

A MIXED-INTEGER LINEAR PROGRAMMING MODEL FOR THE FACULTY-ROOM ASSIGNMENT PROBLEM WITH DISCRETE PREFERENCE CONSTRAINTS

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ABSTRACT

This study addresses the University Course Timetabling Problem (UCTP) in resource-constrained environments using a Mixed-Integer Linear Programming (MILP) model based on Utility Maximization. Distinct from penalty-based cost-minimization frameworks, this model employs a weighted-sum objective function to reward satisfied binary faculty preferences while enforcing capacity constraints. Testing across three behavioral datasets—Baseline, Compressed Week, and Polarized Preferences—reveals that in over-constrained environments (32 subjects vs. 27 slots), physical limitations dictate schedule volume, forcing convergence to maximum utilization regardless of weighting strategies. However, in balanced scenarios, the weighting mechanism proved critical for fine-tuning assignments and strategically resolving high-demand conflicts. This research provides a transparent tool to quantify the trade-off between institutional efficiency and faculty well-being to manage scarce academic resources.

Keywords: University Course Timetabling Problem; Utility Maximization; Mixed-Integer Linear Programming; Faculty Preferences; Resource-Constrained Scheduling; Engineering Education

1. INTRODUCTION

The advent of the Thailand 4.0 policy has catalyzed a paradigm shift in engineering education, prioritizing practical, computer-aided instruction over traditional theoretical models. Core competencies such as Computer-Aided Design (CAD) and Artificial Intelligence (AI) have become central to the curriculum; however, this transition has created significant infrastructure bottlenecks. The demand for specialized computer laboratories now frequently exceeds available supply, severely complicating the University Course Timetabling Problem (UCTP). This challenge is further intensified by the need to accommodate complex faculty preferences, as instructors must balance teaching loads with research and consultancy obligations. Academic administrators face a

critical trade-off: disregarding faculty preferences risks professional burnout, while strict adherence may lead to scheduling infeasibility or institutional inefficiency.

From an organizational behavior perspective, the challenge of scheduling can be understood through the lens of the Job Demands-Resources (JD-R) model. According to this theory, disruptive teaching schedules and poor resource allocation act as significant "job demands" that accelerate physical and emotional exhaustion, ultimately leading to faculty burnout. Conversely, granting instructors control over their schedules—by satisfying temporal preferences—acts as a vital "job resource" that buffers against these demands and fosters academic engagement. Furthermore, principles of Resource Management Theory dictate that in environments with fixed infrastructure (such as specialized CAD laboratories), the strategic allocation of these scarce resources is not merely a logistical puzzle, but a critical driver of overall organizational effectiveness.

While existing approaches to UCTP typically focus on minimizing "penalty costs" or dissatisfaction, such frameworks remain inherently reactive. This research addresses the limitations of traditional models by proposing a Mixed-Integer Linear Programming (MILP) model designed for Utility Maximization. Unlike standard penalty-based or fuzzy models, this approach utilizes a weighted-sum objective function to actively reward the satisfaction of binary preferences. By quantifying the trade-off between institutional efficiency and faculty satisfaction, the model provides a robust decision-making tool for the optimal allocation of scarce resources.

This study develops a mathematical framework that optimizes the utilization of scarce computer laboratory resources while simultaneously addressing the multi-dimensional preferences of faculty members. Specifically, the research seeks to maximize the efficiency of fixed-supply facilities against the burgeoning demand for computer-based engineering subjects, thereby eliminating scheduling conflicts such as double-bookings and reducing underutilization during peak hours.

The study aims to integrate diverse faculty requirements—including temporal preferences for morning or afternoon sessions and specific teaching days—into the scheduling process. By employing a weighted-sum utility function within a Mixed-Integer Linear Programming (MILP) model, the research ensures that institutional resource management and individual faculty satisfaction are balanced through a proactive, utility-based approach.

2. Literature Review

2.1 Evolution of UCTP Modeling Paradigms

The theoretical foundation of the University Course Timetabling Problem (UCTP) in academic literature is primarily established as a constraint-satisfaction challenge. Early and

foundational research focuses on the mathematical necessity of fitting academic events into a finite spatial-temporal grid. However, as noted by Babaei et al. [1] and Chen et al. [2] in their comprehensive surveys, the problem is inherently NP-hard, meaning that as variables such as student numbers and specialized room requirements increase, finding an optimal solution becomes exponentially difficult. This difficulty has historically led researchers to prioritize "hard" constraints—such as physical room capacity and the prevention of double-booking—while treating qualitative factors like faculty satisfaction as secondary "soft" constraints that can be traded off for mathematical feasibility.

When examining the UCTP within the Southeast Asian context, and Thailand specifically, the constraints are distinctly physical and developmental [3]. Regional institutions are rapidly adapting to support national initiatives, such as the 'Thailand 4.0' policy, which emphasizes STEM, AI, and computer-aided education. However, this pedagogical shift often outpaces infrastructural expansion. Recent regional studies highlight this friction. For instance, research conducted at Prince of Songkla University in Thailand demonstrated the necessity of binary integer programming to manage strict teacher preferences against a limited supply of specialized laboratory rooms [4]. Similarly, broader Southeast Asian research, such as studies from Pancasila University in Indonesia [8], underscores that as the volume of technical and lab-based activities increases while physical spaces remain static, scheduling transitions from a mere timetabling issue to a critical resource allocation bottleneck. While these regional studies successfully highlight the need to balance localized constraints and faculty preferences, many still rely heavily on manual post-solution adjustments or reactive heuristics, reinforcing the need for the proactive, exact MILP approach proposed in this study.

In the realm of penalty-based modeling, classical studies have focused on minimizing the "cost" of schedule disruptions. Davison et al. [5] recently expanded this by considering the added complexity of hybrid teaching environments, while Ceschia et al. [6] provided state-of-the-art benchmarks for these educational models. The dominant strategy used by researchers like El Halaby [7] and Burke et al. [8] involves the use of Max-SAT formulations and decomposition techniques to minimize "penalty costs." This standard OR approach aligns closely with Simon's theory of Bounded Rationality and "Satisficing" [9], which posits that complex administrative decisions often default to finding solutions that are merely "good enough" by avoiding negative thresholds. Under these frameworks, every violated faculty preference is assigned a numeric penalty; the goal of the algorithm is to produce a schedule with the lowest possible aggregate penalty. Consequently, these models are theoretically and operationally reactive—they are designed defensively to mitigate dissatisfaction and penalize constraint violations, rather than proactively generating positive utility or maximizing faculty well-being.

As institutional requirements have grown more diverse, the literature has shifted toward multi-objective and multi-section considerations. Ozkan et al. [10] highlighted the necessity of room stability and lecturer preferences within the context of business schools, while Darmawan et al. [11] explored multi-objective modeling as a way to reconcile conflicting departmental goals. These studies acknowledge that a single objective—such as cost-minimization—is often insufficient to capture the nuanced needs of a modern university. By modeling several objectives simultaneously, these researchers attempt to find a "Pareto optimal" balance where no single stakeholder's needs are completely ignored, yet the focus remains largely on finding an acceptable compromise rather than a high-utility outcome.

Finally, recent advancements in the field have introduced sophisticated computational intelligence to handle environmental ambiguity. Maspiyanti et al. [12] and Muklason [13] have demonstrated the efficacy of genetic algorithms, fuzzy cross-over, and tabu-simulated annealing hyper-heuristics in navigating complex datasets. Furthermore, Hua et al. [14] surveyed evolutionary algorithms specifically designed for irregular Pareto fronts, offering tools to solve multi-objective problems that traditional linear methods cannot reach. Despite these technical leaps, a critical conceptual gap remains: the majority of these advanced models are reactive. They prioritize the mitigation of dissatisfaction and the management of irregular variables rather than the proactive maximization of institutional and faculty utility. This research identifies that while the "tools" for solving UCTP have evolved, the "philosophy" must shift toward utility-based optimization to meet the demands of modern engineering education.

2.2 Comparing Penalty-Based and Utility-Based Paradigms

The fundamental distinction between traditional penalty-based frameworks [6, 10] and the proposed utility-based approach lies in both their mathematical formulation and organizational philosophy. In penalty-based models, the scheduling environment is inherently deficit-oriented. The objective function is formulated to minimize aggregate cost, typically expressed as $\min Z = \sum(p_i \times v_i)$, where p_i represents the penalty weight and v_i represents a constraint violation [8]. Consequently, faculty preferences are treated mathematically as liabilities; the algorithm seeks the "least bad" schedule by mitigating the most severe violations, a methodology closely aligned with defensive "satisficing" behavior [9]. In contrast, the utility-based paradigm is asset-oriented. The objective function is designed to maximize aggregate satisfaction, formulated as $\min Z = \sum(w_i \times u_i)$, where w_i is the strategic weight and u_i is the achieved preference utility. Rather than penalizing failure, this model actively rewards the fulfillment of discrete preference constraints. From an organizational behavior perspective, transitioning from penalty to utility transforms the algorithm from a reactive damage-control mechanism into a proactive value-creation tool, generating a vital "job resource" that fosters faculty

well-being [13-14]. While both models may yield mathematically similar spatial-temporal grids in highly constrained scenarios, the utility-based model provides a more transparent, positive decision-support framework that aligns institutional efficiency with faculty well-being. A detailed comparison of these paradigms is summarized in Table 1.

Table 1. Theoretical and Mathematical Comparison of UCTP Modeling Paradigms

Feature	Penalty-Based Approaches (Traditional)	Utility-Based Approach (Proposed MILP)
Primary Objective	Mitigate dissatisfaction and avoid conflicts.	Maximize resource efficiency and faculty satisfaction.
Mathematical Goal	Minimize Total Cost: $\min Z = \sum(p_i \times v_i)$	Maximize Total Utility: $\min Z = \sum(w_i \times u_i)$
Organizational Philosophy	Deficit-oriented (Reactive formulation).	Asset-oriented (Proactive formulation).
Treatment of Preferences	Viewed as "soft constraints" resulting in penalties if broken.	Viewed as active goals yielding reward scores if met.
Decision Transparency	Obscures trade-offs by combining varied penalties into a single "cost."	Clearly quantifies the trade-off between institutional policy and faculty needs.

3. Research Methodology

3.1 Data Collection

The scheduling horizon T is discretized into 9 distinct time slots per week. The specific mapping of time slots to actual weekdays is defined as follows: Monday (Slots 1-2), Tuesday (Slots 3-4), Wednesday (Slot 5), Thursday (Slots 6-7), and Friday (Slots 8-9). Note that Wednesday afternoon is excluded from the set T , reserved for faculty-wide activities. To enforce the faculty's administrative policy of "Early-Week Utilization," a priority score (P_t) is assigned to each time slot. The policy dictates that courses should be filled from the beginning of the week (Monday Morning) to the end (Friday Afternoon) to maximize energy efficiency and operational flow. Therefore, Monday Morning ($t = 1$) is assigned the highest priority (9), while Friday Afternoon ($t = 9$) is assigned the lowest (1), as detailed in Table 2.

Teaching assignments define the demand for 25 course sections distributed among 19 instructors (A1–A19), as detailed in Table 3. Instructor preferences, derived from historical schedules, establish two parameters for each faculty member i a Preferred Time (t_{pref}) and a Least Preferred Time (t_{avoid}). This data drives the optimization model, designed to maximize assignments to t_{pref} while minimizing allocations to t_{avoid} to enhance faculty satisfaction.

Furthermore, the objective function of the MILP model is a Weighted Sum that balances two conflicting goals: satisfying the administrative policy (Time Priority) and satisfying the faculty members (Instructor Preference). For this experimental setup, the weights are determined based on the department's strategic focus, as Table 4.

Table 2. Time Slot Mapping and Priority Scores (P_t)

Time Slot (t)	Day / Session	Priority Score (P_t)	Rationale
1	Monday Morning	9	Highest Priority (Start of week)
2	Monday Afternoon	8	Mid-week
3	Tuesday Morning	7	
4	Tuesday Afternoon	6	
5	Wednesday Morning	5	
6	Thursday Morning	4	
7	Thursday Afternoon	3	
8	Friday Morning	2	
9	Friday Afternoon	1	Lowest Priority (End of week)

Table 3. Instructor Preference and Instructor-Subject Assignment Mapping

Instructor (i)	Preferred Time (t_{pref})	Least Preferred (t_{avoid})	Subject (s)
A1	3 (Tue AM)	9 (Fri PM)	S1
A2	3 (Tue AM)	1 (Mon AM)	S2
A3	6 (Thu AM)	9 (Fri PM)	S3
A4	5 (Wed AM)	1 (Mon AM)	S4
A5	5 (Wed AM)	8 (Fri AM)	S5
A6	4 (Tue PM)	1 (Mon AM)	S6
A7	7 (Thu PM)	9 (Fri PM)	S7
A8	2 (Mon PM)	5 (Wed AM)	S8
A9	1 (Mon AM)	9 (Fri PM)	S9, S10
A10	3 (Tue AM)	9 (Fri PM)	S11
A11	6 (Thu AM)	2 (Mon PM)	S12
A12	4 (Tue PM)	8 (Fri AM)	S13
A13	5 (Wed AM)	9 (Fri PM)	S14, S15
A14	2 (Mon PM)	1 (Mon AM)	S16
A15	3 (Tue AM)	9 (Fri PM)	S17
A16	7 (Thu PM)	4 (Tue PM)	S18
A17	6 (Thu AM)	1 (Mon AM)	S19
A18	8 (Fri AM)	9 (Fri PM)	S20
A19	4 (Tue PM)	1 (Mon AM)	S21, S22

Table 4. Objective Function Weights

Parameter	Symbol	Value	Description
Time Weight	w_{time}	0.7	The high importance of the administrative policy to fill early-week slots.
Preference Weight	w_{pref}	0.3	The secondary goal of accommodating individual instructor requests.

3.2 Mathematical Model Formulation

This section details of University Course Timetabling Problem (UCTP) using Mixed-Integer Linear Programming (MILP). The mathematical model fundamentally separates non-negotiable physical limitations (Hard Constraints) from desirable behavioral goals (Soft Constraints). Soft Constraints and the Objective Function: Faculty preferences and administrative time priorities represent Soft Constraints. Rather than formulating these as traditional inequalities that trigger penalties if broken, they are integrated into the Objective Function as Equation (1). This allows the solver to maximize Total Weighted Utility (Z) by fulfilling as many Soft Constraints as physically possible.

Hard Constraints: Equations (3), (4), and (5) represent the Hard Constraints of the UCTP. The solver must achieve a 100% satisfaction ratio for these conditions; any violation renders the schedule mathematically infeasible. Constraint 2 (Equation 3) is the Room Capacity Constraint, ensuring $\sum x \leq 1$ Constraint 3 (Equation 4) is the Instructor Availability Constraint, ensuring an instructor cannot be scheduled in two different rooms simultaneously. Constraint 4 (Equation 5) restricts the decision variables to binary values.

The Mathematical Logic of Dropped Subjects: Constraint 1 (Equation 2), the Subject Assignment Limit, is deliberately formulated as an inequality ($\sum x \leq 1$) rather than a strict equality ($=1$). In an over-constrained environment where the total Demand exceeds total Capacity, enforcing an equality would cause the MILP solver to return an "Infeasible" status. By utilizing the ≤ 1 inequality, the solver is permitted to assign a value of 0 to a subject across all time slots and rooms, effectively "dropping" it. Because the objective function seeks to maximize Z, the algorithm will naturally assign as many subjects as the Hard Constraints permit. The specific subjects chosen to be dropped are those whose inclusion would block other high-utility assignments, thus minimizing the overall loss to the system's total aggregate utility.

Indices

- I : Set for Instructors, $i \in \{A1, A2, \dots, A19\}$
- S_i : Set for Subjects taught by instructor i
- T : Set for Available time slots, $t \in \{1, 2, \dots, 9\}$
- R : Set for Computer rooms, $r \in \{1, 2, 3\}$

Parameters

- w_{time} : Weight assigned to time priority (0.7)
- w_{pref} : Weight assigned to instructor preference (0.3)
- P_t : The priority score of time slot t (based on administrative policy, 9...1)
- U_{it} : The preference utility of instructor i for time slot t , defined as:

$$U_{it} = \begin{cases} 1 & \text{if } t = t_{pref} \text{ (Preferred)} \\ -1 & \text{if } t = t_{avoid} \text{ (Least Preferred)} \\ 0 & \text{otherwise (Neutral)} \end{cases}$$

Decision Variables

x_{istr} : is 1 if instructor i teaches subject s at time t in room r , 0 otherwise

Objective Function

$$\text{Maximize } Z = \sum_{i \in I} \sum_{s \in S_i} \sum_{t \in T} \sum_{r \in R} ((w_{time} \times P_t) + (w_{pref} \times U_{it})) \times x_{istr} \quad (1)$$

Constraints 1

$$\sum_{t \in T} \sum_{r \in R} x_{istr} \leq 1 \quad \forall i \in I, \forall s \in S_i \quad (2)$$

Constraints 2

$$\sum_{i \in I} \sum_{s \in S_i} x_{istr} \leq 1 \quad \forall t \in T, \forall r \in R \quad (3)$$

Constraints 3

$$\sum_{s \in S} \sum_{r \in R} x_{istr} \leq 1 \quad \forall i \in I, \forall t \in T \quad (4)$$

Constraints 4

$$x_{istr} \in \{0,1\} \quad \forall i \in I, \forall s \in S_i, \forall t \in T, \forall r \in R \quad (5)$$

The objective Function as Equation (1) is to maximize the Total Weighted Utility (Z), which is the sum of the administrative time efficiency and the individual instructor satisfaction. The term $(w_{time} \times P_t)$ rewards the assignment of classes to high-priority slots (e.g., Monday Morning). The term $(w_{pref} \times U_{it})$ rewards assigning an instructor to their preferred slot (+0.3) and penalizes assigning them to their least preferred slot (-0.3). Constraints 1 as Equation (2), named Subject Assignment Limit, that each subject s taught by instructor i may be assigned to at most one time slot and room. This inequality allows the solver to leave a subject unassigned ($x = 0$) if no feasible slot exists, preventing infeasibility in overcrowded scenarios. Constraints 2 as Equation (3), named Room Capacity Constraint, that each computer room r can accommodate at most one subject at any specific time slot t . Constraints 3 as Equation (4), named Instructor Availability, that an instructor i cannot teach more than one subject at the same time t . This prevents the model from scheduling a multi-section instructor (e.g., A9) to two different rooms simultaneously. Constraints 4 as Equation (5), named Binary Variable Constraint, that this constraint defines the domain of the decision variables, restricting them to binary values. It ensures that the scheduling decision is discrete and definitive: a value of 1 indicates that a specific assignment (Instructor i teaching Subject s at Time t in Room r) is active, while 0 indicates it is not.

3.3 Computational Implementation

To implement the proposed optimization framework, the mathematical model was developed using the Python programming language, chosen for its extensive support in data manipulation and scientific computing. The PuLP library served as the linear programming modeler, providing the interface to define the decision variables, objective function, and constraints within a Python environment. To solve the resulting Mixed-Integer Linear Programming (MILP) problem, the CBC (Coin-OR Branch and Cut) solver engine was employed. This solver was selected for its capability to efficiently process binary constraints and guarantee an exact optimal solution for the scheduling parameters defined in this study.

3.4 Scenario Testing

To evaluate the robustness of the proposed model and understand the trade-offs between institutional policy and faculty satisfaction, a sensitivity analysis was conducted. The model was solved under five distinct weight scenarios, ranging from a balanced approach to a strong bias toward either time priority or instructor preference. The objective is to observe how changing the weights (W_{time} and W_{pref}) affects the final schedule structure. The five scenarios defined for this experiment are detailed in Table 5.

Moreover, Table 6 presents two distinct datasets designed to stress-test the robustness of the proposed scheduling model under extreme behavioral scenarios. These datasets represent conflicting faculty cultures that create specific mathematical challenges for the optimization algorithm.

Compressed Week (High Conflict) simulates a scenario where the majority of faculty members compete for the same "prime time" slots. As observed in the table, nearly all instructors (A1–A26) strictly prefer mid-week sessions (Tuesday, Wednesday, and Thursday), specifically time slots 3, 4, 5, 6, and 7. Conversely, there is a universal aversion to the "edge" slots of the week, with almost every instructor listing Monday Morning (Slot 1) or Friday Afternoon (Slot 9) as their least preferred time. This dataset creates a high-congestion environment that tests the model's ability to maximize utility when ideal resources are scarce and forcing assignments into unpopular slots is unavoidable.

AM vs. PM Split (Polarized) represents a divided faculty culture. In this scenario, the instructors are split into two distinct groups with opposing preferences. The senior group (A1–A13) exclusively prefers morning sessions (Slots 1, 3, 5, 6, 8) and avoids afternoons, while the junior group (A14–A26) prefers afternoon sessions (Slots 2, 4, 7, 9) and avoids mornings. This dataset tests the model's capacity to handle temporal segregation and effectively implement "block scheduling" without creating gaps or conflicts between the two groups.

Table 5. Weight Scenarios for Sensitivity Analysis

Scenario Weight	Time Weight (w_{time})	Preference Weight (w_{pref})	Description
SW1	0.5	0.5	Balanced: Equal importance to policy and people
SW2	0.4	0.6	Preference-Leaning: Slight bias toward faculty needs
SW3	0.6	0.4	Time-Leaning: Slight bias toward administrative policy
SW4	0.3	0.7	Faculty-Centric: Strong focus on individual satisfaction
SW5	0.7	0.3	Policy-Centric: Strong focus on maximizing priority time slots

Table 6. Instructor Preference Datasets for Robustness Testing

Inst.	Scenario Preference			
	SP 1: Compressed Week		SP 2: AM vs. PM Split	
	Preferred (t_{pref})	Least Preferred (t_{avoid})	Preferred (t_{pref})	Least Preferred (t_{avoid})
A1	3 (Tue AM)	1 (Mon AM)	1 (Mon AM)	2 (Mon PM)
A2	4 (Tue PM)	9 (Fri PM)	3 (Tue AM)	4 (Tue PM)
A3	5 (Wed AM)	1 (Mon AM)	5 (Wed AM)	7 (Thu PM)
A4	6 (Thu AM)	9 (Fri PM)	6 (Thu AM)	9 (Fri PM)
A5	7 (Thu PM)	1 (Mon AM)	8 (Fri AM)	2 (Mon PM)
A6	3 (Tue AM)	9 (Fri PM)	1 (Mon AM)	4 (Tue PM)
A7	4 (Tue PM)	1 (Mon AM)	3 (Tue AM)	7 (Thu PM)
A8	5 (Wed AM)	9 (Fri PM)	5 (Wed AM)	9 (Fri PM)
A9	6 (Thu AM)	1 (Mon AM)	6 (Thu AM)	2 (Mon PM)
A10	7 (Thu PM)	9 (Fri PM)	8 (Fri AM)	4 (Tue PM)
A11	3 (Tue AM)	1 (Mon AM)	1 (Mon AM)	7 (Thu PM)
A12	4 (Tue PM)	9 (Fri PM)	3 (Tue AM)	9 (Fri PM)
A13	5 (Wed AM)	1 (Mon AM)	5 (Wed AM)	2 (Mon PM)
A14	6 (Thu AM)	9 (Fri PM)	2 (Mon PM)	1 (Mon AM)
A15	7 (Thu PM)	1 (Mon AM)	4 (Tue PM)	3 (Tue AM)
A16	3 (Tue AM)	9 (Fri PM)	7 (Thu PM)	5 (Wed AM)
A17	4 (Tue PM)	1 (Mon AM)	9 (Fri PM)	6 (Thu AM)
A18	5 (Wed AM)	9 (Fri PM)	2 (Mon PM)	8 (Fri AM)
A19	6 (Thu AM)	1 (Mon AM)	4 (Tue PM)	1 (Mon AM)
A20	7 (Thu PM)	9 (Fri PM)	7 (Thu PM)	3 (Tue AM)
A21	3 (Tue AM)	1 (Mon AM)	9 (Fri PM)	5 (Wed AM)
A22	4 (Tue PM)	9 (Fri PM)	2 (Mon PM)	6 (Thu AM)
A23	5 (Wed AM)	1 (Mon AM)	4 (Tue PM)	8 (Fri AM)
A24	6 (Thu AM)	9 (Fri PM)	7 (Thu PM)	1 (Mon AM)
A25	7 (Thu PM)	1 (Mon AM)	9 (Fri PM)	3 (Tue AM)
A26	3 (Tue AM)	9 (Fri PM)	2 (Mon PM)	5 (Wed AM)

4. Results

4.1 Comparative Analysis of Preference Scenarios and Weighting Scenarios

Table 8 provides a comprehensive summary of the optimization outcomes across three distinct preference datasets (SP0, SP1, SP2) and varying objective function weights. Crucially, capacity structurally converged across all scenarios, regardless of the faculty preference distribution or weight settings, the model consistently achieved the maximum possible resource utilization (27 assigned slots) and the maximum theoretical Time Score (135). This confirms that in an over-constrained environment (32 subjects vs. 27 slots), the physical limitations of the facility dictate the overall volume of the schedule.

Dropped Subject consistency: While the number of dropped subjects remained fixed at 5 (due to the 27-slot capacity), the identity of these subjects varied by dataset. This confirms that the specific combination of dropped courses is a function of the local conflicts created by specific preference overlaps in each dataset.

Table 7. Summary of Preference Scenarios and Weighting Scenarios

Scenario		Assigned	Time Score	Pref Score	Dropped Subject
Preference	Weight				
SP0	SW1, SW3, SW5	27	135	21	5 (A1-S1, A9-S9, A13-S14, A19-S22, A21-S24)
SP0	SW2, SW4	27	135	21	5 (A1-S1, A9-S9, A13-S15, A19-S22, A21-S24)
SP1	All Sce.	27	135	15	5 (A9-S9, A10-S11, A18-S20, A19-S22, A26-S32)
SP2	All Sce.	27	135	25	5 (A9-S9, A13-S15, A19-S22, A25-S29, A26-S32)

4.2 Comparative Analysis of Scheduling Outcomes

The comparison within the SP0 (Baseline) dataset reveals that the schedule remains highly stable across different weight distributions, with approximately 95% of assignments remaining identical. However, a critical trade-off emerges between Policy-Dominant scenarios (SW1, SW3, SW5) and Faculty-Centric scenarios (SW2, SW4) regarding the allocation of the high-demand Wednesday Morning slots. In the Policy-Dominant patterns (Table 8, the algorithm prioritizes Instructor A4 (Subject S4) for Room 3 on Wednesday morning, forcing Instructor A5 (Subject S5) into the low-priority Friday Afternoon slot. Conversely, when the model leans towards faculty preferences (Table 9), it successfully reconfigures the schedule to grant A5 their preferred Wednesday morning slot. This adjustment creates a ripple effect: Instructor A4 is displaced to Friday Afternoon, and the multi-section Instructor A13 swaps which specific section is dropped (retaining S14 in the first pattern versus S15 in the second). This demonstrates that while resource saturation

dictates the overall structure, increasing the preference weight (W_{pref}) allows the model to fine-tune specific "winning" assignments at the margins.

Beyond the baseline fine-tuning, the model's structural adaptability to extreme faculty cultures is evident in the remaining datasets. Table 10 illustrates the schedule topology for the Compressed Week dataset (SP1), where all weight scenarios converged into a single identical schedule. This demonstrates that heavily avoided Monday and Friday slots are populated entirely due to capacity limitations rather than preference. Similarly, Table 11 presents the Polarized AM vs. PM dataset (SP2), which generates a distinct, converged topology that strictly clusters specific instructors into morning blocks while reserving afternoon blocks for the opposing group. The total convergence observed in both Table 10 and Table 11 confirms that in highly constrained behavioral environments, physical resource limitations completely override the algorithmic weighting parameters.

Table 8. Schedule Topology of the Polarized AM vs. PM Dataset SP0 with weight SW1, SW3, SW5

Days	Time	Room 1	Room 2	Room 3
Mon	AM	A24 (S27)	A9 (S10)	A15 (S17)
	PM	A20 (S23)	A8 (S8)	A14 (S16)
Tue	AM	A2 (S2)	A24 (S28)	A10 (S11)
	PM	A19 (S21)	A12 (S13)	A6 (S6)
Wed	AM	A25 (S29)	A13 (S14)	A4 (S4)
Thu	AM	A22 (S25)	A3 (S3)	A17 (S19)
	PM	A26 (S32)	A16 (S18)	A7 (S7)
Fri	AM	A26 (S31)	A18 (S20)	A23 (S26)
	PM	A5 (S5)	A11 (S12)	A25 (S30)

Table 9. Schedule Topology of the Polarized AM vs. PM Dataset SP0 with weight SW1, SW3, SW5

Days	Time	Room 1	Room 2	Room 3
Mon	AM	A24 (S27)	A9 (S10)	A15 (S17)
	PM	A20 (S23)	A8 (S8)	A14 (S16)
Tue	AM	A2 (S2)	A24 (S28)	A10 (S11)
	PM	A19 (S21)	A12 (S13)	A6 (S6)
Wed	AM	A25 (S29)	A5 (S5)	A13 (S15)
Thu	AM	A22 (S25)	A3 (S3)	A17 (S19)
	PM	A26 (S32)	A16 (S18)	A7 (S7)
Fri	AM	A26 (S31)	A18 (S20)	A23 (S26)
	PM	A4 (S4)	A11 (S12)	A25 (S30)

Table 10. Schedule Topology of the Polarized AM vs. PM Dataset SP1 with All Scenario

Days	Time	Room 1	Room 2	Room 3
Mon	AM	A26 (S31)	A14 (S16)	A6 (S6)
	PM	A21 (S24)	A25 (S29)	A7 (S7)
Tue	AM	A1 (S1)	A16 (S18)	A11 (S12)
	PM	A22 (S25)	A12 (S13)	A2 (S2)
Wed	AM	A23 (S26)	A3 (S3)	A13 (S15)
Thu	AM	A19 (S21)	A4 (S4)	A24 (S27)
	PM	A25 (S30)	A5 (S5)	A20 (S23)
Fri	AM	A17 (S19)	A8 (S8)	A24 (S28)
	PM	A15 (S17)	A13 (S14)	A9 (S10)

Table 11. Schedule Topology of the Polarized AM vs. PM Dataset SP0 with All Scenario

Days	Time	Room 1	Room 2	Room 3
Mon	AM	A6 (S6)	A11 (S12)	A1 (S1)
	PM	A18 (S20)	A22 (S25)	A14 (S16)
Tue	AM	A2 (S2)	A12 (S13)	A7 (S7)
	PM	A15 (S17)	A19 (S21)	A23 (S26)
Wed	AM	A3 (S3)	A13 (S14)	A8 (S8)
Thu	AM	A9 (S10)	A4 (S4)	A24 (S27)
	PM	A20 (S23)	A16 (S18)	A24 (S28)
Fri	AM	A26 (S31)	A5 (S5)	A10 (S11)
	PM	A17 (S19)	A25 (S30)	A21 (S24)

4.3 Varying Physical Constraints

Table 12 summarizes the macroscopic outcomes of the extended sensitivity analysis, demonstrating that these structural results remain entirely invariant across all five weighting scenarios (SW1 through SW5). In the under-constrained Resource Expansion condition (36 available slots), the model successfully accommodates all 32 required subjects, yielding zero unassigned courses and an 88.8% resource utilization rate. However, when subjected to the over-constrained Baseline (27 slots relative to 32 subjects) and Demand Inflation (27 slots relative to 40 subjects) conditions, rigid physical limitations enforce a strict 100% utilization ceiling, mathematically compelling the solver to drop exactly 5 and 13 subjects, respectively. The fact that the exact same volume of scheduled and dropped subjects occurs regardless of whether the algorithm is configured to be highly faculty-centric (SW4) or policy-centric (SW5) substantiates the primary thesis: irrespective of the strategic priority an institution assigns, absolute physical capacity strictly dictates the aggregate schedule volume, leaving algorithmic weights to govern only the micro-level allocation of finite resources.

Table 12. Impact of Varying Physical Constraints on Model Outcomes (SW1 – SW5)

Scenarios	Supply (Slots)	Demand (Subjects)	Subjects Assigned	Subjects Dropped	Resource Utilization	Algorithmic Flexibility
Resource Expansion (+1 Room)	36	32	32	0	88.80%	High
Baseline (Original)	27	32	27	5	100%	Low
Demand Inflation (+8 Subjects)	27	40	27	13	100%	Negligible

4.4 Theoretical Interpretation of Utility Maximization

The outcomes of the model provide a clear empirical demonstration of Utility Maximization theory in an operational context. In classical microeconomics, a rational agent allocates scarce resources to maximize overall satisfaction, evaluating decisions based on *marginal utility*—the additional satisfaction gained from one specific choice over another. The MILP model acts as this rational agent.

This theoretical mechanism is perfectly illustrated by the "Wednesday War" observed in the Baseline (SP0) dataset. Because the environment is heavily constrained by physical capacity (enforcing a strict ceiling on total assignments), the optimization algorithm cannot increase total utility by simply assigning more courses. Instead, it must evaluate the marginal utility of swapping discrete assignments. Under Policy-Dominant weights, the model calculates that the utility gained from fulfilling the administrative "early-week" policy outweighs the disutility of instructor A5's dissatisfaction. Conversely, under Faculty-Centric weights, the marginal utility of satisfying A5's specific temporal preference mathematically surpasses the time-priority score, triggering a strategic swap that displaces instructor A4.

This confirms that the model does not merely "satisfice" or randomly assign remaining slots once capacity is reached. Instead, the weighted-sum objective function strictly enforces utility-maximizing behavior, dynamically reallocating resources at the margins to ensure the highest possible aggregate value is extracted from the fixed physical infrastructure based on the institution's stated priorities.

As shown in Table 13, under Policy-Dominant weights, the model calculates that fulfilling the administrative early-week policy generates a higher aggregate score, forcing A5 into an unfavorable slot. Conversely, under Faculty-Centric weights, satisfying A5's specific temporal preference provides a superior mathematical return, displacing A4.

This confirms that the model does not merely "satisfice" or randomly assign remaining slots once capacity is reached. Instead, the weighted-sum objective function strictly enforces utility-maximizing behavior, dynamically reallocating resources at the margins to ensure the highest

possible aggregate value is extracted from the fixed physical infrastructure based on the institution's explicitly stated priorities.

Table 13. Marginal Utility Trade-offs in the "Wednesday War" (Baseline Dataset SP0)

Weighting Strategy	Primary Optimization Focus	Wednesday AM Allocation (Prime Slot)	Friday PM Allocation (Low Priority)	Marginal Utility Rationale
Policy-Dominant	Administrative early-week policy	Instructor A4	Instructor A5	The utility gained from maximizing the administrative time-priority score mathematically outweighs the disutility of Instructor A5's dissatisfaction.
Faculty-Centric	Individual instructor preferences	Instructor A5	Instructor A4	The marginal utility of satisfying Instructor A5's specific temporal preference surpasses the institutional time-priority score, triggering a strategic swap.

4.5 Computational Performance and Scalability

To evaluate the computational efficiency of the proposed MILP model, execution times were recorded across the primary behavioral datasets (SP0, SP1, SP2) and the five sensitivity weighting scenarios (SW1–SW5). The Python-based model, utilizing the CBC solver, was executed on a standard computational environment featuring an AMD Ryzen 7 4700U processor (2.00 GHz) with 16.0 GB RAM. The performance metrics, all based on the fixed departmental problem size of 32 subjects versus 27 available slots, are summarized in Table 14.

The CBC solver proved highly efficient for this departmental-scale problem, successfully achieving mathematical optimality in under 0.3 seconds across every tested configuration. The minor variations in CPU time (ranging from 0.2564 seconds to 0.2960 seconds) indicate that neither the faculty behavioral culture (SP1 vs. SP2) nor the applied algorithmic weights (SW1–SW5) introduced significant computational friction at this scale.

Table 14. CPU Execution Time (Seconds) Across Datasets and Weight Scenarios

Dataset (32 Subjects vs. 27 Slots)	SW1	SW2	SW3	SW4	SW5	Optimality Status
SP0: Baseline	0.2652	0.2566	0.2588	0.2564	0.2694	Optimal
SP1: Compressed Week	0.2728	0.2674	0.296	0.2679	0.2819	Optimal
SP2: Polarized Split	0.2636	0.285	0.2623	0.2613	0.2611	Optimal

4.6 Mathematical Proof of Constraint Satisfaction and Subject Dropping

To provide operational transparency for academic administrators managing over-constrained environments, it is necessary to mathematically quantify the system's constraint

satisfaction parameters. In all tested scenarios, the Hard Constraint Satisfaction Ratio was strictly maintained at 100%, as the CBC solver is programmed to intrinsically reject any physical overlaps, such as double-bookings or room capacity violations. Consequently, the necessity of dropping subjects is not an algorithmic flaw, but a direct mathematical consequence of the system's geometric boundaries. The relationship between the physical capacity of the scheduling environment and the instructional demand for the Baseline dataset is detailed in Table 15.

As demonstrated in the table, the system is mathematically constrained to a maximum of 27 assignments, rendering the baseline volume of 5 dropped subjects an unavoidable constant. While the quantity of dropped subjects is dictated entirely by these structural Hard Constraints, the specific identity of the dropped subjects is dictated by the Soft Constraints embedded within the objective function. The MILP algorithm evaluates the potential marginal utility of all possible combinations and isolates the precise subjects that generate the most severe scheduling conflicts. For example, if a multi-section instructor possesses highly restrictive temporal preferences that directly conflict with the administrative early-week policy, the algorithm will drop one of their sections to free up prime-time capacity for instructors whose preferences align more efficiently with the institutional utility weights. This transparent mathematical logic guarantees administrators that dropped subjects are not selected arbitrarily, but are the result of an exact optimization process calculating the minimum possible disruption to overall system utility.

Table 15. Mathematical Derivation of System Capacity and Unassigned Subjects

Parameters	Definitions	Calculation / Value
Physical Capacity (C)	Available Rooms X Time Slots	R
Instructional Demand (D)	Total required subject sections	S
Feasible Assignments	Maximum allowable volume: $\min(D, C)$	$\min(32, 27) = 27$ assignments
Unassigned Subjects (U)	Baseline dropped volume: $\max(0, D - C)$	$\max(0, 32 - 27) = 5$ dropped subjects

4.7 Discussion and Comparative Analysis

Comparing the schedules across the three datasets (SP0, SP1, and SP2) highlights the model's structural adaptability to extreme faculty cultures. While SP0 shows a balanced distribution, SP1 (The Compressed Week) results in a schedule where Monday and Friday slots are utilized purely for capacity reasons rather than preference. For instance, slots like Monday Morning and Friday Afternoon are populated effectively despite universal aversion to these times. In contrast, SP2 (The Polarized Split) generates a completely distinct topology that respects the "AM vs. PM" tribal division, heavily clustering specific instructors into distinct morning and afternoon blocks. Notably, both the SP1 and SP2 datasets resulted in total convergence for all scenarios, indicating that in highly constrained behavioral environments, the physical limitations of the facility

(27 slots vs. 32 subjects) override the weighting parameters, forcing the model into a single, geometrically optimal solution to maximize resource utilization.

While physical constraints dictated the schedule's volume, weighting strategies proved critical for fine-tuning assignment quality at the margins, particularly in the Baseline (SP0) dataset. The analysis highlighted a specific trade-off—the "Wednesday War"—where shifting weights determined the allocation of prime slots between Instructors A4 and A5. Policy-Dominant weights forced A5 to a Friday afternoon, whereas Faculty-Centric weights granted A5 the Wednesday slot. This demonstrates the model's value as a fine-tuning instrument that distributes inevitable sacrifices according to specific administrative priorities.

To contextualize the efficacy of the proposed utility-maximizing MILP model, it is essential to compare these outcomes with established findings in the University Course Timetabling Problem (UCTP) literature. The results of this study demonstrate both critical consistencies with regional infrastructural constraints and significant functional divergences from traditional penalty-based methodologies.

- Consistency Regarding Physical Bottlenecks: The finding that extreme physical constraints dictate schedule volume—forcing algorithmic convergence regardless of preference weights—is highly consistent with recent regional studies. Similar to the findings by Choosawang et al. [4] at Prince of Songkla University and Maspiyanti et al. [13] in Indonesia, this study confirms that in developing or rapidly expanding technological faculties, physical space (supply) represents an absolute hard constraint that easily overrides soft preference variables.
- Consistency in Multi-Objective Trade-offs: The model's ability to fine-tune assignments at the margins aligns with the multi-objective observations made by Darmawan et al. [12] and Ozkan et al. [11]. These prior studies noted that a single objective is insufficient for modern universities, and our findings corroborate that adjusting strategic weights allows administrators to successfully navigate competing departmental goals without causing systemic scheduling failure.
- Divergence in Mathematical Philosophy and Transparency: Where this study strongly diverges from the classical literature is in its operational philosophy and mathematical transparency. Foundational UCTP models, such as those by Burke et al. [10], Ceschia et al. [7], and Davison et al. [1], rely heavily on deficit-oriented, penalty-based heuristics. While those reactive models successfully identify "least bad" schedules by minimizing constraint violations, they obscure specific trade-offs by aggregating penalties into a single "cost." In contrast, our

proposed utility-based MILP model proved divergent by operating as a transparent, proactive tool. It quantified the exact marginal utility of satisfying a faculty member versus an administrative policy, actively generating scheduling value rather than merely mitigating scheduling damage.

Ultimately, while the geometric realities of scheduling remain consistent with broader academic consensus, the utility-maximization approach offers a divergent, highly transparent decision-support mechanism that is better suited for managing faculty well-being in resource-scarce environments.

Despite its strengths, this study has limitations. First, the model uses binary preferences, failing to account for degrees of desire handled better by fuzzy logic models (Maspiyanti et al. [13]). Second, as an exact MILP formulation, scalability poses a challenge compared to the heuristic speeds of algorithms reviewed by Chen et al. [6] and Muklason [14]. Finally, the framework assumes a static environment and does not currently account for dynamic disruptions such as maintenance or schedule changes.

5. Conclusion

This research addressed the critical bottleneck of computer laboratory scarcity in Thai engineering education by proposing a Mixed-Integer Linear Programming (MILP) model focused on Utility Maximization. Unlike traditional cost-minimization approaches that penalize soft constraint violations, this study utilized a weighted-sum objective function to actively reward the satisfaction of faculty preferences while adhering to strict physical capacity limits. Key Findings:

- Dominance of Physical Constraints: In over-constrained environments where demand exceeds supply (32 subjects vs. 27 slots), physical infrastructure dictates the schedule's volume. The model consistently achieved maximum resource utilization (100%) across all scenarios, confirming that facility limitations override algorithmic weighting regarding total capacity.
- Convergence in Extreme Scenarios: Under rigid behavioral constraints—such as the "Compressed Week" (SP1) or "Polarized" preferences (SP2)—the solution space converged to a single optimal geometric arrangement. This indicates that when resources are scarce and preferences are highly correlated, the trade-off between administrative policy and faculty preference becomes negligible.
- Marginal Utility and Fine-Tuning: In balanced environments (Baseline SP0), the weighting strategy proved critical for resolving specific conflicts at the margins. Administrators successfully used the model to "fine-tune" high-demand allocations (e.g., the "Wednesday

War"), distributing inevitable sacrifices based on set priorities without compromising overall system efficiency.

- Transparency of Trade-offs: The shift from penalty-based logic to positive utility maximization offers a psychological and administrative advantage. It allows decision-makers to explicitly visualize the "cost" of favoring policy over preference, transforming the scheduling process from a damage-control exercise into a value-creation mechanism.
- Validation of Algorithmic Flexibility Thresholds: Extended physical sensitivity analysis confirmed that the weighting mechanism's effectiveness is inversely proportional to resource saturation. In under-constrained environments (e.g., expanded room capacity), the utility objective function freely optimizes faculty preferences. However, as demand inflation pushes utilization toward 100%, the model shifts mathematically from a preference-optimizer to a strict capacity-packing algorithm.

Future Research Directions

- Fuzzy Preference Integration: Future work should extend the objective function to include Fuzzy Preference Weights, enabling faculty to rank their time slots (e.g., 1st choice vs. 2nd choice) rather than relying on a simple binary selection.
- Pareto Frontier Analysis: Integrating Pareto Frontier analysis could help visualize the set of optimal solutions, providing administrators with a menu of "non-dominated" schedules rather than a single static output.
- Hybrid Environment Application: Applying this model to a hybrid environment—mixing restricted computer laboratories with general lecture halls—would test its versatility and effectiveness across broader academic departments.
- Scalability and Hybrid Algorithms: To deploy this utility-maximization framework at a university-wide scale, future research should explore hybridizing this MILP formulation with meta-heuristic algorithms (such as Genetic Algorithms or Simulated Annealing) to overcome the exponential computational time of NP-hard environments.

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