same could be explored for classroom-type 29 from 13:00 to 14:30 on Tuesdays. For classroom-types 33 and 35, the problem is that the classroom-type is closed (0 capacity, when 12 and 18 units, respectively, are physically available), so modifying classroom cleaning schedules for one and up to four units could solve the issue.

**Table 3.** Classroom-types with capacity exceeded.

Classroom-type	Conflicted times	Capacity	Exceeded by	Physical availability
2	17:00-19:00 Monday and Tuesday	1	1	1
29	13:00-14:30 Tuesday	1	1	1
33	18:00-21:00 Monday-Friday	0	1	12
35	14:00-21:00 Monday-Wednesday & Friday	0	1 through 4	8

Table 4 shows the course section overlap analysis. The first column includes the course ( $j$ ), the second shows the schedule ( $t$ ), the third shows the number of sections assigned to that schedule, the fourth column shows the total demand in sections of the course, and the fifth column indicates the number of possible schedules in which the course could be allocated. One can see on the first three rows that course CO00801 requires 19 sections, but only 15 type schedules are allowed; thus, at least four sections (one at 11\_2L, one more at 7\_3M, and two at 11+\_3M) will overlap with others of the same course, which is precisely what the first three rows show. The same happened for H00805, with seven sections (16 sections demanded and only 9 possible schedules allowed) overlapping with others. Course H00807 has 7 overlapped sections with others (22 demanded with 15 different schedules). Course H00809 has three sections overlapping with others (12 demanded and 9 available schedules). Courses in the rest of the table manifest the same phenomenon. So, if TT would like to reduce these overlaps, more schedules should be added to the set of possible schedules related to the courses in question.

**Table 4.** Courses and sections with overlaps.

Course	Schedule	Sections	Demand	Schedule type members
CO00801	11_2L	2	19	15
CO00801	7_3M	2	19	15
CO00801	11+_3M	3	19	15
H00805	7_2D	4	16	9
H00805	10_2D	4	16	9
H00805	12_2D	2	16	9
H00807	9_2L	6	22	15
H00807	10_2L	3	22	15
H00809	7_2D	2	12	9
H00809	8_2D	2	12	9
H00809	14_2D	2	12	9
OR00801	7_3M	4	18	15
OR00803	14_2L	3	17	11
OR00803	16_2L	5	17	11
RI00801	7_3M	6	20	15



Table 5 shows an example of a particular undergraduate program and term. The first column of Table 5 shows the course ( $j$ ) using one section per row, the second column shows the course schedule ( $t$ ), the third column shows the classroom-type ( $c$ ), and finally, the last column shows the faculty member teaching this course-section. This report aids program coordinators in helping students register for that program and term. Since a report like Table 5 is generated for every undergraduate program ( $p$ ) and term, there are many reports (990 in this instance) like Table 5 in the output file included in the above link.

**Table 5.** Courses and sections with overlaps in a particular program  $p$  at one specific term.

Course	Schedule	Classroom-type	Faculty member
IN00862	9_2L	41	96
IN00862	15_2L	41	492
IN00862	13_3M	41	96
IN00862	14+_3M	41	96
IS00841	7_3M	41	484
IS00841	8+_3M	41	479
IS00841	7_2L	41	484

The TT's task is to make these model-guided decisions to solve all these operational infeasibilities. Notice that at this point, all the operational infeasibilities discussed above (of the current solution) could be solved without running the model one more time. If so, the next and final operational step is to assign course-sections to physical classroom identifiers. This can be achieved using a simple greedy procedure. Otherwise, the process stipulates a return to Step 11 until all operational infeasibilities are solved. The guiding aim is to systematically improve the EAP while adhering to the model's constraints, thus ensuring optimal resource utilization and schedule alignment with stakeholder preferences.

#### 4.4. The relevance of the transdisciplinary team

The framework in Table 2 moves beyond theoretical models, marking a significant phase in applying academic timetabling within the HEI setting. This framework aids the critical transition from abstract modeling to the tangible execution of schedules and plans.

Although the model has provided a mathematically optimal solution, it is imperative to understand that this isn't the sole aim of the endeavor. The overarching goal is to enhance the EAP within the HEI. This ambition extends beyond numerical optimality, seeking to meet a broader spectrum of needs and objectives. As noted by Bertsekas (1995), mathematical models serve as pivotal tools in decision-making, highlighting that the 'mathematical optimal solution' is an essential step in a larger journey rather than the final destination.

At this crucial juncture, the TT assumes a key role. Armed with the outputs from the initial model, the TT is responsible for scrutinizing and potentially revising these findings. Its task involves making strategic decisions that may include the adjustment of cleaning schedules, reassignment of classroom-types to a number of course-sections, the integration of new faculty members, the accurate inventory of course teaching capacities, along the identification of faculty training programs. These actions are not merely administrative but are pivotal in further elevating the EAP.

Subsequently, the TT embarks on an essential phase of refining this solution, aiming to align it more closely with the institution's practical needs and realities. This interdisciplinary approach, advocated by Choi and Pak in 2008 (Choi and Pak, 2008), underscores the importance of integrating varied academic perspectives in decision-making. In line with Gooding et al. (2023), while there isn't a unanimous consensus on the benefits of TD for effective collaboration or bridging various disciplines, the model does acknowledge the need to integrate different methodologies and knowledge systems. The team implements strategic adjustments by focusing on key resources such as schedules, facilities, and academic staff. Although these modifications may seem subtle, they are carefully crafted to meet the complex needs of the HEI's academic framework and infrastructure.

This practical application of the model demonstrates its robustness and effectiveness in guiding HEI decision-making processes and transitioning a theoretical framework into a dynamic, impactful tool. The model's success in real-world scenarios signifies a considerable advancement for academic institutions, revealing previously unexplored efficiencies and significantly enhancing stakeholder satisfaction. The demonstrated efficacy and scalability of the transdisciplinary framework establish it as a valuable asset, especially for larger and more complex institutions.

Looking ahead, continuous efforts will be directed towards refining and enhancing this framework. The goal is to bolster its effectiveness and utility for educational establishments, ensuring that it remains adaptable and responsive to evolving educational landscapes and standards.

## 5. Conclusions and further research

The timetabling problem persists as a notably complex challenge within the optimization realm. This research contributes significantly to the field by demonstrating the viability of applying a transdisciplinary approach to an actual size HEI campus, as evidenced in section 4. It also introduces a novel mathematical model for integrating various stakeholder preferences into the timetabling process, ensuring that the interests of professors, students, and institutional requirements are balanced. Furthermore, including dummy variables for both professors and classroom-type capacities is a distinctive feature of this model, which not only avoids the pitfall of infeasibility but also provides a foundation for continuous refinement of the timetable to optimize the EAP. Thus, this article reaffirms the utility of the transdisciplinary framework, expands its applicability, and introduces a refined methodology for achieving more effective timetabling solutions in complex educational settings. The replicability of this approach in handling the timetabling problem in large and complex campus HEI settings has been successfully demonstrated, thus reinforcing its adaptability. In addition, the critical role of stakeholder preferences and institution-specific variables in crafting a practical timetable has been highlighted. This approach challenges the traditional silo-based knowledge systems by considering the institution's holistic operational needs and the stakeholders involved. The success of this extended research not only emphasizes the potential of transdisciplinary methods in addressing scheduling challenges but also provides a foundation for future studies and practical tools for HEIs. It underscores how a transdisciplinary approach can metamorphose into an organizational capability, improving operational efficiency and stakeholder satisfaction.

Further research pends ahead, finding a way to enhance the efficiency of the timetabling problem-solving process beyond the mathematical model and the encompassing framework. Future developments could focus on integrating a more digital version of this framework, capable of proposing solutions to overlapping assignments generated by the model's soft constraints. This advanced tool could also aid in simplifying the interpretation of results, suggesting alternatives, and facilitating a smoother decision-making process for the TT. The core challenge, as indicated by Holmes et al. (2022), lies in translating complex, specialized knowledge into user-friendly systems and workflows, nurturing a transdisciplinary culture that breaks through conventional operational silos and aligns with contemporary digital practices. Adopting such an approach is imperative to ensure that the principles of Transdisciplinarity are embedded in the institution's daily operations, thereby enhancing its overall functionality and responsiveness.

Other potential areas of exploration emerge from this work. One clear path is extending the deterministic model to embrace more stochastic variables to accommodate demand variability based on current and anticipated enrollments. However, it's important to note that this extension should be conceived and developed by digitizing educational institutions' operations. Digitizing operations and integrating the transdisciplinary framework within this digital context could naturally provide real-time, variable data. This allows a more dynamic response to the ever-changing educational environment, ultimately enhancing the robustness and adaptability of the scheduling process. Therefore, the seamless merging of this transdisciplinary framework into a modern digital operation environment and the continuous evolution of the model to accommodate more nuanced institutional realities will significantly strengthen its capability as a potent tool for addressing the multifaceted challenges faced by modern HEIs.

## 6. References

- Abdullah, S., Muthusamy, M., & Kaur, H. (2015). An improved genetic algorithm for university course timetabling problems. *Procedia Computer Science*, 76, 470-475.
- Bertsekas, D. (1995). The role of mathematical models in decision making. *IEEE Transactions on Automatic Control*, 40(11), 1813-1825.
- Bettinelli, A., Cacchiani, V., Roberti, R., & Toth, P. (2015). An overview of curriculum-based course timetabling. *Top (Madrid)*, 23, 313-349.
- Burke, E. K., & Petrovic, S. (2002). Recent research directions in automated timetabling. *European Journal of Operational Research*, 140(2), 266-280.
- Burke, E., Kingston, J., & De Werra, D. (2004). Applications to timetabling. In J. L. Gross & Y. Yellen. *Handbook of graph theory* (Vol. 445, p. 4). Boca Raton: CRC Press.
- Ceschia, S., Di Gaspero, L., & Schaerf, A. (2023). Educational timetabling: problems, benchmarks, and state-of-the-art results. *European Journal of Operational Research*, 308(1), 1-18.
- Chen, M. C., Goh, S. L., Sabar, N. R., & Kendall, G. (2021). *A survey of university course timetabling problem: perspectives, trends and opportunities*. *IEEE Access*, vol. 9, pp. 106515-106529.
- Choi, B., & Pak, A. (2008). Transdisciplinarity in the classroom and beyond: a review of the challenges and promise of integrating multiple academic perspectives. *Ecosystem Health*, 4(1), 31-37.
- Clark, B. R. (1986). *The higher education system: academic organization in cross-national perspective*. Berkeley: University of California Press.

- Eleyan, D., Arnaout, J. P., & Diabat, A. (2018). A comprehensive survey of course timetabling in universities. *Computers & Industrial Engineering*, *117*, 253-265.
- Franco Sánchez, V. (2020). *Pre-processing techniques for Integer Linear Programming* (Bachelor's thesis). Universitat Politècnica de Catalunya, Barcelona. Retrieved in 2023, December 5, from <https://upcommons.upc.edu/bitstream/handle/2117/339357/151791.pdf>
- Froese, A. D., Gantz, B. S., & Henry, A. L. (1998). Teaching students to write literature reviews: a meta-analytic model. *Teaching of Psychology*, *25*(2), 102-105.
- Gooding, H., Lattanzio, S., Parry, G., Newnes, L., & Alpay, E. (2023). Characterising the transdisciplinary research approach. *Product: Management and Development*, *20*(2), e20220012. <https://doi.org/10.4322/pmd.2022.024>.
- Holmes, R. C., Zhang, Z., Mallison, B., Saldaña, S., Francis, J., & Moser, B. R. (2022). Prioritization of Digital Innovation Team projects using a utility model and tradespace analysis. *Product: Management and Development*, *20*(1), e20220010. <https://doi.org/10.4322/pmd.2022.022>.
- ILOG Cplex. (2023). *Pre-processing data*. Retrieved in 2023, December 5, from <https://www.ibm.com/docs/en/icos/20.1.0?topic=sources-preprocessing-data>
- Kheiri, A., Keedwell, E., & Gheorghe, M. (2018). A novel algorithm for the university exam timetabling problem using an immune algorithm with a new feasible individual generation mechanism. *Applied Soft Computing*, *64*, 440-453.
- Kingston, J. H. (2022). *Timetabling research: a progress report*. Retrieved in 2023, December 5, from [https://patatconference.org/patat2022/proceedings/PATAT\\_2022\\_paper\\_23.pdf](https://patatconference.org/patat2022/proceedings/PATAT_2022_paper_23.pdf)
- MirHassani, S. A., & Habibi, F. (2013). Solution approaches to the course timetabling problem. *Artificial Intelligence Review*, *39*, 133-149.
- Mokhtari, M., Vaziri Sarashk, M., Asadpour, M., Saedi, N., & Boyer, O. (2021). Developing a model for the university course timetabling problem: a case study. *Complexity*, *2021*, 9940866.
- Muklason, A., Parkes, A. J., Özcan, E., McCollum, B., & McMullan, P. (2017). Fairness in examination timetabling: student preferences and extended formulations. *Applied Soft Computing*, *55*, 302-318.
- Nurmi, K., & Kyngäs, J. (2008). A conversion scheme for turning a curriculum-based timetabling problem into a school timetabling problem. In *Proceedings of the 7th International Conference on the Practice and Theory of Automated Timetabling (PATAT 2008)*. PATAT. Retrieved in 2023, December 5, from <https://patatconference.org/patat2008/proceedings/Nurmi-TC1a.pdf>
- Özcan, E., Bilgin, B., & Yilmaz, T. (2013). A simulated annealing algorithm with a new neighborhood structure for university exam scheduling. *Applied Soft Computing*, *13*(8), 3593-3602.
- Özcan, E., De Causmaecker, P., & Berghe, G. V. (2022). Advances in the practice and theory of automated timetabling. *Journal of Scheduling*, *25*(3), 259-259.
- Pillay, N. (2014). A survey of school timetabling research. *Annals of Operations Research*, *218*, 261-293.
- Qu, R., & Burke, E. K. (2009). Bridging the gap: from theoretical models to practical solutions in university course timetabling. *The Journal of the Operational Research Society*, *60*(10), 1345-1355.
- Qu, R., Burke, E. K., McCollum, B., Merlot, L. T., & Lee, S. Y. (2009). A survey of search methodologies and automated system development for examination timetabling. *Journal of Scheduling*, *12*, 55-89.
- Sabin, G., & Winter, G. (1986). The impact of automated timetabling on universities: a case study. *The Journal of the Operational Research Society*, *37*(7), 689-693.
- Schaerf, A. (1999). A survey of automated timetabling. *Artificial Intelligence Review*, *13*, 87-127.
- Selimi, S., Arbnesi, L., Sylejmani, K., & Musliu, N. (2022). Iterated Local Search for the examination timetabling problem with constructive-based initial solution. In *Proceedings of the 13th International Conference on the Practice and Theory of Automated Timetabling-PATAT (Vol. 3)*. PATAT.
- Tan, J. S., Goh, S. L., Kendall, G., & Sabar, N. R. (2021). A survey of the state-of-the-art of optimisation methodologies in school timetabling problems. *Expert Systems with Applications*, *165*, 113943.
- Timetabling PMD 2023. (2023). Retrieved in 2023, December 5, from <https://www.dropbox.com/scl/fo/boyjguiy9x0qh60ten2a6/h?rlkey=3qmgbar4b4encm4konpbct42k&dl=0>
- Trigos, F. (2002). Sobre la reducción de modelos de programación lineal. *Métodos Numéricos en Ingeniería y Ciencias Aplicadas*, *1*, 409-418.
- Trigos, F., & Coronel, R. (2023). *A transdisciplinary approach to the academic timetabling problem*. Advances in Transdisciplinary Engineering, Vol. 44, pp. 591-600. Amsterdam: IOS Press. <https://doi.org/10.3233/ATDE230654>.
- Van Bulck, D., & Goossens, D. (2023). The international timetabling competition on sports timetabling (ITC2021). *European Journal of Operational Research*, *308*(3), 1249-1267.
- Wren, A. (1995). Scheduling, timetabling and rostering a special relationship? In *International Conference on the Practice and Theory of Automated Timetabling* (pp. 46-75). USA: Springer.