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# Addressing staffing challenges through improved planning: Demand-driven course schedule planning and instructor assignment in higher education

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ABSTRACT

This paper presents a novel decision support system (DSS) to address the University Course Timetabling Problem (UCTP). The solution decomposes the NP-complete UCTP into two sub-problems, allowing a structured approach to addressing the complexities inherent in the UCTP process. A mixed integer linear programming (MILP) model is proposed to integrate academic year course schedule planning and instructor assignment, accommodating various constraints to meet student demands. The model optimizes the number of course sections and strategically schedules instructors, aiming to reduce the number of new and distinct courses assigned to them. Historical data from an academic department encompassing multiple disciplines, including Computer Information Systems, Business Management, and Business Analytics, at a large public university in the U.S. is used to develop the model, and the results are compared with the actual course schedule and instructor assignment. The results demonstrate that the proposed DSS would result in a 14 % reduction in the number of course sections offered, translating to approximately $130,000 in annual savings. Additionally, it could significantly reduce the number of new courses assigned to instructors by up to 81 % and the number of distinct course sections assigned to them by 29 %.

## 1. Introduction

In the last decade, universities have faced considerable financial challenges stemming from a continuous decline in enrollment and underfunding [1,2]. The recent Covid-19 pandemic has further intensified these difficulties [3]. To maintain financial stability, many universities have adopted proactive measures, such as freezing faculty hiring, reducing salaries for faculty and staff, using additional scholarships to attract potential students, and deploying part-time instructors. However, due to pedagogical, accreditation, and other strictures, the use of part-time instructors may be limited, especially if course staffing can be strategically managed with efficient scheduling models.

Staff costs, including salaries and other benefits, typically constitute the largest portion of university expenditures. For example, the National Center for Education Statistics (NCES) reported that instruction accounted for 26 % of total expenses for 4-year public institutions in 2019–20 [4], while Stanford University noted that 64 % of total expenditures for the fiscal year 2022–23 were spent on salaries and benefits [5]. Consequently, addressing staff costs is vital for effective cost control and optimization in universities. This study, therefore, aims to minimize staff costs by better aligning the number of course sections with students' course demand within the University Course Timetabling (UCT) framework. The efficient allocation of instructors, facilities, and other resources is critical for universities to offer the best possible education to their students, facilitating timely progression toward graduation through well-designed course timetables and other services. The University Course Timetabling Problem (UCTP) is a complex, multi-dimensional assignment problem that involves assigning students and instructors to course sections at designated timeslots and classrooms [6].

The UCTP has been proven to be NP-complete [7]. While many NP-complete problems can be solved efficiently in practice, integrating all dimensions of the UCTP into a comprehensive model presents a particularly challenging problem. This complexity arises due to the numerous binary variables involved across all assignment problems, necessitating the use of advanced heuristic algorithms to achieve solutions of uncertain accuracy within a reasonable timeframe. The existing literature on UCT is abundant with models and methods [8]. However, only a few studies, such as [9–11], detailed actual implementations of automated

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timetabling systems. The survey study in [12] also identified a persistent gap between UCT literature and its practical application in academia. While the literature tends to focus on developing more sophisticated methods for solving timetabling problems, academic practice often prioritizes the design and development of user-friendly and interactive tools that cater to the institution's instructional needs [8]. Consequently, there is an ongoing demand for automated approaches that facilitate the effective transfer of past knowledge to final schedules, addressing timetabling problems in academic institutions. The aim of the International Timetabling Competition (ITCs) series, initiated in 2002, is to address the common UCTP by incorporating practical considerations. One of the recent iterations, ITC 2019, sought to optimize the assignment of times, rooms, and students to courses [13]. However, the competition did not consider course schedule planning, which establishes the number of sections for each course, or the instructor assignment problem, which determines a university's teaching capacity. As a result, universities intending to implement this system must first determine the number of sections for each course and assign instructors accordingly.

This study aims to bridge the gap between advanced models and algorithms available in academia and the practical needs of colleges and universities in optimizing course scheduling and instructor assignments using historical data. The resulting schedules should meet students' course demands with a minimum number of course sections while maximizing instructor preferences. To achieve this, we first propose a process-based DSS framework (detailed in Section 2) that incorporates primary decision problems before the publication of the final schedule.

Subsequently, we introduce an integrated model for course schedule planning and instructor assignment that generates the optimal number of sections for each course and assigns instructors to each section to satisfy forecasted course demands with minimal staff cost. Meeting students' course demands is treated as a hard constraint, while instructors' preferences are addressed by minimizing the number of new course preparations and the number of distinct courses they are assigned each semester. Limiting the number of new course preparations allows instructors to spend more time refining their existing materials and pedagogy, thereby increasing their effectiveness in the classroom. Similarly, reducing the number of distinct courses assigned to each instructor during each semester fosters deeper content expertise and reduces the cognitive load associated with switching between different subjects, leading to improved instructional quality and higher job satisfaction. The proposed framework is adaptable and parameterized, allowing for adjustments in weighting to enable departments to prioritize either the minimization of distinct course sections or new course preparations based on the collective faculty preferences.

The study makes several contributions to the UCTP literature: (1) it proposes a process-based decision support system that simplifies the NP-complete UCTP into two more manageable hierarchical models; (2) it integrates the deeply interconnected tasks of course schedule planning and instructor assignment into a single comprehensive model, efficiently generating optimal course-section-instructor combinations from basic inputs; (3) it considers instructors' preferences by assigning them fewer new courses and distinct courses, thereby minimizing their course preparation time and enhancing teaching quality; and (4) it demonstrates the practical application of the proposed flexible model, showing positive results in reducing staff costs and alleviating financial pressures on universities. The practicality of the proposed model is particularly crucial. A recent comprehensive survey of UCTP solutions in the literature indicates that many existing solutions are not viable in real-world settings due to their limited flexibility and the impractical nature of these methodologies [14]. Our research can assist department chairs in efficiently planning timetables, minimizing complaints from both instructors and students, and reducing staffing costs while accounting for various practical constraints.

The organization of the paper is as follows: In Section 2, the proposed process-based DSS framework is presented. In Section 3, the related literature on UCTP is reviewed. In Section 4, the integrated model of course schedule planning and instructor course assignment is introduced. Section 5 utilizes a case study from a large public university in the United States to validate the proposed model. The proposed solution is analyzed and compared with the actual course schedule and instructors' assignment in the subsequent academic year. Finally, in Section 6, conclusions and directions for future research are presented and discussed.

## 2. Process-based decision support system framework

In response to the complex NP-complete nature of the UCTP, which involves the intricate process of determining course sections, instructor assignments, and the allocation of classrooms and timeslots, this study introduces a process-based DSS that effectively decomposes the UCTP into two more manageable sub-models. This approach facilitates a more structured method for addressing the complexities inherent in the timetabling process, as shown in Fig. 1.

Initially, course demands are forecasted by leveraging current student enrollment and historical course registration data. Employing advanced data mining and predictive modeling techniques can enhance the accuracy of these predictions [15]. Nonetheless, predicting course demands is a complex undertaking as factors such as changes in the economy, demographics of the student population, students' individual preferences, and unexpected events such as natural disasters or public health emergencies can influence course demands [3]. Furthermore, these uncertainties are more pronounced when predicting demand for classes for new incoming students. Fortunately, a certain degree of inaccuracy in demand prediction is tolerable, as subsequent instructor and classroom assignments can offer flexibility by accommodating some margins of error in demand prediction.

Subsequently, the course schedule planning problem is considered to determine the optimal number of sections for each course in the upcoming academic year given the forecasted course demands. Inputs encompass the number of students eligible to register for each course, the proportion of qualified students registering for each course, the threshold for opening a new section, the maximum capacity for each section, and courses scheduled in the same semester of the previous academic year, among other factors. The output of this model, the number of sections for each course, serves as input for the instructor assignment problem.

Additional inputs include the number of full-time faculty members, the courses taught by each faculty member in the prior academic year, the qualifications of each faculty member to teach specific courses, each faculty member's annual teaching load, the minimum required percentage of course sections taught by full-time faculty, and other pertinent factors. The output of the instructor assignment problem, which is the primary focus of this study, is the course-section-instructor combination, which subsequently serves as input for the timeslot and classroom assignment problems. In the event that the available full-time faculty members cannot fully staff all course sections, administrators may need to consider additional strategies. These strategies could include hiring adjunct instructors from a pool of qualified candidates, negotiating overload assignments with full-time faculty (with appropriate compensation upon mutual agreement), or, in rare cases, canceling course sections. The specific strategy adopted by a university will depend on its unique situation and requirements, which may vary from one institution to another. While these decisions are ultimately the responsibility of university administrators and fall outside the direct scope of the proposed decision support system, they represent important considerations in the broader context of university course scheduling.

Owing to the high interdependence between the two aforementioned problems, they should be optimized concurrently. The integrated optimization of highly interactive decision layers has demonstrated remarkable performance in manufacturing and supply chain systems [16,17]. In the present study, we propose an integrated optimization

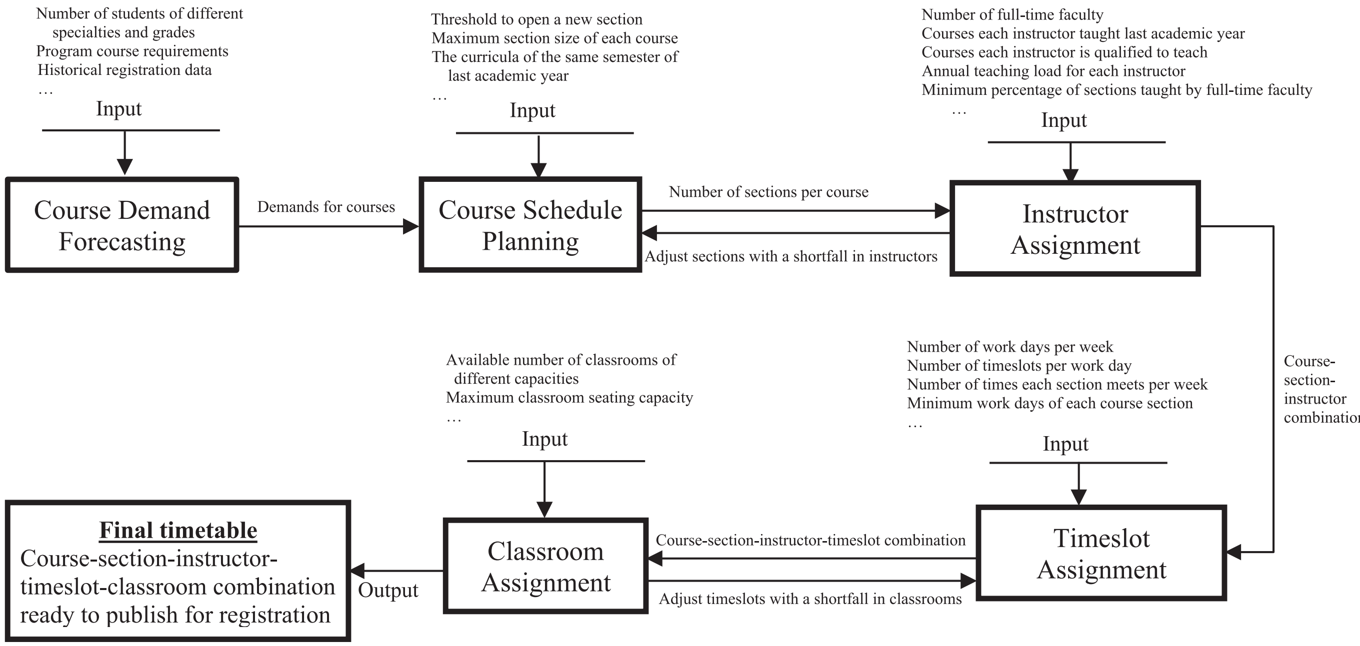


**Fig. 1.** Overview of the University Course Timetabling Problem (UCTP) and the decomposition into sub-models for the DSS.

model for the Course Schedule Planning and Instructor Assignment problems, denoted as *CSPIA*, in the planning horizon of one academic year to satisfy the forecasted students' demand for courses. The model defines and minimizes the number of new courses and sections of distinct courses to be taught by faculty members, as these necessitate considerable preparation and may not align with their teaching preferences. The integrated model determines the optimal number of sections for each course and optimally assigns full-time faculty to teach each section in the fall and spring semesters of the subsequent academic year based on their teaching expertise (or preference) and other qualifications. The output of our model, the course-section-instructor combination, effectively bridges the gap between UCTP literature and practical applications in academia.

Subsequently, the timeslot assignment part of the model determines the timeslots allocated to course section and instructor combinations, considering factors such as the number of work days per week, the number of timeslots per work day, the number of times each course meets per week, and the minimum and maximum work days for each faculty and course section. The output consists of section-instructor-timeslot combinations.

Lastly, the classroom assignment part of the models assigns classrooms to each course section based on predetermined section-instructor-timeslot combinations as well as other factors, such as the available number of classrooms with varying capacities and the maximum seating capacity of each classroom. If there is a shortfall in classrooms, the timeslots of course sections must be adjusted to ensure that a classroom is assigned to each lecture. Due to the interaction between timeslots and classroom assignment problems, they should be optimized simultaneously. While assigning some course sections to non-traditional classrooms, such as university libraries, and converting some sections to online instruction may alleviate the need for department-owned classrooms, it remains practical to reduce classroom requirements. Lindahl et al. [18] recognize this as a strategic decision in UCTP.

## 3. Related studies

The UCTP has garnered significant interest from both researchers and academic administrators over the years. Comprehensive reviews of the problem are documented in both early works [19–21] and more recent studies [14,22,23]. The course timetabling problem is categorized into two distinct types: master timetables and demand-driven systems [19]. Extensive surveys cover various formulations for automated timetabling, including techniques such as graph coloring, integer linear programming, network flow techniques, Tabu search, rule-based approaches, and constraint logic programming [20].

A study in [14] provides a comprehensive and recent overview of the methodologies applied to the UCTP, classifying them based on chronology and datasets. This review discusses perspectives, trends, challenges, and opportunities in UCTP, noting the popularity of meta-heuristic and hybrid methodologies. It also highlights the gap between state-of-the-art academic solutions and their practical real-world application, attributing this to their limited flexibility and inability to provide comprehensive solutions. Table 1 summarizes the methodologies, findings, and limitations of past UCTP studies.

Considering the studies listed in Table 1, only a few address the quantity of course sections [24–26]. The study in [24] introduces a demand-driven, multi-objective hierarchical mathematical model for departmental course scheduling in undergraduate courses. The generated course schedules determine which courses to offer, the number of sections for each course, the timeslots for course sections, and the assignment of faculty to each course section. However, the hierarchical models are solved sequentially, disregarding the inherent interaction between course schedule planning and instructor assignment problems, which may affect the feasibility of the solutions in practice. Additionally, the balance between full-time and adjunct instructors is ignored, impacting the practicality of the solution.

The mathematical formulation of the UCTP is presented in [25] and is solved through lexicographical optimization with four ILP sub-problems solvable sequentially with CPLEX. This approach, however, disregards instructors' preferences for courses and timeslots, making the solution less practical. Moreover, the hierarchical solution may affect the feasibility of the upper-level solutions. In [26], traditional operational issues are broadened to include strategic concerns that may influence resulting timetables that cannot be altered at short notice. This study explores two strategic decisions concerning the teaching period problem (e.g., determining the number of timeslots or whether to add extra timeslots) and the room planning problem (e.g., selecting which rooms to use), which have received limited attention in the literature. However, the instructors' preferences are expressed as the minimum working days and curriculum compactness, ignoring new and distinct

**Table 1**
Summary of methodologies, findings, and limitations of previous UCTP studies.

| Source | CSP | IA | TA | CA | Methodology | Findings | Limitations |
|---|---|---|---|---|---|---|---|
| [24] | X | X | X | | Multi-objective MIP | The faculty schedules can address important priorities, such as minimizing expected course conflicts. | Models are solved sequentially, leading to potential infeasibility of upper-level model; full-time and adjunct instructor balance is ignored. |
| [25] | X | | X | | Decomposed metaheuristic approach | The proposed sequential procedure generates similar or better solutions with lower solution complexity. | Instructor preference for courses is ignored and the hierarchical solution may affect the feasibility of the upper-level solutions. |
| [26] | X | | X | X | Bi-objective MIP | The models show that the rooms, teaching periods and timetable quality affect one another. | The preferences are expressed as the minimum working days and curriculum compactness, ignoring new course preparation. |
| [27] | | X | | | MIP | The results show high performance in maximizing teachers' preferences. | The section quantity for each course is fixed and the model is not adaptable to dynamic student demands. |
| [28,29] | | X | X | | MIP | The approach improves instructor satisfaction and utilization of rooms. | The section quantity for each course is fixed and the course preference of instructors is ignored. |
| [30] | | X | X | | MIP | The method produces better solutions better than the manual allocation. | Hard to solve the large-scale MILP model and instructors' preferences for courses are ignored. |
| [31] | | X | X | | Multi-objective LP | The model balances the instructors' and administration's preferences. | The course schedule, including section quantity and instructors that teach each section, is predetermined. |
| [32] | | X | X | | stochastic programming | The approach with cancellation risk of courses shows good performance. | Not adaptable to dynamic course demands and doesn't consider course preferences of teachers. |
| [33] | | X | X | X | IP | The proposed method generates better timetables than the current practice. | The approach considers the preference of teachers for rooms and timeslots but ignores that for courses. |
| [10] | | X | X | X | IP | The proposed system improves use of classroom capacity when assigning courses to classrooms. | Ignoring multiple sections of the same course and the course preference of instructors. |
| [34] | | | X | X | MIP | The proposed adaptive tabu search algorithm is effective compared with other reference algorithms. | Lack of adaptability to dynamic student demands and instructors' preferences for courses to teach. |
| [35] | | | X | X | Two-stage IP | The proposed two-stage model can find high quality solutions and reduce student flows between lectures. | Ignoring the determination of course-section-instructor combination. |
| [36] | | | X | X | IP | The obtained schedule can reduce idle periods for students and utilize classrooms more efficiently. | This study only assigned courses to timeslots and rooms, ignoring the determination of course sections quantities and instructor assignment. |
| [37] | | | X | X | MIP | The approach considers the allocation of students to classes and assignment of rooms and time periods to classes. | The course-section-instructor combination is known in advance and not adaptable to dynamic course demands; instructor preference is ignored. |
| [38] | | | X | X | MIP | The approach assigns classes to rooms when room capacities are drastically reduced during COVID. | Instructors' preference is not considered, and the model is not applicable to dynamic course demands. |
| [39] | | | X | X | Simulated annealing | The proposed solver with penalization generates satisfactory solutions. | Lack of adaptability to dynamic demands and ignoring instructor assignment. |
| [40] | | | X | X | NA | This paper added student sectioning to traditional UCTP. | Knowing the section quantity and instructor assignment in advance. |
| [41] | | | X | X | IP | The multi-stage process can adjust the timetable to satisfy the varying demands for different student groups. | Ignoring the assignment of instructors. |
| [42] | | | X | | MIP | The model ensures that students choose their preferred time slots. | Ignoring the effects of course demands on section quantities of each course and instructor preference. |
| [3] | | | | X | IP | The method for classroom assignment problems offers a systematic solution. | Lack of adaptability to dynamic student demands and instructor/timeslot availability. |

Notes: CSP-course schedule planning, IA-instructor assignment, TA-timeslot assignment, CA-classroom assignment, MIP-mixed integer programming, IP-integer programming.

course preparation.

Another stream of research focuses solely on assigning instructors, timeslots, and/or classrooms to predetermined course sections, ignoring the determination of the quantity of course sections to satisfy dynamic course demands and the course preferences of instructors [10,27–34]. In [27], a MILP model is presented that balances instructors' load and preferences with instructor assignment to courses with preset schedules across two semesters, but the number of sections per course is regarded as constant. Mixed-integer programming models for assigning timeslots and faculty to different course sections [28,29] address gender issues across multiple departments. While these models incorporate features aimed at minimizing class conflicts and enhancing traffic flow, they do not consider the number of sections per course or variations in course demand.

Addressing the UCTP, a model proposed in [30], concurrently integrates instructor assignment and course scheduling. However, this model, similar to [31], is unable to accommodate variations in student demand or determine the optimal number of sections for each course, limiting its practicality and effectiveness. The study in [32] considers the risk of course cancellation, focusing on maximizing satisfaction for students and professors. Yet, the proposed integrated model does not address course schedule planning and is not adaptable to dynamic course demands. An integrated integer programming model for generating a comprehensive timetable in a term is proposed in [33]. The aim of this model is to minimize the violation of preferences and rules associated with different penalties. However, it does not consider student demands and preferences for courses or the consequent impact on the number of course sections. An integer programming model for instructor-course-time-slot assignments is introduced in [10], addressing practical issues like back-to-back classes and inter-departmental classroom leveling. However, this study neither considers the optimal number of sections for each course nor accounts for variations in course demand.

Without considering course schedule planning and instructor assignment, several studies concentrate on assigning classrooms and/or timeslots to predetermined course sections [34–42]. In [34], a mathematical formulation for the conventional UCTP is presented, utilizing a hybrid Adaptive Tabu Search algorithm for its solution. Despite this, the model fails to incorporate crucial elements such as course schedule planning and instructor assignment, which detracts from its practicality. The study in [35] proposes a two-stage model to optimize student flows between consecutive lectures, but it also overlooks course schedule planning related to student demands and instructor assignment. In [36], integer programming is employed to assign groups of courses to groups of timeslots and rooms. However, the model does not account for the number of sections of each course, faculty assignment to courses, or the variations in course demand. The mixed integer programming model in [37] allocates students to classes and assigns rooms and timeslots to classes while [38] only formulates the classroom assignment problem into a mathematical model. However, their course-section-instructor combination is also predetermined, making it less adaptable to dynamic course demands, and instructors' preferences for taught courses are ignored. The study in [39] introduces student sectioning and distribution constraints to the traditional UCTP, proposing a simulated annealing solver to find optimal solutions. Similarly, Müller et al. [40] integrate time slot and classroom assignment with student sectioning, an approach inspired by the practical challenges faced in ITC 2019. In contrast, the research in [41] focuses specifically on scheduling common courses for students in parallel groups. Meanwhile, [42] employs data analytics to identify key issues contributing to delayed graduations and developed a model to optimize class scheduling, ensuring that students could select their preferred time slots. In [3], a mixed integer programming model is proposed to assign course sections to classrooms when room capacities are drastically reduced during COVID. However, these studies are all constrained by a fixed course-section-instructor combination, limiting their flexibility to adapt to changing demands and conditions.

As shown in Table 1, the majority of the existing literature focuses on timeslot and classroom assignment or related operational aspects, often neglecting course schedule planning and instructor assignment. These elements are typically viewed as predetermined when addressing UCTP. From a methodological perspective, various approaches have been proposed to address UCTP, as evidenced in [25,31,34]. However, recent advances in computer software and hardware have led to increased attention on MILP models, as highlighted in [26]. Examples include integer programming models for classroom assignment [38], analysis of student flows between lectures [35], and MILP models for balancing instructor workload [27]. While these approaches offer valuable insights, they often overlook crucial aspects of course schedule planning, such as accommodating fluctuating student demands and assigning instructors effectively. Additionally, treating the number of sections per course as constant may limit the adaptability of solutions.

In summary, prior research has notably advanced the understanding of the UCTP, yet they fall short in certain areas. Specifically, these studies often overlook the variation in course requirements and the preferences of both students and instructors. Moreover, reviewing existing literature highlights the need for an integrated optimization model that considers the interrelated nature of course schedule planning, instructor assignment, and student course demands, to bridge the gap between the literature and academic practice. The present study aims to address these limitations by proposing an integrated optimization model for course schedule planning and instructor assignment, considering both student and instructor preferences and ensuring the feasibility of the solutions in practice.

## 4. Model development

The proposed integrated model can simultaneously determine the optimal number of sections of each course and the optimal section-instructor combination based on students' demand for courses in an academic year.

### 4.1. Entities

The key entities in the proposed integrated model of curricula design and faculty course assignment are as follows.

**Courses, Sections, and Meeting Frequency:** Each course in the schedule typically comprises one or more sections, and each section is organized to meet one or more times a week at specified days and times. For instance, courses that meet once a week are scheduled for 2.75 h on either Monday, Tuesday, Wednesday, or Thursday. Conversely, courses meeting twice a week are scheduled for 1.25 h per session, typically on Mondays and Wednesdays or Tuesdays and Thursdays. The maximum number of students allowed in each course section is a function of the specific pedagogical requirements of the course and room capacity. Each course section is assigned a timeslot that corresponds to its meeting period.

**Instructors:** The model in this study includes all full-time faculty members (both tenure-track and non-tenure-track) with predetermined qualified courses to teach. A prevalent practice in academic institutions is to prioritize the assignment of courses to full-time faculty to whom the institution has a financial commitment. If available full-time instructors are insufficient to meet all course staffing requirements, administrators often resort to various strategies depending on their preferences and circumstances. These strategies include tapping into a pool of eligible adjunct instructors, negotiating overload assignments with full-time faculty for additional compensation, temporarily increasing the capacity of some of the existing sections to reduce the number of sections if possible, or even canceling a section in extreme cases. Depending on their needs, requirements, policies, and available resources, each department may adopt a different approach or a mix of these solutions to address the problem when the capacity of their full-time faculty cannot meet course demands. Consequently, the model in this study is primarily focused on assigning full-time instructors.[1]

**Students:** Students are allowed to enroll in the offered course sections provided they satisfy the prerequisite requirements for each course. Student demand for each course is estimated based on the number of students qualified to enroll in each course during the target academic year.

### 4.2. Assumptions

For the designated academic year, the model incorporates the following assumptions, which are made without loss of generality:

- Instructors are sensitive to changes in course scheduling, particularly when assigned to teach new or distinct courses. This assumption is based on the reasonable belief that compared with maintaining a consistent schedule of familiar courses, significant alterations in course assignments can demand extra preparation and effort from instructors, potentially impacting their satisfaction. Additionally, reducing the number of distinct courses assigned to each instructor fosters deeper content expertise and reduces the cognitive load associated with switching between different subjects, leading to improved instructional quality and higher job satisfaction.
- The teaching responsibilities of full-time faculty are distributed evenly across semesters to facilitate efficient schedule planning. If a faculty member's total teaching load for the year is an even number, it is divided equally between the two semesters. If it is an odd number, it is split into two nearly equal parts. This predetermined

[1] If needed, adjunct instructors can be included in the initial scheduling with minimal modifications by adding a penalty for the number of course sections assigned to them. Different adjuncts can be assigned varying penalties to reflect the preference to deploy them based on such factors as qualifications and experience.

distribution considers various factors, including research activities, service commitments, and tenure status.

- There is a limit to the proportion of courses taught by adjunct faculty in compliance with accreditation requirements.
- Each course section has a set maximum enrollment capacity, which is determined based on the specific educational requirements of the course.
- The number of full-time faculty remains consistent throughout the academic year; no considerations are made for new hires or attrition.
- A single instructor teaches each course section.
- Only tenure-track faculty who are actively engaged in research are permitted to teach graduate-level courses.
- The number of undergraduate students eligible to register for any given course and the percentage of those who do enroll are both predictable and can be forecasted with a high degree of accuracy.

### 4.3. Notations

The notations for the integrated model *CSPIA* are shown in Table 2.

### 4.4. Model formulation

In Model *CSPIA*, the objective is to minimize the sum of the number of new courses as well as sections of distinct courses assigned to full-time faculty and the penalty of unstaffed sections:

$$min\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s=1}^{2}\left[\alpha\bullet V_{ijs}+(1-\alpha)\bullet Y_{ijs}\right]+\sum_{j=1}^{J}\sum_{s=1}^{2}M\bullet X_{0js}-\alpha\bullet\sum_{i=1}^{I}\sum_{j=1}^{J}G_{ij} \tag{1}$$

In this objective function, minimizing the sum of $V_{ijs}$ across all instructors and courses means minimizing new preparations, and minimizing $Y_{ijs}$ across all instructors and courses translates to minimizing the total number of distinct courses assigned to instructors. The parameter, α, varies between 0 and 1 and is chosen based on collective faculty preferences, where a higher α (closer to 1) places more weight on reducing the number of new courses, and values closer to 0 put more emphasis on reducing the number of distinct course sections. In practice, α should not be exactly set to 0 or 1, as these extreme values would result in imbalanced considerations: $\alpha = 0$ would completely ignore whether a course assigned to an instructor has been previously taught by them, and $\alpha = 1$ may lead to the assignment of sections of several different courses to each instructor. Moreover, we have defined a dummy instructor ($i$=0) with a very large teaching capacity (i.e. $l_0 = M$) and qualifications to teach all courses (i.e., $a_{0j} = 1, \forall j$) to absorb all unstaffed sections, ensuring optimization feasibility. The sum of $X_{0js}$ over all courses and semesters, represents the number of course sections assigned to the dummy instructor (i.e. unstaffed course sections). Therefore, adding the penalty term, $\sum_{j=1}^{J}\sum_{s=1}^{2}M\bullet X_{0js}$, to the objective function aims to discourage assigning course sections to the dummy instructor unless there is no feasible solution. If an instructor is assigned to teach the same new course in both semesters of the academic year, the course should not be treated as new in the second semester. Therefore, the effect of applying a double penalty in the model should be adjusted. This is achieved by deducting the applied penalty (i.e., $\alpha$) when this scenario occurs, indicated by $G_{ij}$ being equal to 1.

s. t.,

$$\sum_{j=1}^{J}\sum_{t=1}^{2}X_{ijs}\leq l_i \qquad \forall i \tag{2}$$

$$\sum_{j=1}^{J}X_{ij1}-\sum_{j=1}^{J}X_{ij2}\leq 1 \quad \forall i>0 \tag{3}$$

$$-\left(\sum_{j=1}^{J}X_{ij1}-\sum_{j=1}^{J}X_{ij2}\right)\leq 1 \quad \forall i>0 \tag{4}$$

$$U_{js}\leq\frac{q_{js}\bullet r_{js}}{m_{js}}\leq U_{js}+1 \quad \forall j,s \tag{5}$$

$$M\bullet\left(Z_{js}-1\right)\leq q_{js}\bullet r_{js}-m_{js}\bullet U_{js}-th<M \quad \forall j,s \tag{6}$$

$$W_{js}=U_{js}+Z_{js} \quad \forall j,s \tag{7}$$

$$X_{ijs}\geq Y_{ijs} \quad \forall i>0,j,s \tag{8}$$

$$X_{ijs}\leq M\bullet Y_{ijs} \qquad \forall i>0,j,s \tag{9}$$

$$Y_{ijs}\leq a_{ij} \quad \forall i>0,j,s \tag{10}$$

**Table 2**
Notations for Model *CSPIA*.

*Indices:*
- $i = 0,1,2, \ldots, I$, index of full-time instructor. Index 0 represents a dummy instructor to ensure feasibility.
- $j = 1,2, \ldots, J$, index of course.
- $s = 1,2$, index of semester.

*Parameters:*
- $l_i$ = fixed workload of instructor $i$ in an academic year.
- $a_{ij}$=1, if instructor $i$ is qualified to teach course $j$; and 0 otherwise.
- $b_{ij}$ =1, if instructor $i$ taught course $j$ in last academic year; and 0 otherwise.
- $q_{js}$= number of qualified students to register for course $j$ in semester $s$.
- $r_{js}$= percentage of qualified students to register for course $j$ in semester $s$.
- $m_{js}$ = maximal number of students registering for course $j$ in semester $s$.
- $th$ = new section opening threshold.
- $pt$ = minimum percentage of sections taught by full-time faculty.
- $n$ = the total number of undergraduate courses (the first $n$ courses in all $J$ courses are undergraduate)
- $\alpha$ = parameter balancing between minimizing the number of new courses and distinct courses assigned to instructors
- $M$: a large number.

*Variables:*
- $Z_{js}$ = 1, if the number of students who cannot be accommodated by $U_{js}$ sections of course $j$ in semester $s$ exceeds the threshold $th$, that is, the remainder of $q_{js}r_{js}/m_j$ is larger than or equal to the threshold $th$, meaning opening a new section; and 0 otherwise.
- $X_{ijs}$ = number of sections of course $j$ taught by instructor $i$ in semester $s$.

*Auxiliary variables:*
- $W_{js}$ = actual number of sections of course $j$ in semester $s$.
- $Y_{ijs}$ = 1, if instructor $i$ teaches course $j$ in semester $s$; and 0 otherwise.
- $V_{ijs}$ =1, if instructor $i$ teaches new course $j$ in semester $s$; and 0 otherwise.
- $U_{js}$ = lower bound of sections of course $j$ in semester $s$ determined by the course demand.
- $G_{ij}$ =1, if instructor $i$ is assigned new course $j$ in both semesters $s$ = 1 and $s$ = 2; and 0 otherwise.

$$G_{ij} \le V_{ijs} \quad \forall i > 0, j, s \tag{11}$$

$$G_{ij} \ge V_{ij1} + V_{ij2} - 1 \quad \forall i > 0, j \tag{12}$$

$$W_{js} \ge \sum_{i=0}^{I} X_{ijs} \quad \forall s, j = 1, \dots, n \tag{13}$$

$$W_{js} = \sum_{i=0}^{I} X_{ijs} \quad \forall s, j = n+1, \dots, J \tag{14}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s=1}^{2} X_{ijs} \ge pt \bullet \sum_{j=1}^{J}\sum_{s=1}^{2} W_{js} \tag{15}$$

$$X_{0js} = W_{js} - \sum_{i=1}^{I} X_{ijs} \quad \forall s, j \tag{16}$$

$$Y_{ijs}, V_{ijs}, Z_{js}, G_{js} \in \{0, 1\} \quad \forall i > 0, j, s \tag{17}$$

$$X_{ijs}, U_{js} = 0, 1, 2, \dots \quad \forall i, j, s \tag{18}$$

Constraints (2) specify the maximum annual workload for each full-time faculty member. Constraints (3) and (4) are the linearized versions of $|\sum_{j=1}^{J} X_{ij1} - \sum_{j=1}^{J} X_{ij2}| \le 1$, representing that the difference in the number of sections a faculty member can teach across consecutive semesters cannot exceed 1. Constraints (5) define the minimum and maximum number of sections that should be opened each semester, which is dependent on the course demand (calculated as total enrollment times the percentage of each student type enrolled in each course). The parameters $r_{js}$ are forecasted from historical data. Constraints (6) dictate whether an additional section is required to meet the course demand. If the difference $r_{js} \bullet p_{js} - m_{js} \bullet U_{js}$ (representing the number of students unable to enroll in course $j$ due to the capacity limitation of $U_{jt}$ sections) equals or exceeds the threshold $th$, then an additional section ($Z_{js} = 1$) is to be opened.

Constraints (7) are responsible for calculating the actual number of sections for each course that are available for registration. Constraints (8) and (9) guarantee that if an instructor is assigned to teach one or more sections of a course, a binary variable indicating this assignment is set to 1; if not, it is set to 0. Constraints (10) ensure that instructors are assigned only to courses for which they are qualified. Constraints (11) and (12) introduce a binary variable to indicate whether an instructor is assigned to teach the same new course in both the first and second semesters. Constraints (13) ensure that the number of undergraduate course sections taught by instructors in each semester does not surpass the actual number of available sections. Constraints (14) stipulate that only tenure-track and research-active full-time faculty are eligible to teach graduate courses. Constraints (15) define the teaching capacity limits, mandating that the proportion of sections taught by full-time faculty complies with the accreditation requirements for each academic year. Constraints (16) define the number of unstaffed course sections in each semester, which are assigned to the dummy instructor.

## 5. Model implementation

The proposed model is implemented in the Department of Management and Information Systems (M&IS), at Kent State University (KSU) to assist in its course schedule planning and instructor assignment in the target academic year.

### 5.1. Case introduction

In the M&IS Department, the current 20 full-time faculty, some of whom teach across various majors, offer courses in four undergraduate majors: Business Management (BMGT), Computer Information Systems (CIS), General Business (GBUS), and Human Resource Management (HRM). They also teach in the Master of Science in Business Analytics (MSBA) program, the Master of Business Administration (MBA) program, and PhD concentrations in information systems and management. Each undergraduate major has a corresponding minor, and there are additional minors in Leadership, Healthcare, and Military & Leadership Studies. The diverse range of disciplines and faculty in this department makes it an ideal setting for implementing the UCTP, whose solutions are applicable and scalable to university systems' scheduling needs. Adjunct instructors and PhD students supplement the teaching workforce in undergraduate programs when needed.

The teaching qualifications and workload of the current full-time faculty are summarized in Table 3. Model *CSPIA* is used to address the integrated optimization of course scheduling and instructor assignment for two semesters of the target academic year. The model's output includes the maximum percentage of course sections taught by full-time faculty and the optimal instructor assignments for these sections. During the target academic year, the M&IS department offered 45 undergraduate and 17 graduate courses, many with multiple sections. Of the 178 sections taught, full-time faculty delivered 102 course sections (57.3 %). The College's accrediting agency requires that at least 60 % of sections be taught by full-time faculty ($pt$). Hence, the department must carefully plan its course schedule to meet this requirement.

Graduate courses in the department are exclusively taught by tenure-track and research-active full-time faculty. However, during fall and spring semesters of the target year, three graduate courses (64,005, 64,036, and 64,038) were taught by doctoral-qualified, non-tenure-track full-time faculty. Faculty workload, defined as the number of course sections taught per academic year, is capped based on their research productivity and service commitments. Currently, the threshold for opening a new section is set at 4, meaning a new section is created when student registrations exceed this number.

Courses in the PhD program vary each semester but are known in advance and typically taught by doctoral-qualified, tenure-track full-time faculty. The workload for these faculty members can be adjusted when they are assigned to teach doctoral-level courses. Consequently, doctoral-level courses are not included in our model, as their exclusion does not significantly affect the scheduling of undergraduate courses. This is because the teaching capacity at the doctoral level can be supplemented with adjunct instructors at the undergraduate level if necessary.

The Course Numbers (CNs) for the target academic year, the number

**Table 3**
Faculty information.

| Faculty | List of Courses | Workload per Year |
|---|---|---|
| 1 | 44,285, 64,185 | 4 |
| 2 | 44,285, 64,185 | 5 |
| 3 | 44,043, 64,042, 64,082 | 6 |
| 4 | 24,163, 34,167, 44,062, 44,163, 64,042 | 4 |
| 5 | 30,062, 34,180, 44,763 | 3 |
| 6 | 24,053, 34,054, 34,070, 44,040, 44,140, 44,292 | 12 |
| 7 | 34,165, 34,180, 34,185, 64,158 | 4 |
| 8 | 34,164, 34,165, 34,180, 34,185, 44,660, 64,158 | 5 |
| 9 | 24,167, 34,036, 34,170 | 4 |
| 10 | 34,180, 44,091, 44,185, 64,271 | 5 |
| 11 | 44,192 | 4 |
| 12 | 24,056, 34,156, 34,060, 44,062, 44,152, 64,005, 64,041 | 6 |
| 13 | 34,034, 34,068, 64,005, 64,082 | 4 |
| 14 | 24,163, 34,060, 34,175, 44,062, 44,152, 44,392 | 8 |
| 15 | 24,053, 34,054, 64,005, 64,036, 64,037, 64,038, 64,060, 64,061, 64,092 | 4 |
| 16 | 24,163, 34,157, 34,158, 34,159 | 1 |
| 17 | 24,053, 34,156, 64,005, 64,011, 64,018, 64,036, 64,037, 64,038, 64,060, 64,061, 64,099 | 4 |
| 18 | 24,053, 24,165, 44,048 | 6 |
| 19 | 34,165, 34,180, 44,445,44,183, 44,292, 44,499,68,051 | 14 |
| 20 | 64,005, 64,011, 64,018, 64,060 | 4 |

of students eligible to enroll in these courses (as derived from teaching and learning platforms like Blackboard), the registration percentages for each course, and the projected course demands are all detailed in Table 4. In the fall semester of the target year, the department offered 41 courses, while in the spring, the number of courses increased to 50.

### 5.2. Model performance and results

Model *CSPIA* is solved with the branch-and-bound method in LINGO18 on a Microsoft Surface Pro 4.0 computer with 8.0G RAM and Inter (R) Core (TM) i5-6300u CPU @ 2.49 GHz processors. In the model, there are 9052 integer variables and 16,936 constraints. The model achieves its optimal solution in an impressively short timeframe of under 5 s.

Table 5 presents the outcomes of applying model *CSPIA* under three distinct values of the parameter α. As discussed, a smaller α prioritizes minimizing the number of new courses assigned to instructors, whereas a larger α emphasizes reducing the number of distinct courses per instructor each semester. The academic year under consideration consisted of 86 sections in the fall semester and 92 in the spring. When utilizing the proposed model *CSPIA*, the department could have efficiently met course demand with only 72 sections in the fall and 81 in the spring. This reduction of 25 sections (14 %) over the year translates to an estimated annual decrease in staffing costs of approximately $130,000. Moreover, the percentage of sections staffed by full-time instructors increased from 57 % (102 out of 178) to 65 % (100 out of 153), meeting the accreditation requirements.

The benefits of using the model *CSPIA* extend beyond reducing the total number of course sections and increasing the percentage of sections delivered by full-time instructors. Notable improvements are observed in the number of new courses and distinct course sections assigned to full-time instructors, impacting instructor satisfaction and teaching

**Table 4**
Course registration forecast.

| Fall 2019 | | | | | Spring 2020 | | | | |
|---|---|---|---|---|---|---|---|---|---|
| CN | MS | QS | RP (%) | RF | CN | MS | QS | RP (%) | RF |
| 24,053 | 180 | 1527 | 24.23 | 370 | 24,053 | 240 | 1527 | 43.55 | 665 |
| 24,056 | 360 | 1527 | 13.03 | 199 | 24,056 | 320 | 1527 | 19.32 | 295 |
| 24,163 | 210 | 1527 | 33.92 | 518 | 24,163 | 230 | 1527 | 34.38 | 525 |
| 24,165 | 100 | 187 | 23.53 | 44 | 24,165 | 100 | 187 | 24.60 | 46 |
| 24,167 | 40 | 187 | 14.97 | 28 | 24,167 | 40 | 187 | 21.39 | 40 |
| 34,036 | 38 | 150 | 16.00 | 24 | 34,054 | 50 | 828 | 11.84 | 98 |
| 34,054 | 50 | 828 | 11.35 | 94 | 34,060 | 185 | 993 | 30.61 | 304 |
| 34,060 | 135 | 993 | 32.83 | 326 | 34,068 | 30 | 150 | 15.33 | 23 |
| 34,068 | 40 | 150 | 24.67 | 37 | 34,070 | 38 | 150 | 24.67 | 37 |
| 34,070 | 40 | 150 | 26.67 | 40 | 34,156 | 40 | 978 | 5.93 | 58 |
| 34,156 | 40 | 978 | 4.19 | 41 | 34,158 | 50 | 60 | 23.33 | 14 |
| 34,157 | 50 | 200 | 17.50 | 35 | 34,159 | 50 | 60 | 18.33 | 11 |
| 34,165 | 50 | 843 | 20.52 | 173 | 34,164 | 50 | 643 | 1.71 | 11 |
| 34,167 | 40 | 150 | 22.67 | 34 | 34,165 | 60 | 843 | 16.84 | 142 |
| 34,180 | 45 | 843 | 25.27 | 213 | 34,167 | 40 | 150 | 22.67 | 34 |
| 34,185 | 50 | 843 | 10.79 | 91 | 34,170 | 30 | 150 | 16.00 | 24 |
| 44,007 | 40 | 150 | 12.67 | 19 | 34,175 | 40 | 843 | 2.85 | 24 |
| 44,009 | 50 | 473 | 7.61 | 36 | 34,180 | 60 | 843 | 18.98 | 160 |
| 44,043 | 55 | 150 | 36.67 | 55 | 34,185 | 55 | 843 | 12.10 | 102 |
| 44,048 | 25 | 150 | 3.33 | 5 | 44,007 | 40 | 150 | 22.67 | 34 |
| 44,062 | 50 | 473 | 21.14 | 100 | 44,009 | 55 | 473 | 8.03 | 38 |
| 44,091 | 20 | 100 | 11.00 | 11 | 44,043 | 40 | 150 | 38.00 | 57 |
| 44,152 | 50 | 473 | 22.62 | 107 | 44,048 | 30 | 150 | 13.33 | 20 |
| 44,163 | 25 | 473 | 19.24 | 91 | 44,062 | 50 | 473 | 18.60 | 88 |
| 44,183 | 45 | 100 | 56.00 | 56 | 44,140 | 30 | 93 | 11.83 | 11 |
| 44,185 | 40 | 100 | 53.00 | 53 | 44,152 | 50 | 473 | 27.48 | 130 |
| 44,192 | 25 | 80 | 16.25 | 13 | 44,163 | 26 | 473 | 19.45 | 92 |
| 44,284 | 45 | 100 | 20.00 | 20 | 44,187 | 25 | 473 | 1.27 | 6 |
| 44,285 | 45 | 575 | 33.91 | 195 | 44,192 | 20 | 80 | 10.00 | 8 |
| 44,292 | 25 | 93 | 45.16 | 42 | 44,284 | 40 | 100 | 24.00 | 24 |
| 44,293 | 35 | 93 | 37.63 | 35 | 44,285 | 45 | 575 | 65.39 | 376 |
| 44,392 | 44 | 473 | 14.59 | 69 | 44,292 | 20 | 93 | 10.75 | 10 |
| 44,660 | 50 | 100 | 44.00 | 44 | 44,392 | 50 | 93 | 87.10 | 81 |
| 64,005 | 40 | 60 | 90.00 | 54 | 44,395 | 10 | 80 | 3.75 | 3 |
| 64,018 | 30 | 28 | 121.43 | 34 | 44,445 | 25 | 100 | 47.00 | 47 |
| 64,036 | 30 | 88 | 51.14 | 45 | 44,492 | 20 | 100 | 11.00 | 11 |
| 64,060 | 30 | 28 | 103.57 | 29 | 44,499 | 45 | 100 | 45.00 | 45 |
| 64,082 | 40 | 88 | 32.95 | 29 | 44,763 | 38 | 100 | 38.00 | 38 |
| 64,158 | 40 | 60 | 58.33 | 35 | 64,011 | 21 | 28 | 67.86 | 19 |
| 64,185 | 40 | 60 | 18.33 | 11 | 64,037 | 30 | 28 | 103.57 | 29 |
| 68,051 | 40 | 60 | 46.67 | 28 | 64,038 | 30 | 28 | 103.57 | 29 |
| | | | | | 64,041 | 35 | 60 | 80.00 | 48 |
| | | | | | 64,042 | 35 | 60 | 78.33 | 47 |
| | | | | | 64,060 | 30 | 28 | 10.71 | 3 |
| | | | | | 64,061 | 30 | 28 | 96.43 | 27 |
| | | | | | 64,082 | 40 | 28 | 107.14 | 30 |
| | | | | | 64,092 | 25 | 28 | 21.43 | 6 |
| | | | | | 64,099 | 25 | 50 | 30 | 15 |
| | | | | | 64,158 | 30 | 60 | 25.00 | 15 |
| | | | | | 64,185 | 40 | 60 | 41.67 | 25 |
| | | | | | 64,271 | 35 | 60 | 75.00 | 45 |

Notes: CN: course number, MS: maximum seat, QS: quantity of qualified students; RP: registration percentage, RF: registration forecast.

**Table 5**
Performance improvement of model *CSPIA*.

| | Actual value | | | Model output ($\alpha = 0.01, 0.5, 0.99$) | | | Difference |
|---|---|---|---|---|---|---|---|
| | Fall | Spring | Total | Fall | Spring | Total | |
| Section quantity | 86 | 92 | 178 | 72 | 81 | 153 | 25 |
| Sections by full-time faculty | 48 | 54 | 102 | (50,51,51) | (50,49,48) | 100 | 2 |
| Remaining sections | 38 | 38 | 76 | (22,21,21) | (31,32,33) | 53 | 23 |
| Distinct course sections assigned to full-time instructors | 42 | 50 | 92 | (30,32,33) | (34,33,38) | (64,65,65) | (28,27,27) |
| New course sections assigned to full-time instructors | 8 | 19 | 27 | (4,4,3) | (2,1,1) | (6,5,5) | (21,22,22) |

Notes: A single value for the cell under "Model output" indicates that this value remains constant for different $\alpha$ values.

performance. For instance, with α = 0.5, the total number of new sections assigned to instructors falls from 27 to 5, representing an 81 % reduction. Similarly, the number of distinct course sections assigned to full-time instructors decreases from 92 to 65, representing a 29 % reduction. These reductions enable instructors to spend more time engaging deeply with their courses, ultimately enhancing teaching quality and satisfaction.

Furthermore, as the results suggest, increasing α from 0.5 to 0.99 does not yield any changes in this particular case, as the total number of new course sections and distinct course sections assigned to full-time instructors remains the same. The impact of variations in α on the model's performance is examined in more detail in the following section, particularly under different teaching load conditions. Finally, setting α to extreme values of 0 or 1 is not recommended as discussed. Extreme values would entirely ignore one of the model's goals (i.e., reducing the number of new or distinct course sections) without substantially improving the other goal. For example, setting α to zero leads to 64 distinct course sections assigned to instructors (the same as when α is 0.01) but increases the number of new course sections assigned to 76, as the model completely disregards whether an instructor has taught a specific course before the assignment. Similarly, with α set to 1, the number of new course sections assigned to instructors remains at 5 (the same as when α is 0.99), but the number of distinct course sections assigned to instructors increases to 73.

In summary, the model *CSPIA* offers significant benefits and improvements, including reduced staffing costs, increased percentage of course sections delivered by full-time instructors, and enhanced instructor satisfaction and performance by minimizing the number of new and distinct course sections assigned.

### *5.3. Impact of variations of α parameter on model performance*

To gain deeper insights into the model *CSPIA*, it is crucial to understand the trade-offs between the two goals integrated into its objective function. Specifically, it is important to understand how the total number of distinct course sections assigned to instructors can be exchanged for the number of new courses assigned to them under different course demands, and vice versa. This is achieved by examining the effect of the α parameter on the model *CSPIA*'s performance under various teaching loads.

Fig. 2 shows the sum of distinct course sections assigned to full-time instructors when hypothetically varying the number of course sections they are required to deliver. Results are presented for three α values: 0.01, 0.5, and 0.99. As the figure demonstrates, the sum of distinct course sections assigned to instructors increases with teaching load. For any given teaching load, the number of distinct sections is one or two fewer when α is 0.01 compared to 0.99. Interestingly, results for α = 0.5 are sometimes similar to the lower extreme and sometimes to the upper.

Similarly, Fig. 3 illustrates the number of new course sections assigned to instructors under the same varying teaching loads as in Fig. 2. Comparing the two figures reveals noteworthy insights. For instance, when instructors are required to deliver 70-course sections, with α = 0.01, they are assigned 36 distinct sections, while this increases

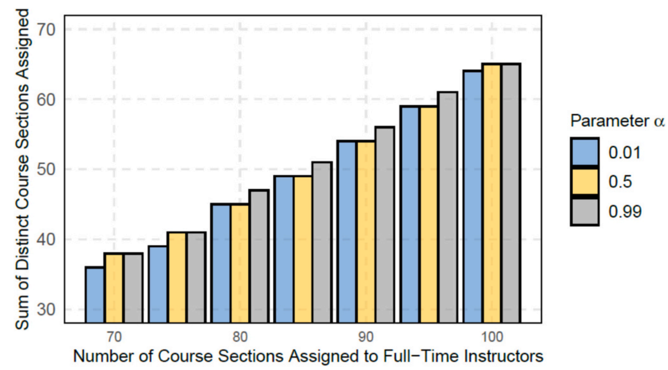


**Fig. 2.** Total number of distinct course sections assigned to full-time instructors under varying total teaching load requirements.

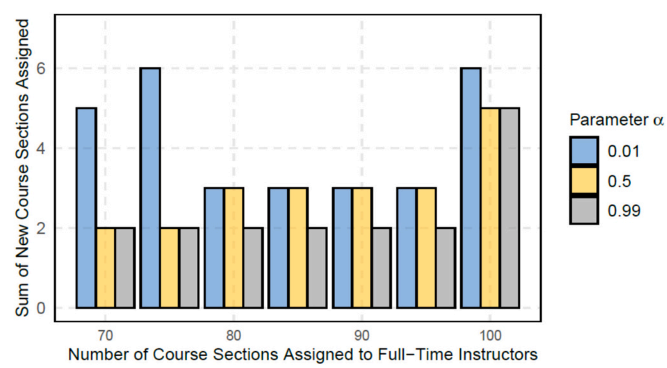


**Fig. 3.** Total number of new course sections assigned to full-time instructors under varying total teaching load requirements.

to 38 when α is 0.99. However, as shown in Fig. 3, this leads to instructors having to deliver three additional new course sections (5 with α = 0.01 compared to 2 with α = 0.99). This difference becomes more pronounced at a teaching load of 75 sections, where a reduction of two distinct sections results in 4 new sections being assigned. However, the difference in new courses assigned remains about one or two courses for the remaining demand values.

These observations suggest that under most demand scenarios, a decrease in the number of distinct course sections assigned to instructors is often accompanied by a corresponding increase in the number of new course sections they are required to teach. Understanding this relationship allows administrators to leverage the α parameter to balance these two competing objectives in alignment with collective faculty preferences. Furthermore, the model's robustness to variations in α, as evidenced by its consistent performance across different α values, enhances its usability and practicality. This means that administrators can achieve desirable outcomes with the model *CSPIA* without extensive fine-tuning or precise parameter optimization, thereby streamlining the decision-making process and facilitating the efficient allocation of instructional resources.

### 5.4. The impact on timeslot and classroom assignments

While the primary objective of the proposed model *CSPIA* is to optimize the assignment of instructors to course sections, the resulting output serves as a critical input for the subsequent phase of academic scheduling. Notably, the allocation of timeslots and classrooms to each section is contingent upon the determination of course-section instructor combinations, underscoring the pivotal role of the model's output in the comprehensive scheduling process.

Moreover, the model's emphasis on minimizing the number of sections through efficient scheduling significantly contributes to the subsequent timeslot and classroom assignment problem. A reduced number of sections not only streamlines the scheduling process but also enhances flexibility in assigning optimal timeslots and classrooms. Furthermore, instructors assigned to new courses or those with a higher number of distinct courses are prioritized in the selection of their preferred timeslots and classrooms. This prioritization recognizes the additional preparation required for new courses and the challenges associated with managing a diverse course load, promoting a more equitable and satisfactory scheduling outcome for instructors.

## 6. Conclusions and future work

### 6.1. Overview and key findings

The ideal DSS framework for addressing the UCTP is expected to provide a solution that encompasses the comprehensive scheduling of courses, sections, instructors, timeslots, and classrooms. Due to the inherent complexity and unique characteristics of UCTP, this study proposed a novel process-based DSS framework that simplifies the UCTP by breaking it into two more manageable hierarchical models. The upper-level model, which was also the primary focus of this study, is an integrated model addressing course schedule planning (determining the number of sections per course) and instructor assignment (assigning instructors to sections) to minimize costs and maximize instructor satisfaction by seeking to minimize the number of new and distinct course sections assigned to them during each semester. The lower-level model would address timeslot and classroom assignments.

Departing from much of the existing literature, which often focuses on assigning instructors, timeslots, or classrooms to pre-determined course sections [18,21,28,34], this study proposed a novel mixed-integer linear programming (MILP) model to integrate course schedule planning and instructor assignment, aiming to meet the forecast demands for courses over two consecutive semesters (fall and spring). The model was successfully applied to a real-world UCTP setting within a multi-disciplinary academic department at a large U.S. public university. The model's focus on minimizing instructor course preparation and its integration of common departmental constraints suggest applicability to other institutions. Results demonstrated a potential reduction of up to 14 % in the number of sections (approximately $130,000 in savings), an increase in the percentage of course sections taught by full-time faculty from 57.3 % to 66 %, and reductions of up to 81 % in new course assignments and 29 % in the number of distinct courses assigned to instructors. These combined benefits contribute to significant cost savings, improved resource allocation, and enhanced instructor satisfaction and performance.

Further analysis examined the trade-offs between minimizing new course assignments and reducing the number of distinct courses per instructor using the $\alpha$ parameter. The impact of varying $\alpha$ on model performance was investigated under different teaching loads, providing insights into balancing these competing objectives. In summary, the proposed model *CSPIA* offers a practical and effective solution for universities in cost reduction, resource allocation, and instructor satisfaction, highlighting its potential value for academic departments facing similar scheduling challenges.

### 6.2. Contributions to research

The first theoretical contribution is the introduction of a novel process-based decision support system (DSS) framework that decomposes the complex UCTP into two manageable hierarchical optimization models. The higher-level model generates course-section-instructor combinations to meet forecasted demands and minimize instructors' preparation. The lower-level model then assigns timeslots and classrooms to these combinations. This approach ensures courses, sections, and instructor assignments are optimized, prioritizing instructors with new or many distinct courses for preferred timeslots and classrooms, thereby enhancing overall fairness and satisfaction. Decomposing a complex NP-hard UCTP problem into manageable hierarchical problems that can be solved sequentially is particularly advantageous as it reduces computational complexity without sacrificing performance. Moreover, it provides insights into different steps of the solution, allowing for user interventions and modifications if necessary.

The second contribution is the conceptualization and formulation of an integrated optimization model that simultaneously addresses course schedule planning and instructor assignment, filling a critical gap in the existing literature. This integration is crucial for generating feasible solutions, as the number of course sections and the availability of qualified instructors are inherently interdependent. Each course section must be taught by a qualified instructor, necessitating an integrated approach to generate feasible solutions for both models. To the best of our knowledge, this is the first study to integrate course schedule planning and instructor assignment problems in UCTP. Prior studies either ignored one of them [10,25–33] or both [3,34–38], leading to potentially infeasible course schedule when assigning instructors. By incorporating both aspects into a joint optimization framework, the proposed model enhances the practicality and applicability of UCTP solutions in real-world academic settings. The final theoretical contribution of this study lies in formulating a multi-objective optimization framework that seeks to prioritize instructors' preferences by minimizing the number of new courses assigned to them and minimizing the number of distinct courses assigned to them during each semester. Although these two objectives may not always be optimized simultaneously, the proposed optimization framework allows administrators to balance these competing objectives based on the collective preferences of the instructors.

### 6.3. Contributions to practice

In addition to its theoretical contributions, this study introduces several practical advancements that directly address the needs of academic institutions. The proposed DSS framework is a user-friendly, interactive tool that bridges the gap between theoretical models and practical application, effectively catering to the specific instructional needs of academic institutions. Distinctively, this research is the first to prioritize the practical concerns of instructors, in contrast to previous studies that predominantly focused on optimizing course preferences, which often led to scheduling conflicts. Our approach centers on two key objectives for instructors: minimizing the number of new course preparations and reducing the number of distinct courses assigned each semester. The proposed DSS framework is parameterized, allowing institutions to balance these objectives based on the collective preferences of their faculty, thereby facilitating a flexible tradeoff between the two goals.

The proposed DSS further enhances fairness and instructor satisfaction by decomposing the scheduling problem into two hierarchical models. The higher-level model determines the offered courses, their sections, and identifies instructors assigned to new or multiple distinct courses. These instructors are then prioritized in the lower-level model to select their preferred timeslots and classrooms.

A major challenge in the development of DSS for UCTP has been the lack of practicality and user-friendliness. Many existing solutions have failed to gain widespread acceptance due to these limitations [14]. However, the DSS framework developed in this study has been successfully implemented and evaluated within a large department at a public university in the United States. Implementing this DSS not only led to a substantial 14 % reduction in staffing costs, equivalent to approximately $130,000 annually, thereby alleviating financial pressures on the university, but also yielded significant improvements in instructor satisfaction. The number of new course sections assigned to instructors decreased by up to 81 %, and the number of distinct courses assigned to instructors was reduced by 29 %. These reductions in course preparation burden and cognitive load directly contribute to improved instructional quality.

Beyond these tangible benefits, the proposed DSS is notable for its ability to improve both student and instructor satisfaction by addressing course demands and preferences, resulting in a more optimized and effective learning environment. Its user-friendly interface, seamless integration with existing systems, and reliance on readily available input data further enhance its practicality and ensure widespread adoption within academic institutions.

### *6.4. Limitations*

This study is not without limitations. Firstly, the study relies on forecasts to determine the number of students for each course. These forecasts may not be entirely accurate, particularly for courses taken by new students joining the college, such as freshman or first-year graduate courses. This issue is exacerbated by unexpected changes, such as pandemics or rapid economic shifts, which can significantly impact enrollment. Additionally, factors like the introduction of new majors or minors, or the termination of existing ones, which are not explicitly considered in this study, can also affect course enrollments.

Despite these limitations, it is important to note that the proposed solution in this study demonstrates some resiliency against student enrollment forecasts, provided the forecast deviation is not so substantial that it necessitates the addition of an extra section or the cancellation of a section due to significant under-enrollment. Furthermore, while the benefits of deploying the proposed solution were benchmarked using data from a department in a public US university, it would be advantageous to benchmark these benefits in other settings, such as smaller private universities or academic institutions in other countries. While we believe that the core principles underlying the solution are adaptable and generalizable, evaluating the proposed solution in more diverse settings would provide a more comprehensive understanding of its potential advantages.

### *6.5. Future research extensions*

This study serves as a foundation for several potential research extensions. First, the model's scope can be expanded by incorporating additional features such as faculty recruitment and retention, as well as the impact of reduced teaching capacity due to factors like layoffs or sabbaticals. Second, the integration of advanced predictive analytics techniques, such as artificial neural networks, can be explored to enhance the accuracy and precision of course demand forecasts based on historical enrollment and external data. Finally, implementing functionalities that allow for conducting what-if analyses under various future demand scenarios can provide insights into the model's sensitivity and robustness, thereby enabling more informed decision-making regarding course offerings and resource allocation.

## CRediT authorship contribution statement

**Guisen Xue:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **O. Felix Offodile:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rouzbeh Razavi:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation. **Dong-Heon Kwak:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Investigation. **Jose Benitez:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition.

## Declaration of competing interest

None of the authors has any financial or personal relationships that influenced the development of this work.

## Data availability

Data will be made available on request.


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