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Faculty-Course Assignment Under Faculty Preferences and Institutional Policies Using Priority-Weighted Multi-Objective MILP: A Case Study in a Philippine University

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Abstract *– This study proposes an exact optimization approach based on a priority-weighted multi-objective Mixed-Integer Linear Programming formulation for a variant of the Faculty-Course Assignment Problem, an initial phase of a decomposed University Course Timetabling Problem. The variant incorporates key factors such as student course demand, faculty course eligibility, faculty maximum allowable overload, preferred courses, preferred section limits, and seniority considerations, while minimizing violation of institutional policies on underload and overload. The model is implemented in Python using a mathematical optimization framework. Despite the mathematical complexity of the problem, the instance examined remains computationally tractable and yields optimal solutions in under one minute for the real-world instance of a Philippine university department. Results demonstrate that the model can generate operationally interpretable faculty teaching load assignments while also providing insights into deficiencies in available resources in the event of supply-demand mismatch. Sensitivity analysis further demonstrates the robustness of the model under variations in demand, faculty size, and preferences, highlighting its practical applicability for academic scheduling and resource allocation.*

Keywords*: faculty-course assignment problem, university course timetabling problem, FCAP, UCTP*

I. INTRODUCTION

Universities all around the world are regularly faced with the task of providing courses to university students. This process is much more complex than it may seem, as it involves several considerations, including student count, faculty complement, conflicts in schedules, facility requirements, and other university-specific policies such as class size, time slot restrictions, and class durations. Papers studying such problems can be found to use multiple soft and hard constraints involving students, instructors, rooms, and institutional policies, leading to distinct variants of the problem [1, 4, 8, 11]. In the case of the study site for this paper, which has a semestral structure, this procedure is done twice a year, before each semester starts. Oftentimes, the process of determining a schedule of courses to offer becomes very tedious, unstructured, and requires several people to execute properly. Failure to effectively execute this process leads to faculty missing their minimum teaching load requirements, and students not getting enough classes that they require [3].

This study focuses on a selected Philippine university department and considers its existing procedures. The process of generating the required course offerings begins with the parallel collection of two key datasets: course demand and faculty preferences. Faculty preferences refer to the faculty's preferred courses to teach and the faculty's preferred section limit for each preferred course. A preferred course is a course that a particular faculty prefers to teach. These steps establish the general supply and demand of each course by determining how many students need each one, and how many faculty are willing and able to teach them. Considering the number of students requiring each course, the exact number of sections per course is then determined, and these sections are assigned to faculty. Next, schedules and classrooms are assigned to each section, all under various existing policies and conflicts (i.e., a faculty cannot be assigned more than one section at any given time).

The establishment of these two key datasets (course demand and faculty preferences) is primarily done through online electronic surveys. Processing of the results of these datasets is handled by the Philippine university department's registration planner, executed manually through spreadsheets. The transformation of these datasets into implementable teaching load assignment plans takes the department's registration planner around 8 hours of work per semester. Another 8 hours of work is estimated to be needed for the schedule and classroom assignments. Verification with the faculty and additional adjustments are done in increments prior to the enrolment period of the student body. On average, at least 5 revisions per semester are conducted before the final teaching load assignment plan is implemented.

This overarching problem is formally called the university course timetabling problem (UCTP) and is a problem that has been studied extensively [8, 11]. In 1995, a conference series focusing on the UCTP was established, and a competition to provide solutions to the problem, the International Timetabling Competition, was started in 2002. This highlights not just the importance of the UCTP, but also its complexity, as addressing the problem and its variants takes years of study by several experts around the world [17].

As it has been established that the UCTP is a very complex problem, this study focuses on the initial phase of the course offering process: faculty course assignments, given course demand, and faculty preferences. This phase of the process, henceforth referred to as the Faculty-Course Assignment Problem (FCAP), is performed under several soft and hard constraints involving faculty preferences and institutional policies.

Prior work on the FCAP has been conducted in differing forms [9-10, 15, 25-26]. Existing studies have considered different formulation, including models that maximize faculty preference satisfaction, evaluate faculty-course suitability, or incorporate additional institutional considerations through changes to the objective functions or constraints. These are discussed in greater detail in Section II of this paper.

Despite the diversity of FCAP formulations, challenges remain in existing models regarding representing the combination of faculty preferences, institutional policies, and practical resource limitations encountered in the university course offering process. Existing studies demonstrate different approaches to faculty-course assignment; however, their applicability may vary depending on the institution's operational requirements and faculty availability. These differences highlight the need for further investigation of FCAP formulations suitable for more practical implementation.

The rest of the paper is structured as follows: Section II investigates literature that is relevant to the problem context and solutions, Section III formally defines the problem to be addressed by this research and states its mathematical formulation, and Section IV discusses the solution methodology used to solve the problem. Section V discusses the results of the case study and explores the model's robustness by performing some sensitivity analyses. Section VI states the conclusion of the study, and Section VII provides recommendations and potential areas to explore in future work.

II. LITERATURE REVIEW

The UCTP is a well-known combinatorial optimization problem commonly seen in academic scheduling. Due to the varied factors of resource constraints and institutional policies, the specific formulation of UCTP can differ significantly across academic institutions. Comprehensive reviews [1, 12] describe various modelling and solution approaches to the UCTP and reflect that such problems involve two general aspects: the strict adherence to hard constraints and the penalization for violation of soft constraints.

The UCTP is a known NP-hard problem [24]. Thus, many studies have focused on heuristic and metaheuristic approaches, including graph coloring formulation [18] genetic algorithm [27], tabu search [6], simulated annealing [2], and particle swarm optimization [14].

Some early works [22, 5] pioneered the partitioning of the UCTP into two sequential phases. Through this decomposition, the problem's search space is reduced to a size that can be more effectively managed with optimization than the full UCTP problem.

While integrated formulations of the full UCTP exist, decomposition remains valuable from both a computational and operational perspective. The decomposition of the UCTP is consistent with the practical workflow of the university course offering process. In practice, determining faculty-course assignments is often performed before assigning specific schedules and classrooms. Additionally, the full UCTP simultaneously considers multiple interdependent decisions, including faculty assignment, time scheduling, and classroom allocation, resulting in a substantially larger search space and increased computational complexity. By addressing the faculty-course assignment phase first, potential faculty resource deficiencies may be identified earlier, allowing departments to address faculty supply-demand gaps before proceeding to the detailed scheduling phase.

Subsequent studies [7, 23] adopted similar approaches, typically modelling the first phase with a binary goal programming model to incorporate multiple institutional policies such as balancing faculty workload and satisfying faculty preferences.

The variant of the FCAP considered in this study, however, is NP-hard, as it seeks to determine an optimal assignment that maximizes satisfaction of multiple objectives rather than merely verifying the existence of a feasible assignment. In practice, when the FCAP subproblem of the UCTP is applied to the context of real-world academic institutions, such as a university faculty department, results show that exact methods still give reasonable performance, owing to the moderate size of real-world problems [7, 23]. This suggests that exact optimization methods are still viable solution methods in real-world sizes despite the NP-hardness of the variant of FCAP this study tackles.

In many cases, the objectives of satisfying various faculty preferences and other institutional policies are essential components in solving the UCTP [10, 16, 20]. Some studies consider seniority or other administrative intervention [2, 9] in weighting faculty-course allocations, while others consider more equitable approaches, such as implementing mechanisms for course assignment rotations over time [22].

Recent works on the FCAP show the range of modelling choices in the objective function and decision variable structure. The study by Bhoi & Dhodiya [9] allows incorporating result- and feedback-based preferences on faculty-course assignments using fuzzy multi-objective goal programming, where preferences are in the form of a ranking of a faculty over their candidate course assignments. Meanwhile, Qu et al. [21], Torres et al. [26], and Khorbotly & White [15] utilize single-objective linear programming models maximizing an aggregate preference satisfaction or faculty-course suitability measures. Ongy [19] took a different approach by utilizing the maximization of evaluation ratings (i.e., faculty mastery of the course handled based on student evaluations) as the sole objective of a mixed-integer programming FCAP model. Tejada & Martinez [25] consider uncertain faculty preferences in the FCAP by decomposing the problem into two phases: forecasting faculty preferences and assigning courses to faculty. In the assignment phase, they employ a weighted objective function to balance the objectives of minimizing deviations from recommended teaching load and maximizing recommendation value score, with other considerations treated as feasibility constraints. A more complex approach is also taken by Gunawan et al. [13] using a genetic algorithm to handle a more complex objective function of teaching load variance minimization. The differing formulations reflect varying institutional priorities, modelling assumptions, and operational requirements across academic settings.

Despite the diversity of existing FCAP formulations, the simultaneous inclusion of detailed faculty preference structures, particularly those involving preferred section limits, together with institutional policy considerations such as faculty seniority, within a single exact optimization model under scenarios with potentially insufficient resources remains limited. Building upon prior FCAP and UCTP formulations, this study considers an FCAP variant solved using a priority-weighted multi-objective MILP that simultaneously incorporates faculty preferences and institutional policies while preserving the faculty preference data structure used at the study site. Specifically, the preference data structure the model can capture includes not only the set of preferred courses of each faculty, but also the corresponding preferred section limit for each preferred course. Meanwhile, institutional policies relate to underloading, overloading, and seniority considerations.

Although the FCAP represents only the first stage of the broader UCTP, it remains computationally non-trivial due to its previously mentioned NP-hard nature. Nevertheless, the FCAP constitutes a comparatively more tractable subproblem because of its smaller solution search space, while still providing information that is operationally valuable for the teaching load planning process. In particular, the introduction of dummy variables enables the model to explicitly identify mismatches in available resources and demand when resources are insufficient. Such information is valuable from a planning perspective because these mismatches between resource and demand need to be resolved to later obtain a feasible solution to the complete UCTP.

The decision to focus on the FCAP rather than the fully integrated UCTP is also motivated by the existing literature adopting decomposition-based approaches for large-scale academic timetabling problems. Under this perspective, improving the quality and interpretability of the first phase directly contributes to the effectiveness of subsequent scheduling stages of the UCTP.

III. PROBLEM DEFINITON & FORMULATON

The overarching problem that the study is concerned with is the UCTP, which involves the generation of a set of sections to open that will satisfy the total course demand from students. Each of these sections must be assigned a specific course, schedule, faculty that would teach it, and a classroom. All of these must consider multiple constraints, with the main one dictating that there should be no schedule conflicts for any given faculty, and any given classroom.

As discussed in the preceding section, the UCTP can be decomposed into two sequential phases: the assignment of courses to faculty, and the assignment of these faculty-course combinations to feasible room and time schedules.

This study focuses exclusively on the FCAP. The second phase of the decomposition of the broader UCTP is not addressed in detail; however, the output of the first phase serves as a key input to subsequent scheduling decisions within the broader UCTP. This problem can be viewed as a variant of the traditional assignment problem, but with numerous institutional policies and faculty preference considerations that must be satisfied.

3.1 Actual Procedure

As mentioned, the current procedure for faculty-course assignment in this paper's site of study is a tedious procedure that takes a significant amount of time to complete. This is done ahead of each semester and involves coordination and data gathering on multiple levels. Before the assignment can be made, the demand for courses must be established, along with potential supply (i.e., who can teach).

3.1.1 Determining Course Demand

Months ahead of the start of every semester, the Department's registration committee that handles course offerings sends out a course demand survey to all students in the Department to determine the number of students who would require each course. Each response in the survey would constitute a basket of courses. Students usually take 18-21 units per semester, and courses taken can be from 2 units to 5 units. This translates to a basket containing as little as one course (special cases) and as much as eight courses.

Once the data on the course baskets are consolidated, the exact demand of each course can be established. From here, a standard class size per course is used to compute the number of sections each course requires by dividing the total demand by this class size and rounding up the result.

3.1.2 Gathering Faculty Preferences

Usually done at the same time as the establishment of course demand, the preferences of each faculty are also gathered through a survey. This faculty loading survey is given to all full-time faculty of the Department. In the survey, each faculty gives a set of pairwise information: the courses they prefer to teach, and the preferred section limit that faculty is willing to teach for that specific course. An example of this output is found in Table 1.

Table 1. Example of faculty preference survey responses.

Faculty	Sample Preference Survey Response
Faculty 1	Course 1 (3), Course 3 (3), Course 5 (3), Course 12 (3)
Faculty 2	Course 3 (2), Course 7 (1)
Faculty 3	Course 1 (2), Course 2 (1), Course 3 (1), Course 8 (3), Course 10 (3)

By policy, each faculty of the Department is required to have at least 12 units of workload per semester, which may consist of any combination of teaching load, research load, administrative load, extension load, and study load. Consequently, faculty with other non-teaching load need less teaching load units to meet their minimum workload requirement for the semester. Going below the minimum units results in underloading, while going above results in overloading.

In terms of teaching load, 12 units of workload translates to an average of 4 sections assigned per faculty. Thus, faculty with other non-teaching load units may only need 3 courses or less to avoid underloading. While faculty can also optionally exceed 12 units of workload, this is generally avoided as too much workload has adverse effects on the capacity of the faculty to perform their duties.

As shown in Table 1, the equivalent total number of units indicated in the faculty preference survey can exceed the minimum required workload since the information collected represents all options that the faculty is willing to take, not the most preferred option (i.e., totalling 12 units). The faculty is considered willing to teach any combination of the course-count pairs indicated in their survey response.

3.1.3 Other Considerations

It is rarely the case that the demand for courses perfectly matches the preference of the faculty that can teach it. As such, certain measures are taken by the Department to address the inevitable supply-demand mismatch.

If all full-time faculty have been assigned full teaching load, and there are still sections that need to be assigned a faculty, the Department employs lecturers, usually from the industry or department alumni, to serve as part-time faculty that can handle any teaching load up to a maximum of 6 units. In practice, since there is an abundance of industry practitioners and department alumni, there is a virtually inexhaustible pool of potential lecturers that the Department can hire. This means that there will never be a case where there is not enough faculty to teach the courses established from the course demand survey.

As a last resort, if there is not enough time to hire lecturers, the Department can also decrease class size such that the overall number of sections that need to be opened would decrease. This measure is avoided as much as possible, as going beyond the standard class size would present classroom restrictions (i.e., cannot be assigned to smaller classrooms) and would deteriorate the quality of teaching arising from the decrease in teacher-to-student ratio.

When assigning courses to faculty, two other sources of information are taken into consideration: faculty specialization and relative seniority. On specialization, each faculty is a member of one or more research laboratories within the Department. The faculty specialization gives a general guideline on what courses the faculty can teach (as opposed to what courses the faculty prefers to teach). This distinction between faculty course preference and faculty specialization is an important consideration, should the need arise for additional faculty to teach courses that may not be within their preferences but are known to be courses that the faculty are able to teach. In the actual process, this step is taken based on the personal knowledge and experience of the course offering planner. That is, there is no formal database on who can teach each course; decisions are often made based on information such as historical data on courses taught and the specialization of the faculty.

On seniority, there are cases where there are numerous faculty that indicate a preference for teaching a specific course to the point that there is more than needed. To decide which faculty gets priority for assignment, a seniority component serves as the tie-breaking criteria. A faculty who has more years of teaching in the Department (i.e., higher seniority) would be given priority over one who has less, with the rationale being that more years of teaching would translate to a better taught course.

At the end of this faculty-course assignment process, each section of a course that needs to be taught should be assigned either a full-time faculty or a lecturer. On the side of the faculty, each full-time faculty must meet the minimum teaching load requirement, and each lecturer should not exceed their maximum teaching load.

3.1.4 Process Diagram

The process diagram presented below in Figure 1 visualizes the actual procedure of the faculty-course assignment process.

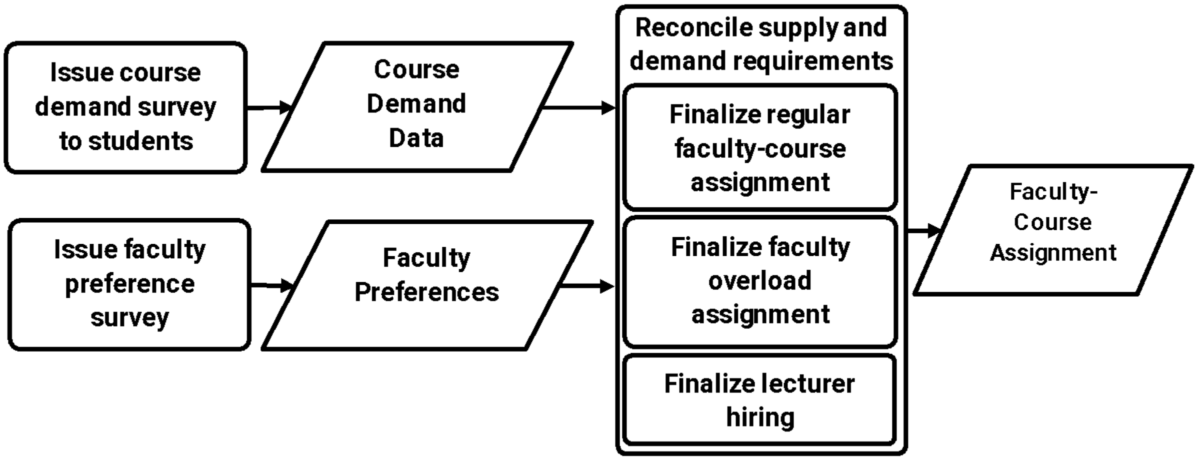

Figure 1. Process diagram of the faculty-course assignment process.

3.2. Mathematical Formulation

3.2.1 Assumptions, Scope and Limitations

To make the problem manageable and clearly defined, the study is based on several key assumptions.

1. The capacity per section for each course is known and fixed. While capacities may vary across courses depending on their nature, all sections of the same course have the same capacity.
2. Faculty seniority is determined based on the number of years a faculty has been teaching in the university, and not the actual age of the faculty.
3. Student demand is assumed to be accurate, as it is based on survey data that covers the entire population.
4. A faculty's eligibility to teach a course is based on the courses they have previously handled and their research laboratory or departmental affiliation.
5. Any active faculty can handle up to a maximum of 3 units of overload teaching load beyond their minimum teaching load requirement for the semester.
6. No team-teaching arrangements are included in the modelling. That is, each class of a course must be fully assigned to a faculty, and the full number of units of that class would contribute towards the faculty's target teaching load (i.e., no fractional class assignment).
7. Once submitted, faculty preferences are assumed to remain unchanged throughout the planning period.

Furthermore, the study models the faculty assignment operations for a single department, with a faculty size of around 20 and a student population size of around 400 students. The modelling also only accounts for subjects offered by the department (i.e., major subjects), as those offered by other departments would be too dependent on external conditions.

3.2.2 Problem Formulation

The FCAP variant is formulated as an MILP model to represent discrete decision variables, such as the number of sections to be offered per course and their assignment to faculty, and continuous decision variables, such as the number of units of teaching load a faculty is short of their minimum teaching load requirement for the semester. The model aims to solve the problem of determining an optimal allocation of teaching responsibilities that meets student demand while respecting faculty workload limits, faculty preferences, faculty course eligibility, and institutional policies.

To address the multiple and potentially conflicting objectives of the problem, the formulation adopts a priority-weighted multi-objective MILP, which results in a goal programming approach but solves the MILP only once using a single weighted objective function. Penalty coefficients W_i are assigned to each objective to reflect their relative priority, where objective i is given higher priority than objective $(i+1)$. Larger penalty coefficients are therefore assigned to higher priority objectives to enforce a preemptive preference structure. Penalty coefficient values are generally selected such that:

$$W_i > \sum_{k=i+1}^{6} W_k \; for\ objective\ i = 1,2,3,4,5$$

The indices, parameters, and decision variables used in the formulation are found in Table 2, Table 3, and Table 4, respectively. The source code supporting the findings of this study is available from the corresponding author upon reasonable request.

Table 2. Indices used in the mathematical model.

Index	Description
i	Course index
j	Faculty index

Table 3. Parameters used in mathematical model.

Parameter	Description
W_i	Penalty coefficient for objective i in the objective function (set to 100,000,000,000, 1,000,000,000, 10,000,000, 100,000, 1,000, *and* 1 for W_1,W_2,W_3,W_4,W_5, *and* W_6 respectively for the test instance solved)
U_i	Number of units of teaching load per section of course i
SEN_j	Seniority value for faculty j. Integer values in increments of 10, ranging from 0 to 40. The value 0 is reserved for the dummy variable representing assignment to lecturers (X_{iD}).
CS_i	Standard class size (in number of students) of course i
D_i	Total demand (in number of students) for the semester for course i
L_j	Minimum teaching load requirement for the semester of faculty j
$MAXOVER_j$	Maximum overload teaching units of faculty j. (set to 3 for the problem instance solved)
M	A fixed large number (set to 100 for the test instance solved)
P_{ij}	Number of sections of course i assigned to faculty j within their preferred section limit for the course, as indicated in their submitted preferences
Q_{ij}	Binary variable with value 1 if course i is in the submitted preferences of faculty j, 0 otherwise
C_{ij}	Binary variable with value 1 if course i can be taught by faculty j, 0 otherwise

Table 4. Decision variables used in mathematical model.

Decision Variable	Description
X_{ij}	Total number of sections of course *i* taught by faculty *j* X_{iD} is a dummy variable representing assignment to lecturers
$BELOW_j$	Number of units of underload of faculty *j*
$ABOVE_j$	Number of units of overload of faculty *j*
IN_{ij}	Number of sections of course *i* assigned to faculty *j* that are within their preferred courses to teach and within their preferred section limit for the course
OUT_{ij}	Number of sections of course *i* assigned to faculty *j* that are within their preferred courses to teach but beyond their preferred section limit for the course
CAN_{ij}	Number of sections of course *i* assigned to faculty *j* that are within the set of courses they can teach (inclusive of both their preferred courses and non-preferred courses)

Using the introduced variables and parameters, a Mixed-Integer Linear Program (MILP) formulation of the problem:

$$
\begin{aligned}
Min\ Z = \ & W_1 \sum_i U_i X_{iD} + W_2 \sum_j BELOW_j + W_3 \sum_j ABOVE_j \\
& + W_4 \left(\left(\sum_j \sum_i CAN_{ij} \right) - \left(\sum_j \sum_i IN_{ij} \right) \right) + W_5 \sum_j \sum_i OUT_{ij} \\
& - W_6 \sum_j \sum_i (SEN_j * X_{ij})
\end{aligned} \tag{1}
$$

$s.t.$

$$\sum_j \left(X_{ij} * CS_i\right) = \lceil \frac{D_i}{CS_i} \rceil \ \forall\, i \tag{2}$$

$$\sum_i U_i X_{ij} + BELOW_j - ABOVE_j = L_j \ \forall\, j \tag{3}$$

$$ABOVE_j \leq MAXOVER_j \ \forall\, j \tag{4}$$

$$X_{ij} = IN_{ij} + OUT_{ij} + CAN_{ij} \ \forall\, i, j \tag{5}$$

$$IN_{ij} \leq P_{ij} \ \forall\, i, j \tag{6}$$

$$OUT_{ij} \leq MQ_{ij} \ \forall\, i, j \tag{7}$$

$$CAN_{ij} \leq MC_{ij} \ \forall\, i, j \tag{8}$$

$$X_{ij}, IN_{ij}, OUT_{ij}, CAN_{ij} \in Z \tag{9}$$

$$X_{ij}, IN_{ij}, OUT_{ij}, CAN_{ij}, BELOW_j, ABOVE_j \geq 0 \tag{10}$$

The formulation is an objective function (1) that minimizes the total penalty of terms referring to various objectives. Respectively, these are the total units assigned to lecturers, total units assigned to faculty below their requirement, total units assigned to faculty above their requirement, total number of classes assigned to faculty outside their preferred courses, total number of classes assigned to faculty outside their class count preferences, and finally, the negative of the seniority value assigned to sections (for tie breaks). The penalty coefficients are chosen such that each term is prioritized sequentially. This is achieved through setting values for W_i that are 100 times larger than the previous one. The largest value of these objective function terms would be the seniority value, which will never exceed 1000. Thus, the multiplier for this tier is set to this value. Aside from this, the largest objective function term value would be the number of sections of overload, which will never exceed 100. Thus, with the use of these penalty values, the set hierarchy of objectives will never be disrupted.

For the constraints, Constraint (2) sets the number of sections opened for a course to be equal to the minimum number of sections required to meet course demand, using a ceiling function. Constraint (3) determines how many units of teaching load the faculty is above or below their minimum required teaching load units through a goal programming constraint formulation. Constraint (4) ensures that no faculty may overload more than their maximum allowable overload units. Constraints (5) to (8) jointly define that the total number of sections of a course assigned to a faculty is the sum of the number of sections within their preferred section limit of a preferred course, the number of sections beyond their preferred section limit of a preferred course, and the number of sections of non-preferred courses assigned to them. Constraint (9) ensures that the applicable decision variables are integers, and Constraint (10) ensures that all decision variables are non-negative.

IV. SOLUTION METHODOLOGY

4.1 Data Collection and Preparation

Data for the study were collected from both primary and secondary sources. Surveys were administered to gather information on student demand, faculty preferences, and the maximum number of units each faculty is allowed to teach. The minimum teaching load requirements of faculty may vary depending on their administrative responsibilities and research commitments. Institutional records were also used to obtain past teaching assignments, course descriptions, and previous course offerings. These served as the basis for constructing model inputs such as faculty course eligibility, course unit values, and section capacities.

The processed data were organized into structured formats using dictionaries indexed by courses and faculty to facilitate integration into the optimization model. Course-related data were represented as course_units = {'course1': units, 'course2': units, ...} and course_capacity = {'course1': capacity, 'course2': capacity, ...}, indicating the number of units and section capacity for each course. Faculty-related data were stored as teacher_max_units = {'faculty1': units, ...}, teacher_additional_units = {'faculty1': additional_units, ...}, and teacher_seniority = {'faculty1': score, ...}. Student demand was derived from grouped enrollment data structured as groups = [{'id': 'group_id', 'students': demand, 'course': ['course1', 'course2', 'course3']}, ...], where each group contains the number of students and their enrolled courses; this was then aggregated into course_demand = {'course1': demand, ...}, from which required_sections = {'course1': sections, ...} was computed. Relationships between courses and faculty were modeled using two-dimensional dictionaries, including pref_courses = {'course1': {'faculty1':

0/1, ...}, ...} for faculty preferences and can_teach_courses = {'course1': {'faculty1': 0/1, ...}, ...} for course eligibility, while pref_num_section = {('course1','faculty1'): limit, ...} specifies the preferred section limit of a faculty for a preferred course. These structured representations were used directly in defining the decision variables and constraints of the optimization model.

4.2 Solution Approach

The proposed model is implemented in Python using the PuLP (version 3.3.0) optimization library. It is formulated as an MILP model. Although this class of problems is generally NP-hard, the instance considered in this study remains manageable, allowing the use of an exact optimization approach instead of heuristic or metaheuristic methods.

All decision variables, constraints, and objective components are defined directly in the model. The problem is then solved using a deterministic mixed-integer optimization solver through a Python interface. This setup ensures consistent and reproducible results.

The pseudocode summarizing the overall solution procedure is presented below.

Algorithm 1. Solution procedure for the FCAP.

Input:
- ➔ Course demand, unit teaching load, and capacity data
- ➔ Faculty workload, faculty preference, course eligibility, and seniority data

Output:
- ➔ Optimal faculty-course assignment, opened sections, and faculty workload distribution

Begin
- ➔ Read and preprocess all input data
- ➔ Additional data processing
  - ◆ Aggregate student demand per course from student course demand data
  - ◆ Determine the required number of sections based on course capacity
- ➔ Formulate the MILP model
- ➔ Define decision and auxiliary variables
  - ◆ Define the decision variables for faculty-course assignment
  - ◆ Define auxiliary variables for overload, underload, and non-preferred assignments
- ➔ Construct the objective function by incorporating penalties for workload imbalance and undesirable assignments, together with incentives based on faculty preference and seniority
- ➔ Add constraints
  - ◆ Add the demand constraints
  - ◆ Add the faculty workload constraints
  - ◆ Add the course eligibility constraints
  - ◆ Add the non-preferred assignment constraints
  - ◆ Add the preferred section limit constraints
  - ◆ Enforce integrality and non-negativity restrictions

➔ Solve the MILP model using an optimization solver
➔ Extract the optimal faculty assignments
➔ Compute the resulting faculty teaching loads
➔ Report the number of opened sections for each course
End

V. RESULTS AND DISCUSSION

5.1 Experimental Set-up

This study was conducted by analyzing the Department's faculty-course assignment activities for the 1st semester of the academic year 2025-2026. Only undergraduate courses whose sections are handled by the Department are included, which cover 4 year-levels, 18 courses, and 17 faculty. Each year level has around 100 undergraduate students, and each student may independently contribute to the demand for up to 7 courses. The goal was to produce a faculty-course assignment that meets student demand while respecting faculty workload limits, faculty preferences, faculty course eligibility, and institutional policies.

In the following results discussions, the faculty labelled as "DUMMY" represents the pool of lecturers available for assignment, corresponded to by assignments of the model to the dummy variable. This allows the model to allocate course sections to lecturers when assignment to faculty is either infeasible or suboptimal under the imposed constraints.

5.2 Baseline Results

5.2.1 Baseline Results: Maximizing Demand Accommodation with the Existing Faculty Complement

The Python implementation of the model was executed on a MacBook Pro with an Apple M3 chip. The model successfully solved the problem instance with a total runtime of approximately 37 seconds. From this runtime, it can be seen that running instances for a faculty size of 24 would result in a runtime that would be manageable (i.e., several minutes to a few hours), which would be acceptable in the context of faculty assignment since this is only done once a semester.

Table 5 shows the courses and sections assigned to each faculty. All 17 faculty were assigned at least one section, and a total of 60 sections were assigned.

Table 5. Courses and sections assigned per faculty.

Entity	Courses Assigned and Count of Assigned Sections per Course	Total Count of Assigned Sections
Faculty 1	Course 8 (2), Course 10 (1), Course 11 (1)	4
Faculty 2	Course 9 (3), Course 14 (3)	6
Faculty 3	Course 4 (1), Course 6 (3), Course 10 (1)	5
DUMMY	Course 4 (1), Course 12 (1)	2
Faculty 5	Course 7 (3), Course 14 (1)	4
Faculty 6	Course 9 (1), Course 16 (3)	4
Faculty 7	Course 2 (1), Course 3 (2), Course 17 (1)	4
Faculty 8	Course 13 (3)	3
Faculty 9	Course 1 (2), Course 12 (1)	3
Faculty 10	Course 5 (4)	4
Faculty 11	Course 13 (1), Course 15 (3)	4
Faculty 12	Course 3 (1), Course 8 (1), Course 15 (1)	3
Faculty 13	Course 6 (1), Course 11 (1)	2
Faculty 14	Course 4 (1), Course 16 (2)	3
Faculty 15	Course 2 (1)	1
Faculty 16	Course 4 (1), Course 10 (2)	3
Faculty 17	Course 3 (1), Course 18 (1)	2
Faculty 18	Course 8 (1), Course 17 (1), Course 18 (1)	3
	TOTAL	60

Table 6 summarizes the deviations of the actual faculty assignment from their submitted preferences. Some faculty were assigned sections for courses outside their preferred courses, and some were assigned sections for preferred courses, but exceeded their preferred section limit for the course.

Table 6. Faculty preference deviations summary.

Entity	Total Count of Assigned Sections Outside Preferred Courses	Total Count of Assigned Sections of Preferred Courses Beyond Preferred Section Limit	Course	Preferred Section Limit	Count of Assigned Sections	Count of Assigned Sections Beyond Preferred Section Limit
Faculty 1	1	0	Course 8	2	2	0
			Course 10	1	1	0
			Course 12	0	1	1
Faculty 2	0	2	Course 9	2	3	1
			Course 14	2	3	1
			Course 17	2	0	0
Faculty 3	4	0	Course 4	3	1	0
			Course 6	0	2	2
			Course 10	0	2	2
			Course 15	2	0	0
			Course 16	2	0	0
DUMMY	N/A	N/A	Course 4	N/A	1	N/A

Entity	Total Count of Assigned Sections Outside Preferred Courses	Total Count of Assigned Sections of Preferred Courses Beyond Preferred Section Limit	Course	Preferred Section Limit	Count of Assigned Sections	Count of Assigned Sections Beyond Preferred Section Limit
			Course 11	N/A	1	N/A
Faculty 5	0	1	Course 7	2	3	1
			Course 14	1	1	0
			Course 16	1	0	0
Faculty 6	0	2	Course 9	1	1	0
			Course 16	1	3	2
			Course 17	1	0	0
Faculty 7	1	0	Course 3	2	2	0
			Course 15	0	1	1
			Course 17	1	1	0
Faculty 8	0	1	Course 7	2	0	0
			Course 13	2	3	1
Faculty 9	1	0	Course 1	2	2	0
			Course 2	0	1	1
Faculty 10	0	2	Course 5	2	4	2
			Course 14	1	0	0
			Course 18	1	0	0
Faculty 11	0	2	Course 10	1	0	0
			Course 13	2	1	0
			Course 15	1	3	2
Faculty 12	2	0	Course 3	2	1	0
			Course 8	0	1	1
			Course 12	0	1	1
Faculty 13	2	0	Course 2	0	1	1
			Course 6	0	1	1
			Course 8	2	0	0
Faculty 14	0	0	Course 4	1	1	0
			Course 16	2	2	0
			Course 17	1	0	0
Faculty 15	1	0	Course 11	0	1	1
Faculty 16	3	0	Course 4	0	1	1
			Course 5	1	0	0
			Course 6	0	1	1
			Course 16	1	0	0
Faculty 17	0	0	Course 3	1	1	0
			Course 9	1	0	0
			Course 18	1	1	0
Faculty 18	0	0	Course 8	1	1	0
			Course 17	1	1	0
			Course 18	1	1	0

Table 7 summarizes the teaching load of each faculty for the generated assignments. No faculty was underloaded, and every faculty was overloaded. A total of 231 teaching load units were assigned, of which 51 were overload units. It can be noticed that in this resulting assignment, all faculty have been assigned 3 units of overload. This is the model maximizing the defined allowable overload as specified in the model constraints, which is perfectly within guidelines in the real-world implementation. However, it is often discouraged that several faculty are assigned overload units, as excess teaching load often adversely affects the quality of teaching. As such, before this type of assignment is applied in the real-world, several lecturers are often hired to alleviate the regular faculty of this overload. Aside from this, everything shown in the results is close to what actually happens in the real-world implementation.

Table 7. Faculty teaching load summary.

Entity	Minimum Teaching Load Units Requirement	Maximum Teaching Load Units	Assigned Teaching Load Units	Units Underload	Units Overload
Faculty 1	10.5	13.5	13.5	0	3
Faculty 2	12	15	15	0	3
Faculty 3	13	16	16	0	3
DUMMY	N/A	N/A	5	N/A	N/A
Faculty 5	9	12	12	0	3
Faculty 6	8	11	11	0	3
Faculty 7	10	13	13	0	3
Faculty 8	6	9	9	0	3
Faculty 9	6	9	9	0	3
Faculty 10	9	12	12	0	3
Faculty 11	9	12	12	0	3
Faculty 12	7	10	10	0	3
Faculty 13	3.5	6.5	6.5	0	3
Faculty 14	5	8	8	0	3
Faculty 15	0	3	3	0	3
Faculty 16	6	9	9	0	3
Faculty 17	3.5	6.5	6.5	0	3
Faculty 18	6.5	9.5	9.5	0	3
		TOTAL	180	0	51

Table 8 presents the values of the seven components of the objective function. Five load units were assigned to lecturers, equivalent to two sections. Total faculty underloading was 0 units, while overloading amounted to 51 units. With respect to preferred courses, 15 sections were assigned outside of the faculty's preferred courses, and 25 sections were assigned within the faculty's preferred courses but beyond their specified preferred section limit. Unlike formulations relying solely on aggregate preference satisfaction or faculty-course suitability measures, the proposed model additionally enables explicit analysis of preferred section limit violations and the need for lecturers through the inclusion of multiple objective components and dummy variables. Such information provides operational insight into the extent and nature of resource-demand mismatches within the Department. Seniority satisfaction primarily functioned as a secondary tie-breaking criterion, with the model maximizing its score only after higher-priority objectives had been considered. In the real-world implementation, this seniority tie-breaking criterion is done both as a sign of respect to those who have served in the department for a longer time, and the recognition that more senior faculty have a higher level of mastery when it comes to teaching subjects.

Table 8. Objective function components summary

Objective Function Component	Objective Priority Number	Value	Unit of Measure
Assigned to Lecturers	1	5	Units
Underloading	2	0	Units
Overloading	3	51	Units
Outside Preference Courses	4	15	Sections
Within Preference Courses & Beyond Preferred Section Limit	5	25	Sections
Seniority Satisfaction	6	830	N/A

The baseline results demonstrate that the proposed model can generate a feasible and optimal solution to the FCAP for this real-world problem instance while considering faculty preferences and institutional policies of the Department.

5.2.2 Baseline Results: Practical Demand Accommodation with the Existing Faculty Complement

The proposed methodology is flexible, as it allows the allowable teaching load beyond their advised workload limits to be easily adjusted. Table 9 shows the revised number of additional units that may be assigned to each faculty on top of the advised workload limit. In this scenario, instructors are not allowed to take on overload units, Assistant Professors may be assigned up to 1 additional unit, and Associate Professors and Professors may be assigned up to 3 additional units. This setup reflects a more practical allocation policy, recognizing that not all faculty should be expected to carry the same level of overload.

Table 9. Revised Allowable overload units by faculty rank.

Entity	Original Allowable Overload Units	Revised Allowed Overload Units
Faculty 1	3	1
Faculty 2	3	1
Faculty 3	3	1
DUMMY	Infinite	Infinite
Faculty 5	3	0
Faculty 6	3	0
Faculty 7	3	1
Faculty 8	3	3
Faculty 9	3	1
Faculty 10	3	0
Faculty 11	3	0
Faculty 12	3	3
Faculty 13	3	1
Faculty 14	3	1
Faculty 15	3	1
Faculty 16	3	0
Faculty 17	3	1
Faculty 18	3	0

Table 10 presents the faculty teaching load assignments using the revised allowable overload units. The results show that the assigned teaching loads decreased, with the excess teaching load absorbed by lecturers. This indicates the need to hire lecturers to help alleviate the teaching load of regular faculty. In observing the results of Table 9 and Table 10, Faculty 15 was used as the focus. In Table 9, Faculty 15 has an allowable overload of 1 unit, which means that the faculty can handle a maximum of 13 units. As shown in Table 10, Faculty 15's assigned teaching load decreased from 3 units to 1 unit. However, this refers only to the teaching load, since Faculty 15 still has other assigned duties, such as administrative, research, and other non-academic responsibilities. Thus, Faculty 15 is assigned only 1 unit of teaching load because he/she already has 12 units of non-teaching load.

Table 10. Assigned teaching load of faculty under revised overload unit limits.

Entity	Old Assigned Teaching Load Units	New Assigned Teaching Load Units
Faculty 1	13.5	10.5
Faculty 2	15	13
Faculty 3	16	13
DUMMY	5	46
Faculty 5	12	9
Faculty 6	11	8
Faculty 7	13	10.5
Faculty 8	9	9
Faculty 9	9	7
Faculty 10	12	9
Faculty 11	12	9
Faculty 12	10	10
Faculty 13	6.5	4.5
Faculty 14	8	6
Faculty 15	3	1
Faculty 16	9	6
Faculty 17	6.5	4.5
Faculty 18	9.5	6.5

5.3 System Performance Analysis

In the experiment, the baseline problem instance consists of 18 courses, with an average demand of 78 students per course. A total of 60 sections are required to be opened, and 60 faculty are available for assignment. The average teaching load per faculty is 10.08 units, which already accounts for the allowed 3-unit overload. In this setting, a faculty may handle up to 15 units; however, the average teaching load is lower because some faculty have administrative, research, study load, or extension load, thereby lowering their minimum required teaching load.

On average, each faculty indicates 2.5 preferred courses and is qualified to teach 12.92 courses. The number of teachable courses was intentionally increased to provide greater flexibility in the model, although in actual practice, faculty typically teach only around 5 to 7 courses. To evaluate the computational performance of the proposed model, the problem size was varied across different test instances. The objective was to determine whether the model could still generate solutions within an acceptable runtime as the size of the scheduling problem increases. The results of this experiment are presented in Table 11.

Table 11. Run time analysis under baseline.

Input Parameters					Run Time in Seconds
Changes	**Number of Courses**	**Number of Faculty**	**Units Per Faculty**	**Number of Demand per Course**	
Baseline	18	17	10.08	78	29.85
Practical Demand Accommodation	18	17	8.08	78	0.5s
Additional Courses and Faculty	25	25	11	83.64	150.18
Additional Faculty	25	30	10.78	83.64	177.63

To increase the model size, the highest-load faculty and highest-demand courses were replicated. Faculty replication was based on total teaching capacity, while course replication was based on student demand. The generated faculty-course data followed the same structure as the baseline instance. However, the newly generated block was controlled so that each new faculty was assigned exactly seven teachable courses and three preferred courses selected from the newly generated courses. In addition, each newly generated course was ensured to have at least three eligible faculty who could teach it.

To fully evaluate the model's performance, the faculty-course assignment logic was modified to create a more realistic and challenging test instance. In the revised setup, newly generated faculty beyond the 30-faculty threshold were no longer restricted to newly generated courses only. Instead, these additional faculty were allowed to teach and indicate preferences for courses from both the original and newly generated course sets.

In addition, the demand for each subject was increased to further stress-test the model. This adjustment was made to determine whether the model could still find an optimal solution efficiently under a larger and more demanding instance, particularly when using fast mode. The results of this experiment are summarized in Table 12.

Table 12. Run time analysis under new baseline.

Input Parameters				Run Time in Seconds
Changes	**Number of Courses**	**Number of Faculty**	**Additional Number of Demand per Course**	
New Baseline	25	34	20	Too Long; manually stopped after 1000s

Therefore, the model is considered effective for instances with around 30 faculty, 25 courses, and an average demand of about 84 students per course. Beyond this scale, especially when demand is increased significantly, the model may require additional tuning, decomposition, or solver time limits to remain computationally practical.

5.3 Sensitivity Analysis

To demonstrate the robustness of the model, sensitivity analysis was conducted to emulate actual real-world occurrences. The model's performance was examined under the following scenarios: (1) variations in demand (i.e., increases and decreases); (2) changes in faculty availability (i.e., addition of new faculty and the retirement of existing ones), and (3) constraints related to faculty preferences and course eligibility (i.e., only one faculty both prefers and is qualified to teach a specific course).

5.3.1 Changes in Demand

a. If the Department is promoted to a higher-level unit such as an institution, an increase in student intake is anticipated. To capture this scenario, total course demand was assumed to increase by 10% (Table 13).

Table 13. Resulting teaching load assignment from increased demand.

Entity	Minimum Teaching Load Units Requirement	Maximum Teaching Load Units	Assigned Teaching Load Units	Units Underload	Units Overload
Faculty 1	10.5	13.5	13.5	0	3
Faculty 2	12	15	15	0	3
Faculty 3	13	16	16	0	3
DUMMY	N/A	N/A	21	N/A	N/A
Faculty 5	9	12	12	0	3
Faculty 6	8	11	11	0	3
Faculty 7	10	13	13	0	3
Faculty 8	6	9	9	0	3
Faculty 9	6	9	9	0	3
Faculty 10	9	12	12	0	3
Faculty 11	9	12	12	0	3
Faculty 12	7	10	10	0	3
Faculty 13	3.5	6.5	6.5	0	3
Faculty 14	5	8	8	0	3
Faculty 15	0	3	3	0	3
Faculty 16	6	9	9	0	3
Faculty 17	3.5	6.5	6.5	0	3
Faculty 18	6.5	9.5	9.5	0	3

In the baseline scenario, all faculty were already assigned teaching loads exceeding their maximum teaching load units. Consequently, any further increase in demand was anticipated to require additional resources. This was evident in the model results, where the total teaching load allocated to lecturers increased from 5 to 21 units.

b. Certain scenarios may lead to a decline in demand, such as the implementation of the K-12 educational reform. During this period, the Department experienced reduced student intake over a span of two years. To model this situation, a 20% decrease in demand was assumed (Table 14). This fluctuation in demand (both increase and decrease) is regularly seen within the department, albeit often to a lesser extent. This is often handled by hiring lecturers (for increased demand) or reallocating teaching load to other non-teaching workload types, such as research load (for decreased demand).

Table 14. Resulting teaching load assignment from decreased demand.

Entity	Minimum Teaching Load Units Requirement	Maximum Teaching Load Units	Assigned Teaching Load Units	Units Underload	Units Overload
Faculty 1	10.5	13.5	13.5	0	3
Faculty 2	12	15	13	0	1
Faculty 3	13	16	13	0	0
DUMMY	N/A	N/A	0	N/A	N/A
Faculty 5	9	12	9	0	0
Faculty 6	8	11	9	0	1
Faculty 7	10	13	10.5	0	0.5
Faculty 8	6	9	9	0	3
Faculty 9	6	9	6.5	0	0.5
Faculty 10	9	12	12	0	3
Faculty 11	9	12	10	0	1
Faculty 12	7	10	7	0	0
Faculty 13	3.5	6.5	6.5	0	3
Faculty 14	5	8	8	0	3
Faculty 15	0	3	3	0	3
Faculty 16	6	9	6	0	0
Faculty 17	3.5	6.5	5	0	1.5
Faculty 18	6.5	9.5	7	0	0.5

A 20% reduction in demand was expected to lead to a corresponding decrease in the number of sections offered, thereby lowering the teaching loads assigned to faculty. This effect was reflected in the results, where total overload units decreased from 51 to 24 units, and the teaching load allocated to lecturers was reduced from 5 to 0 units.

To further examine the sensitivity of the model to changes in demand, additional scenarios were tested by uniformly varying the demand per course (i.e., defined as the number of students requiring a course). As shown in Figure 2, the teaching load assigned to lecturers generally increased as additional demand per course increased. When demand was reduced by 5 students per course, no teaching load was assigned to lecturers, while the baseline scenario resulted in 5 teaching load units assigned to lecturers (dummy load). As additional demand increased to 5, 10, 15, and 20 students per course, the dummy load rose to 18, 21, 33, and 45 units, respectively. This pattern suggests that the Department would need additional instructional resources as demand increases.

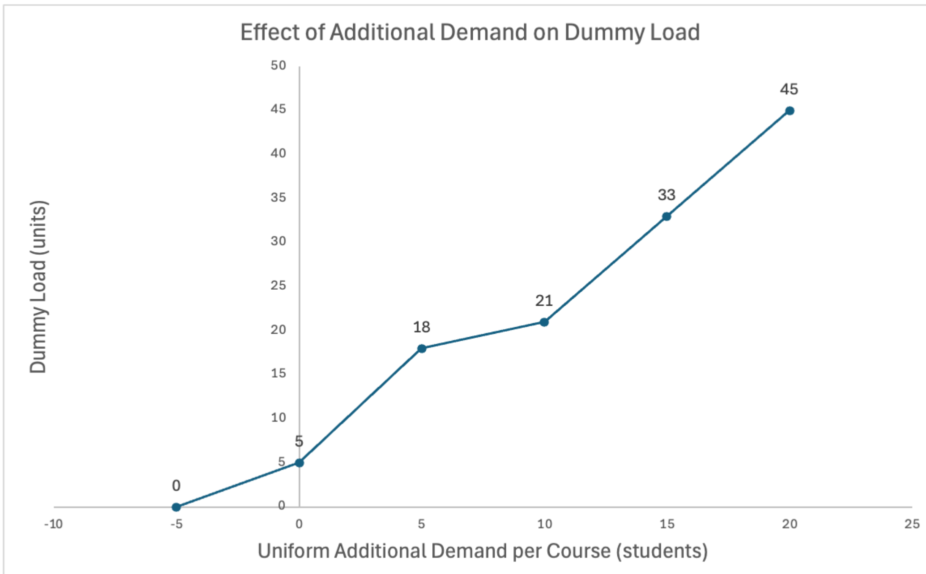

Figure 2. Effect of uniform additional demand per course on dummy load.

5.3.2 Faculty Availability

a. Faculty retirement may occur due to reaching the mandatory retirement age of 65 or the decision to pursue alternative career paths. To simulate this scenario, the oldest faculty (i.e., Faculty 8 and 15) were removed from the faculty pool (Table 15).

Table 15. Resulting teaching load assignment from decreased faculty complement.

Entity	Minimum Teaching Load Units Requirement	Maximum Teaching Load Units	Assigned Teaching Load Units	Units Underload	Units Overload
Faculty 1	10.5	13.5	13.5	0	3
Faculty 2	12	15	15	0	3
Faculty 3	13	16	16	0	3
DUMMY	N/A	N/A	17	N/A	N/A
Faculty 5	9	12	12	0	3
Faculty 6	8	11	11	0	3
Faculty 7	10	13	13	0	3
Faculty 9	6	9	9	0	3
Faculty 10	9	12	12	0	3
Faculty 11	9	12	12	0	3
Faculty 12	7	10	10	0	3
Faculty 13	3.5	6.5	6.5	0	3
Faculty 14	5	8	8	0	3
Faculty 16	6	9	9	0	3
Faculty 17	3.5	6.5	6.5	0	3
Faculty 18	6.5	9.5	9.5	0	3

The removal of two additional faculty was anticipated to increase the workload assigned to lecturers since all faculty were already operating at full capacity. This was evidenced in the model by an increase in lecturers' teaching load from 5 to 17 units.

b. The Department may hire additional faculty if needed. In this scenario, two new faculty were considered. To model this, the faculty preferences and course eligibility of two new faculty (i.e., Faculty 6 and Faculty 16) were replicated (Table 16).

Table 16. Resulting faculty teaching assignment from the increased faculty complement.

Entity	Minimum Teaching Load Units Requirement	Maximum Teaching Load Units	Assigned Teaching Load Units	Units Underload	Units Overload
1New	8	11	11	0	3
2New	6	9	6.5	0	0.5
Faculty 1	10.5	13.5	13.5	0	3
Faculty 2	12	15	13.5	0	1.5
Faculty 3	13	16	16	0	3
DUMMY	N/A	N/A	0	N/A	N/A
Faculty 5	9	12	12	0	3
Faculty 6	8	11	11	0	3
Faculty 7	10	13	10.5	0	0.5
Faculty 8	6	9	9	0	3
Faculty 9	6	9	6	0	0
Faculty 10	9	12	12	0	3
Faculty 11	9	12	10	0	1
Faculty 12	7	10	10	0	3
Faculty 13	3.5	6.5	6.5	0	3
Faculty 14	5	8	7	0	2
Faculty 15	0	3	3	0	3
Faculty 16	6	9	9	0	3
Faculty 17	3.5	6.5	6.5	0	3
Faculty 18	6.5	9.5	7	0	0.5

The addition of two new faculty was anticipated to reduce the teaching load assigned to lecturers and help alleviate the overload among existing faculty. Model results indicate that the dummy load decreased from 5 to 0 units, and total overload units were reduced from 51 to 42 units.

Figure 3 shows how changes in faculty availability affect the dummy load and overload units. This includes both dummy load and overload units beyond the advised teaching load. The y-axis shows the different scenarios where faculty were either removed or replicated, while the x-axis shows the total dummy load and overload units. The results show that total dummy load and overload increase when fewer faculty are available. When additional faculty are added, the total dummy load and overload decrease. This means that if more faculty retire or resign, the Department may need to increase the teaching loads of the remaining faculty or hire lecturers to meet course demand. On the other hand, hiring more faculty can reduce excess teaching load and lessen the need for lecturer assignments.

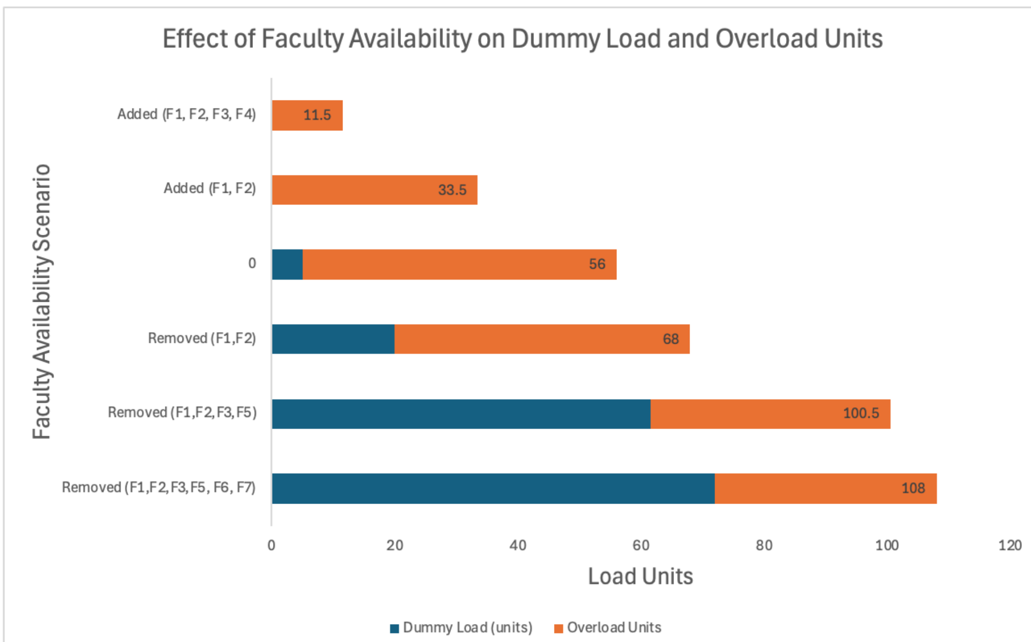

Figure 3. Effect of faculty availability on dummy load and overload units.

5.3.3 Faculty preference and course eligibility

a. In situations where only a limited number of faculty prefer to teach a specific course, the Department must make appropriate adjustments. In the model, this was represented by the adjustment of the preferences for Course 3 across all faculty. Specifically, this was simulated by manipulating the preferred courses data so that only one faculty preferred and simultaneously was the only one eligible to teach Course 3 (Table 17 and Table 18).

Table 17. Resulting course-faculty assignment from varying preferred courses.

Course	Entity	Count of Assigned Sections
Course 1	Faculty 9	2
Course 2	Faculty 1	1
Course 2	Faculty 7	1
Course 3	DUMMY	2
Course 3	Faculty 12	2
Course 4	Faculty 14	4
Course 5	Faculty 10	3
Course 5	Faculty 16	1
Course 6	Faculty 3	2
Course 6	Faculty 7	2
Course 7	Faculty 5	3
Course 8	Faculty 1	3
Course 8	Faculty 18	1
Course 9	Faculty 2	3
Course 9	Faculty 6	1
Course 10	Faculty 11	3
Course 10	Faculty 13	1
Course 11	Faculty 12	1
Course 11	Faculty 18	1
Course 12	Faculty 9	1
Course 12	Faculty 13	1
Course 13	Faculty 8	3
Course 13	Faculty 15	1
Course 14	Faculty 2	2
Course 14	Faculty 10	1
Course 14	Faculty 16	1
Course 15	Faculty 3	3
Course 15	Faculty 17	1
Course 16	Faculty 5	1
Course 16	Faculty 6	3
Course 16	Faculty 16	1
Course 17	Faculty 2	1
Course 17	Faculty 7	1
Course 18	Faculty 17	1
Course 18	Faculty 18	1

Table 18. Resulting teaching load assignment from varying preferred courses.

Entity	Minimum Teaching Load Units Requirement	Maximum Teaching Load Units	Assigned Teaching Load Units	Units Underload	Units Overload
Faculty 1	10.5	13.5	13.5	0	3
Faculty 2	12	15	15	0	3
Faculty 3	13	16	16	0	3
DUMMY	N/A	N/A	7	N/A	N/A

Entity	Minimum Teaching Load Units Requirement	Maximum Teaching Load Units	Assigned Teaching Load Units	Units Underload	Units Overload
Faculty 5	9	12	12	0	3
Faculty 6	8	11	11	0	3
Faculty 7	10	13	13	0	3
Faculty 8	6	9	9	0	3
Faculty 9	6	9	9	0	3
Faculty 10	9	12	12	0	3
Faculty 11	9	12	10.5	0	1.5
Faculty 12	7	10	10	0	3
Faculty 13	3.5	6.5	6.5	0	3
Faculty 14	5	8	8	0	3
Faculty 15	0	3	3	0	3
Faculty 16	6	9	9	0	3
Faculty 17	3.5	6.5	6	0	2.5
Faculty 18	6.5	9.5	9.5	0	3

As seen in the course-faculty assignment in Table 17, when only one faculty both prefers and is the only one eligible to teach a particular subject, lecturers were assigned. The model results showed that Course 3 was assigned to lecturers, increasing its teaching load from 5 to 7, while total overload units decreased from 51 to 49 units. These results are still similar to the results of the main model, demonstrating the robustness of the model under changes to various key parameters associated with real-world scenarios.

5.4 Post-Processing Analysis

The proposed model provides a baseline solution to the FCAP. In practice, the faculty or the department chair may still have additional input after reviewing the initial assignment. These considerations may be accommodated within the proposed model through adjustments to its input parameters.

One common adjustment involves modifying the standard capacity of a section. An increase or decrease in this value affects the number of sections to be offered, consequently influencing the assignments. Another possible consideration is the calibration of allowable overload. By adjusting the maximum allowable overload, the department can rebalance teaching responsibilities across faculty. This is particularly important when overloading in the current solution is either excessive or unnecessary.

Faculty capacity may also be updated through the minimum teaching load requirements parameter to reflect changes in responsibilities, such as administrative load, research load, or other workload-related factors. Accurately updating this parameter is essential to ensure that the faculty availability is properly represented and to avoid impossible or impractical assignments.

These post-processing considerations highlight that the model serves as a decision support tool that can be effectively utilized in this stage of the overall university course timetabling problem faced by academic institutions such as the one studied in this paper.

VI. CONCLUSION

In conclusion, although this variant of FCAP is classified as NP-hard, it can be effectively addressed using exact optimization for manageable problem sizes. This study demonstrated that the problem can be formulated as an exact optimization model based on assumptions grounded in current institutional policies and system practices. The model incorporates key factors such as course demand, faculty course eligibility, faculty minimum teaching load requirements, faculty maximum allowable overload, faculty preferences, and seniority considerations, resulting in feasible and practical assignment solutions. The model successfully minimized inefficiencies such as faculty underload and overload, and non-preferred course assignments, while also accounting for seniority as an important decision factor. Additionally, the processing and transformation of the pre-collected datasets into teaching load assignment plans were translated from a manual spreadsheet process into an implementable Python model. This workflow automation approach reduces the total processing time from 8 hours to essentially around 31 minutes. The actual run time of the Python algorithm is less than a minute, while the pre-processing of the datasets into ingestible inputs to the model takes around 30 minutes of work. Each additional revision prior to the implementation of the final teaching load assignment may be efficiently run using the same model with adjusted parameters as was shown. Overall, the results of this study confirm that the proposed exact optimization model is a viable and effective approach for solving the FCAP in small to medium-sized academic institutions, considering the types of faculty preferences data already being collected at the studied Philippine university department. Furthermore, its implementation in Python and its relatively short computation time for real-world instances make such post-processing analyses feasible and easy to perform.

VII. RECOMMENDATIONS AND AREAS FOR FUTURE WORK

Future research can focus on incorporating course scheduling into the proposed model for solving the FCAP to better reflect real-world academic planning. This includes integrating time slots, room availability, and potential scheduling conflicts into the optimization framework. A possible direction is to develop an extended exact solution approach that determines both faculty-course assignments and time and room schedules while still meeting course demand, considering faculty preferences and institutional policies.

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