Management of energy consumption of the heating sector in educational buildings using the modification of the educational Time Tabling

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Universities, as major energy consumers, play a key role in reducing energy consumption through intelligent planning. Optimizing course scheduling is one of the less explored but highly impactful solutions for reducing energy use in educational buildings. This study aims to develop an energy-efficient class scheduling model that considers temporal, spatial, and infrastructural constraints of academic campuses. The proposed model formulates the scheduling process by incorporating constraints such as building capacity, simultaneous sessions, professor availability, and the need for symmetrical timetables. Unlike conventional scheduling, which is typically based on administrative convenience, this approach leverages real meteorological data (temperature, humidity, wind speed) from the fall semester in Tehran to align class times with periods of lower energy demand. The innovation of this study lies in the integration of energy-saving goals with scheduling algorithms, creating a dual-objective framework that balances academic and environmental priorities. While many studies have addressed either scheduling or energy management, few have proposed an integrated, constraint-based model tailored for postgraduate academic settings. The results show that applying the optimized scheduling model leads to a significant reduction in energy consumption, between 8% to 12% depending on the scheduling scenario. Additionally, the spatial-temporal optimization allows for better use of daylight and ventilation potential, contributing to improved energy performance of buildings without requiring any physical retrofitting.

Keywords: *Optimization, HVAC Systems, CO2 Emission, Energy Management, MATLAB, Anagram Model*

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1. Introduction

On average, the global urban population has grown annually by around 1.24% since 1950, while energy consumption has increased at a rate of approximately 1.82% per year since 1970. These trends highlight the intensifying pressure on energy systems driven by urban and economic expansion. As a result, energy management strategies and efforts to reduce consumption at various levels have gained special importance. National energy policies also focus on reducing consumption and increasing energy efficiency, as optimal use of energy not only reduces costs but also minimizes environmental impacts [1], [2]. The building sector is one of the largest energy consumers, accounting for about 30% of total final energy consumption. The direct greenhouse gas emissions from this sector also make up 15% of total carbon dioxide emissions, a figure that nearly doubles when indirect emissions are considered [3]. Since residential, commercial, and educational buildings have a high share in energy consumption, implementing effective policies in this area can have a significant impact on reducing energy demand and mitigating harmful environmental effects. Advanced technologies, such as Building Management Systems (BMS) and the use of high-efficiency materials, are among the proposed solutions to control energy consumption in this sector [4].

In this context, educational buildings are one of the most important subsectors, as they have a high energy consumption due to long usage hours and dependence on heating, cooling, and ventilation systems (HVAC) [5]. Studies have shown that a significant portion of energy consumption in educational buildings is caused by improper scheduling of classes. For example, a study conducted at the University of Hong Kong indicates that the lack of coordination in class scheduling leads to unnecessary energy consumption, and energy savings can be achieved by optimizing the class schedules [5]. Additionally, other studies have shown that changes in student attendance patterns and the optimization of course scheduling can reduce energy consumption by 11.5% to 24.5% [3]. However, the issue of university scheduling, apart from its energy-saving aspects, is also a complex combinatorial optimization problem that involves multiple variables, such as class capacities,

professor preferences, number of students, and the availability of teaching spaces. Various mathematical models, including Mixed Integer Linear Programming (MILP), have been proposed to solve this problem and provide the optimal allocation of classrooms and teaching hours [6]. Although numerous studies have been conducted on class timetabling, relatively few have proposed comprehensive models that simultaneously address energy consumption, building performance, and academic scheduling in university settings. Among the developed approaches, most have tended to focus on a single dimension of the problem rather than adopting an integrated perspective. Building upon previous foundational studies [7], [8], the present research advances the field by developing a holistic framework that optimizes class timetabling not only to enhance energy efficiency but also to improve educational quality in academic buildings.

2. Literature Review

In recent years, numerous studies have been conducted on optimizing energy consumption in university buildings and class scheduling, showing that optimizing class schedules can significantly reduce energy consumption in these buildings. These studies have used models such as integer programming, energy data analysis, and multi-objective models to find the best solutions. The conducted studies also emphasize the importance of designing ventilation, cooling, and heating systems in optimizing energy consumption in universities. In this regard, optimization algorithms such as genetic algorithms and MILP have been suggested for class scheduling and optimal allocation of educational spaces [9]. A review of related studies shows that only a few of the research works focusing on energy optimization, university buildings, and class scheduling have comprehensively addressed all three aspects. These studies indicate that optimizing class schedules can contribute to reducing energy consumption in educational buildings while also improving educational quality. In contrast, many other studies have focused on only one of these aspects. Some have solely addressed energy optimization in buildings, while others have focused only on class scheduling. Table 1 provides examples of these studies that have focused on a specific aspect.

Building on the classification presented in Table 1, the following studies are discussed in detail to illustrate the various approaches adopted in optimizing energy use and scheduling in academic buildings. Guan et al. [22], a case study conducted at a Norwegian university analyzed energy consumption patterns across campus facilities, including electricity, heating, and water usage. The findings demonstrated that optimizing energy use and implementing strategic scheduling for classrooms and educational buildings can significantly reduce overall energy demand. Furthermore, the study highlighted that buildings with continuous operational demands, particularly educational and laboratory facilities, exhibit the highest energy consumption levels. These insights underscore the importance of tailored energy management strategies for high-occupancy academic infrastructures. Additionally, Allab et al. [23], in a related study conducted at a French university, researchers applied an integrated energy auditing and indoor comfort assessment protocol to enhance environmental quality and reduce energy consumption in educational buildings. The findings demonstrated that deploying energy management systems (EMS) alongside continuous monitoring of indoor comfort parameters, such as temperature, air quality, and humidity, can achieve significant energy savings while maintaining occupant well-being. This study further emphasized that coupling data-driven energy optimization with occupant-centric comfort strategies not only lowers operational costs but also supports sustainable infrastructure management in academic settings.

Table 1. Classification of related studies according to their primary focus areas: class scheduling, university-wide frameworks, building-level implementation, and energy management integration.

	Scheduling	University	Building	Energy Management
Fernandes et al. [10]	✓	✓	×	×
Davison et al. [11]	✓	✓	×	×
Li et al. [12]	✓	×	×	✓
Bashab et al. [13]	✓	✓	×	×
Zhang et al. [14]	×	×	✓	✓
Gui et al. [15]	×	✓	✓	✓
Riviera et al. [16]	✓	✓	×	×
Abdelhalim et al. [17]	✓	✓	×	×
Kadam et al. [18]	✓	✓	×	×
Al-Daraiseh et al. [19]	×	✓	✓	✓
Ferreira et al. [20]	×	×	✓	✓
Jomoah et al. [21]	×	✓	✓	✓

Amaral et al. [24], in a study on university operations related to energy and buildings, reported that despite significant efforts to improve the sustainability of university buildings, many initiatives have faced unsuccessful outcomes. Factors such as inadequate system design, technical problems in maintenance and repairs, and the misalignment of actions with local climatic conditions were among the reasons for these failures. These studies also revealed that comprehensive and realistic assessments of the impact of these actions on energy consumption reduction and environmental performance improvement are often overlooked. Liu et al. [25], in a study on university buildings in China, provided solutions for optimal energy design in universities through green performance analysis. This study demonstrated that optimizing building designs and implementing green strategies can lead to significant reductions in energy consumption in Chinese universities. Jamaludin et al. [26] analyzed energy consumption in residential buildings at the University of Malaya and showed that the use of bioclimatic design strategies can help reduce energy consumption in these buildings. Specifically, the use of natural light and natural ventilation in building designs improved energy efficiency in the hot and humid climate of Malaysia. This research emphasized that many buildings utilizing these strategies have significantly reduced their energy consumption. In another study, Jiang and Luo [27] focused on optimizing university class schedules with regard to students' thermal comfort. This study demonstrated that changing class schedules could help reduce students' thermal discomfort, leading to improved learning conditions and reduced energy consumption in educational buildings. Additionally, they proposed models for optimizing class schedules with the goal of reducing thermal discomfort and saving energy in buildings.

Nagpal et al. [9], in a study on the university buildings of the Massachusetts Institute of Technology, developed two different models to assess energy consumption scenarios. One of these models uses a statistical method based on building energy models to predict energy consumption and evaluate the impact of various optimization measures. The results of this study indicate that urban energy models can achieve significant energy savings on a university scale. In another study, Phillips et al. [28] examined the planning of minimal

changes to optimize class schedules with the least possible adjustments and prevent time conflicts that lead to increased energy consumption. The proposed algorithm was tested on real data from the University of Auckland, and the method demonstrated high accuracy in solving minimal change problems, showing its effectiveness in real-world scenarios. In another study, Gui et al. [29] investigated the impact of the academic calendar on energy consumption in educational buildings. This research revealed that changes in class scheduling and planning can significantly affect energy consumption, and under specific conditions, optimizing the academic calendar could reduce energy consumption by up to 5%.

Algethami and Laesanklang [6] presented a Mixed-Integer Linear Programming (MILP) model for class scheduling in universities, which not only optimizes class schedules but also takes into account constraints related to faculty, class capacities, and the physical space of the university. This model demonstrated that changes in class scheduling can lead to up to a 13% reduction in energy consumption. Additionally, Yeo et al. [5] used the Stochastic Frontier Analysis (SFA) model to examine factors affecting energy consumption and, through the implementation of energy demand management and optimal class scheduling at the University of Hong Kong, showed that energy consumption could be reduced by up to 18.97%. Song et al. [30] developed an algorithm for class scheduling aimed at optimizing energy consumption in university buildings. Using real data from Seoul National University, the algorithm reduced energy consumption during heating and cooling periods, demonstrating that optimal scheduling could result in up to a 4% reduction in energy consumption. Furthermore, this algorithm allows for further energy savings by reducing constraints. In another study, Sun et al. [31] examined the impact of optimizing class schedules on energy consumption in university educational buildings. Using a model based on the Building Controls Virtual Test Bed (BCVTB) platform and a genetic algorithm, the study showed that optimizing class schedules could lead to a 3.6% reduction in energy consumption. The results indicated a reduction in energy consumption as a result of optimal class allocation at specific times, accompanied by a decrease in electricity consumption and an increase in the efficiency of HVAC systems. In other studies, Phillips et al. [28] and Yeo et al. [5] used analytical and simulation models to explore the effects of optimizing class schedules on energy consumption in university buildings. The results of these studies indicate that with optimal scheduling and planning of classes, energy consumption could be reduced by 11.5% to 24.5%.

Additionally, Gui et al. [32] in a study conducted during the COVID-19 pandemic, researchers examined the impact of changes in the conditions of university buildings on energy consumption. This study showed that class cancellations and changes in student attendance patterns, especially in educational buildings, led to a 16% reduction in energy consumption in universities. These results highlight the importance of occupancy condition changes in energy management at universities and can be used as a strategy to reduce energy consumption in similar situations in the future.

Based on a review of previous studies, the results of various research indicate that there are several strategies to reduce energy consumption and enhance the quality of education in university buildings. Table 2 presents these strategies, detailing the advantages and disadvantages. It can be seen that optimizing class schedules has been highlighted as a low-cost and effective strategy for reducing energy consumption and improving educational conditions.

Moreover, since educational planning affects students' learning, it is difficult to find a study that examines optimal educational planning with a dual approach to improving education quality and reducing energy consumption intensity. Therefore, this study will propose a model in which educational planning is carried out with both approaches; reducing energy consumption and enhancing education quality.

Table 1. Comparing strategies to reduce energy consumption.

Strategy	Benefits	Drawbacks
Optimizing Class Schedules [5], [28], [31], [32]	• Reduction in energy consumption • Improved environmental conditions • Increased HVAC system efficiency	• Requires changes in academic schedules • Coordination with faculty and student preferences
Optimizing Ventilation and Heating/Cooling Systems Design [22], [23]	• Reduction in energy consumption • Improved comfort for students and faculty • Energy cost savings	• Higher initial installation costs for optimized systems
Using Optimization Algorithms [9], [28], [32]	• Precise scheduling optimization • Energy consumption savings • Improved class scheduling and space allocation	• Complexity in modeling • Need for accurate and up-to-date data for optimization
Green Design Strategies [25], [26]	• Reduction in energy consumption • Use of natural resources • Environmental improvement	• Requires structural changes in buildings High initial costs
Energy Demand Management [5]	• Reduction in energy consumption Optimization of energy systems during peak times	• Requires changes in energy management and monitoring practices
Managing Academic Calendar [32]	• Reduction in energy consumption by optimizing the calendar and class schedules	• Changes in academic schedules and need for coordination with faculty and students

3. Case Study

The model was implemented for the College of Interdisciplinary Science and Technology, University of Tehran, which comprises departments in renewable energy, aerospace, biological sciences, and interdisciplinary studies. The four-story building includes a dining hall (negative first floor), administrative offices, faculty and training rooms, laboratories, a study hall, and a prayer room (first floor), additional laboratories and classrooms (second floor), and faculty offices plus a council room (third floor).

- The first floor includes the administrative department, 22 rooms for faculty training, a room for group managers, two laboratories, a security office, a study hall, and a prayer room.
- The second floor comprises the educational department, with ten laboratories and fourteen classrooms.
- Third floor: 43 faculty members' rooms and one council room.

University regulations indicate that all courses must be held on different days at the same time intervals. Table 3 provides general information about the college's classes, courses, professors, and class schedules for the fall semester. According to the table, the days of the classes are not symmetrical, which causes a waste of energy and does not provide good satisfaction in terms of energy savings and energy consumption costs.

Table 2. Information on the offered classes in the College of Interdisciplinary Science and Technology, University of Tehran

General Information							
Educational group of study in the College of Interdisciplinary Science and Technology							
	Renewable Energy		Aerospace	biological sciences		interdisciplinary	
Number of faculty members	11		14	7		26	
Number of courses	11		25	9		39	
Days for holding the classes	Saturday-Sunday	Sunday-Tuesday	Sunday-Tuesday	Saturday-Monday	Sunday-Wednesday	Saturday-Monday	Sunday-Tuesday
8-10	1	1	5	2	2	5	4
10-12	1	0	6	1	1	6	2
13-15	2	2	4	1	0	6	4
15-17	0	2	6	0	0	6	3
17-19	0	1	4	0	0	2	3

To advance this research and provide a schedule that reduces energy consumption for the fall semester, data on the weather and temperature in Tehran during this period are needed. Therefore, the data were obtained from September 13 to January 29, encompassing the beginning and end of the fall semester, respectively.

4. Methodology

The linear optimization method is used in this research. This method provides us with simple answers that are close to reality. Building thermal modeling has been done in MATLAB. The model is designed to provide an optimal academic timetable that maximizes the quality of education and minimizes energy consumption. Integer linear programming has been used to solve the equations. To analyze the thermal load of the building, an inverse steady-state method, known as "Anagram," is employed. This method provides a good relationship between the outdoor air temperature and the thermal load consumed by the building. The time required for each run and calculation is about 130 seconds.In this section, the equations related to the building thermal model are introduced, based on the inverse steady-state method and the integer linear programming method, along with their parameters, limitations, and decision variables.

4.1. Objective functions

This research is faced with a two-objective function problem with the objectives of:

- maximum quality of education
- minimum cost of energy

Additionally, the effects of changes in energy consumption on the semester date, class timing, and classroom temperature are examined.

4.1.1. Constraints and Anagram Model

Constraints and requirements are categorized into two general types: hard and soft constraints. The hard and soft constraints result in a difference in the overall structure of the models.

"Hard" constraints MUST be applied to the problem and guarantee the certainty of the answer. The hard constraints considered in this research are as follows:

- Faculty members' available time: faculty members must participate in weekly meetings, educational and social activities, which limit the time for holding classes.
- Concurrent holding of similar courses: If one course is offered by two or more professors at the same time, the quality of education increases since it gives the student the chance of choosing the best professors, without any concern regarding the best time.
- The opportunity of undertaking the courses after falling behind in the academic chart: The organization of courses should be done in a way that prevents the lack of offered courses for students who do not follow the academic chart because of failing in courses.
- Avoid presenting two different courses in one class at the same time: It is not possible to hold two courses in one class at the same time.
- Not offering two classes with one professor at the same time: a professor cannot attend two different classes at the same time.

On the other hand, "soft" constraints express the desirability and preferences of the problem. These constraints are considered to increase the accuracy of modeling, although they are not required for use in the scheduling problem. To obtain more accurate results, the minimum number of violations from soft constraints should be determined. The soft constraints considered in this modeling are as follows:

- The complicated and time-consuming nature of planning limits the problem.
- The main purpose of this model is to find the best class schedule that can also reduce the heating demand and price.
- The scheduling of classes for each semester has several uncertainties, such as the number of students, unpredictable behavior of people, temperature, and radiation intensity.
- Considering these constraints, the desired model should have a small computational load, also should not require accurate input data because of the uncertainties, such as PRISM, single-core analysis, or Anagram.

4.2. Anagram Model

The anagram model is classified as a reverse modeling method. One of the advantages of Anagram compared to more complex models is its reduced need for input data and lower computational load. Complex models typically require more input data to account for uncertainty. However, it doesn't necessarily increase the accuracy. In other words, considering more uncertainties can increase the accuracy at the first step. However, since the nature of some uncertainties is not fully understood, it can lead to random events that regular mathematical functions cannot describe, ultimately resulting in inaccuracies or increased calculation time. Therefore, the Anagram model is chosen in this study. Anagram calculates the heat consumption of a building by considering weather conditions. Simplicity and the avoidance of detailed building data requirements are the main advantages of this model. If the outdoor temperature is lower than the indoor temperature during cold seasons, Anagram will assume a linear function between heating and ambient temperature. Otherwise, the heat energy will be zero. Using this model can be justified by the case study because energy storage in the building is not practical. Also, students use the outside space between classes, and doors and windows are often left open during this time.

4.3. Decision variables

In this research, four parameters, namely, the number of professors, the number of lessons, the number of hours, and the number of school days, have been introduced. A matrix where the rows are the number of constraints and the columns are the number of decision variables has been created. To simplify the modeling, the two parameters of the professor and the lesson are combined and considered as a single decision variable. By reducing the number of columns of the matrix, the computational time and load have been reduced in this study. In the following, the decision variables are described:

- Day: this parameter is indicated by the symbol J, which shows the number of available days during a week to hold classes, J={1,2,..5}.
- Time: This parameter shows the time when courses are planned to be held on a day. For example, it is from 8:00 AM to 7:00 PM, and two hours of studying for each class for the College of Interdisciplinary Science and Technology, University of Tehran. Time period is indicated with K and its values are K={1,2,…, 5} .
- Professors and lessons: in this modelling, a lesson with the teacher teaching that lesson is considered as one parameter. For example, lesson X with Dr. X' is one parameter and lesson Y with Dr. Y' is another parameter .This parameter is indicated with I.

4.4. Assumptions and timing constraints

According to university regulations, all courses must be scheduled on different days but within the same time intervals throughout the semester. The proposed model provides multiple feasible solutions for the timetabling problem. Since there may be considerable differences between the globally optimal solution and subsequent feasible solutions, the prioritization of scheduling alternatives plays a crucial role in determining their implementation. Based on this framework, the key assumptions and time-related constraints applied in the model are summarized below.

- Course Type: Courses are generally categorized as either compulsory or optional. Compulsory courses are those mandated by the department for all students within a particular major, while optional courses are selected by students from a list of electives. The proposed model incorporates both course types in the scheduling process.
- Time Range: A daily time frame is defined during which courses may be scheduled. For example, classes are assumed to be held in 90-minute sessions, starting from 8:00 a.m. to 7:00 p.m. The model operates within this time range to allocate time slots appropriately.
- Course Structure: Academic courses are typically classified into theoretical, practical, research-based, or hybrid (theory-practice) formats. Theoretical courses are usually held in one or two sessions per week, depending on their credit hours. Research-based courses do not require fixed class attendance and are conducted under a professor's supervision. Practical courses involve attendance at workshops, laboratories, or computer/physical training centers. Some courses, such as Information Systems, combine both theoretical instruction and hands-on computer lab components.

Given this diversity, the present model focuses exclusively on theoretical courses, where fixed classroom sessions must be arranged. The mathematical formulation of time-based constraints is based on a binary decision variable x_{ijk} where i∈I, j∈J , and k∈K. The variable x_{ijk} =1 if course i is scheduled on day j at time k; otherwise, it is set to 0.

Constraint 1: A professor cannot be scheduled to teach more than one course at the same time. This is enforced as $x_{ijk} + x_{i\prime jk} \leq 1$. For example, if Dr. A is assigned to both course X and course Y on the same day and time, the constraint will be violated, indicating an infeasible allocation.

Constraint 2: Different professors can teach at the same time in different classrooms. Therefore, two separate courses can be scheduled concurrently, which is expressed as $x_{ijk} + x_{i\prime jk} \leq 2$. For instance, course X taught by Dr. A and course Y taught by Dr. B can occur at the same time on the same day.

Constraint 3: Since the College of Interdisciplinary Science and Technology offers only postgraduate programs (Master's and PhD), prerequisite structures are generally unnecessary. Including such dependencies would unnecessarily increase model complexity and computational load while providing minimal benefit. Therefore, prerequisites are excluded from this study.

Constraint 4: The number of available classrooms is limited and must be accounted for in the scheduling process. The constraint is defined as $\sum_n x_{ijk} = N$. In this study, N=14 classrooms are available. As a result, $\sum_n x_{ijk} = 14$.

Constraint 5: To maintain consistency in scheduling, multi-session courses must occur at the same time across their scheduled days. This improves student experience and facilitates energy-saving measures. Two formulations are proposed for enforcing this constraint; $\sum_m \sum_k x_{ijk} = 1$ or $\sum_n x_{ijk} \leq 1$. For example, if a course is held on both Saturday and Monday, the sessions should occur at the same time slot each day throughout the semester. Previous models failed to enforce this type of parallelism effectively.

Constraint 6: Professors may be unavailable during specific time slots due to personal or institutional constraints. Their availability is modeled by a binary variable $x_{ijk\prime}$. if the instructor is available on day j and time k, $x_{ijk\prime} = 1$ and if the instructor is unavailable at that time, $x_{ijk} = 0$.

4.5. Scenarios

Four scenarios are designed as follows:

Scenario 1: The goal of this scenario is to minimize the cost of energy, and the schedule of classes is planned according to the lowest energy cost. Minimizing the energy consumption depends on the time of classes, the class temperature, and the academic semester date.

Scenario 2: The goal of this scenario is to maximize the quality of education, considering educational issues, class arrangements, and professors' satisfaction, among other factors. The best time for each class was determined through a questionnaire from the professors.

Scenario 3: The third scenario considers the maximum quality of education along with a reduction in energy consumption (the amount of energy consumption should not be higher than normal)

Scenario 4: The goal of this scenario is to achieve the minimum energy consumption while maintaining the quality of education at or above normal levels.

In each scenario, the cost of energy has been calculated and compared. Finally, the best timetable is presented by providing an optimal schedule that reduces energy consumption or enhances the quality of education for each scenario.

4.6. Energy calculation Equations

Since predicting the daily temperature at each hour is a difficult and random matter, it is decided not to make a difference between the average temperature of a certain hour of the day. For example, the average temperature of 8-9 am is similar for all days of the week. In other words, the coefficient of energy cost is considered the same for the temperature between 8 and 9 am throughout the week.

For this purpose, the energy cost is first calculated for each time. Then, the total energy cost at each time during the week (even holidays) is calculated. The final step is to normalize the cost of energy by dividing the cost of energy for each time period by the maximum total energy cost during the week.

For example, there are 5 time periods to hold classes at this college (from Saturday to Wednesday). Therefore, for each hour, there will be a total of 5 energy costs during a week. These five numbers are divided by the largest value among them. Then, the obtained number is considered the coefficient of energy cost for that time on a given day of the week. It should be noted that the coefficient of energy cost of a class in a certain hour does not depend on the day of the week and will be a number between zero and one.

It is essential to note that if the outdoor temperature exceeds the comfortable indoor temperature during the cold season, the heating system is considered to be off. Also, the heating system is off in the rooms when there's no class. The time between turning on the heating system and reaching the desired temperature is negligible compared to the duration of the class and can be ignored.

In this section, the coefficients of the energy cost and the cooling/heating demand for classes are evaluated over periods. An anagram is mostly used to analyze the monthly heating load.

The assumptions for calculating the hourly energy demand in this study are as follows:

- Load depends on the linear function of temperature difference and the optimum point. To obtain maximum accuracy, a smaller time difference between these two variables should be applied. Therefore, this duration is considered half an hour.
- The possibility of using cooling equipment in cold seasons or vice versa is not valid. For example, if the ambient temperature in cold seasons (cooling seasons) is more than the outdoor temperature, energy is not used to adjust the temperature inside the building .
- The energy consumption is a linear function of heating/cooling load. Classroom location and the number of students, as well as effective load, are not included in heating/cooling demand calculations.
- All classrooms are well equipped and have adequate access for disabled people.
- Due to the complexity of predicting the temperature at a specific hour, the coefficient of energy cost for holding a class at a particular hour is considered the same for each hour of the day throughout a week.

Each lesson consists of two sessions on alternate days. The same lessons, taught by different professors, are held simultaneously.

The periods of each class remain the same during a semester.

The first to third assumptions are considered for the Anagram model.

The fourth to seventh assumptions are related to the building and the schedule of the departments.

There is no obligation to apply these assumptions to the building.

At Tehran University, it is common to hold courses on Saturday and Sunday, Saturday and Monday, Sunday and Tuesday, and Sunday and Wednesday.

The dimensions, equipment, and access to the rooms in the building are equal, meaning there is no preference for choosing one class over another.

The heating load depends on the building's materials, plan, location, geography, usage, equipment, number of occupants, and other factors. In the case study, there are a limited number of courses at the same time in the college. However, it cannot affect the number of participants. These classes are often held during the day, and electrical devices such as laptops are not typically used. As a result, the heating load strongly depends on the time during which the course is held. The proposed model calculates the load based on the quantitative characteristics of the buildings, not people's behavior.

Using the anagram method, the annual heating energy consumption of the building is calculated as Equation 1.

$$E_H = 24 * \frac{BLC_V}{\eta_H} * V_B * DD_H * I \quad (1)$$

Where E_H is annual heat energy consumption [kWh], BLC_V is the building loss coefficient [kW/m3 °C], $\eta_H$is the average seasonal energy efficiency of the heating system, V_B is the volume of the heated building [m3], DD_H is the heating day temperature (based on 18 °C), and I is a correction factor to consider the effects of the night refraction coefficient in reducing the heating load of the building (if there is no night refraction, I=0).

Then, Anagram calculates the monthly heat energy consumption using Equation 2.

$$E_{H.m} = 24 * \frac{BLC_V}{\eta_H} * V_B * I * [DD_{H.m} - (18 - T_b) * 30] \quad (2)$$

Where $E_{H.m}$ is the monthly heat energy consumption of the building [kWh], $DD_{H.m}$ is the heating day temperature (based on 18 °C), T_b is the equilibrium temperature of the building? V_B is the volume of the heated building [m3], I is the correction factor, and 30 stands for the number of days in a month.

Therefore, the monthly energy consumption of the building is connected with the temperature of the days of the month with a linear regression.

Based on the defined assumptions, the energy cost factor of holding a class at a certain time is calculated by Equation 3.

$$C_{i-j} = \sum_{Day=st}^{en} \left(\sum_{k=1}^{n} \left(CT - T_{Day-*\frac{j-1}{n}*24+i+\frac{j-i}{n}*k} \right) Heaviside\left(CT - T_{Day*\frac{j-i}{n}} \right) \right) \quad (3)$$

The following equation shows that the calculated cost is divided by the infinite soft or soft maximum.

Where, C_{i-j} is the energy cost of cooling/heating services for holding a class during a time between i and j, T_t The ambient temperature at time t, CT, is equal to comfort temperature, n is the number of temperatures measured during i to j, and finally, st and en are equal to the first and last day of the academic semester. If the average temperature were available every half hour and the duration of classes would be 90 minutes, then n=3.

According to equation 4, the normalized energy cost is:

$$\bar{C} = \frac{C}{C_{\bowtie}} \quad (4)$$

Where C is the vector of the energy cost coefficient to provide the cooling/heating load for holding each professor's class in its respective time frame. The classes can be held on Saturday-Sunday, Saturday-Monday, Sunday-Tuesday, and Sunday-Wednesday at the same hours. This coefficient is a function of the periods and is independent of the days of the class.

C_∞ is the infinity norm and $\bar{C}$ is the normalized energy cost vector .The number of vector elements indicates the number of periods that the class is held.

4.7. Planning and optimization

The optimization problem is formulated in the form of binary integer linear programming. The decision variables are defined as x_{ijk} and they take the value of one if the class is held, and zero if the class is not held. The decision variables determine holding each lesson by the professor (i) at a particular time (k) on the day (j).

4.7.1. Planning based on minimum energy consumption

The arrangement of classes depends on the minimization of annual energy costs. The optimization equation in this case is presented in Equation 5.

$$\min Z = \sum_K \sum_j \sum_i \overline{C_K}\, x_{ijk} \quad (5)$$

4.7.2. Planning based on maximum educational quality

In order to maximize the quality of education, a questionnaire was designed and presented to the professors and heads of the department to prioritize their preferences. In this questionnaire, the professors were asked about the best time frame regarding the quality of teaching and the most efficient time for holding each lesson, regardless of other conditions. The objective function in this case is defined by Equation 6.

$$\max Z = \sum_K \sum_j \sum_i C_{ijk}\, x_{ijk} \quad (6)$$

Where, C_{ijk} It is the coefficient of desirability of holding a class, which is determined by the professor and head of the department through a questionnaire. As there are 5 time periods in this research, the professors assign a value between 1 and 5 to each question to describe the priority. The priority has the highest score, which is 5, and the last priority has the lowest score, equal to one. C_{ijk} is obtained by Equation 7.

$$C_{ijk} = C'_{ijk} + C''_{ijk} \quad (7)$$

C'_{ijk} Is the coefficient of desirability of holding a class defined by the professors and C''_{ijk} is the coefficient of desirability of holding a class determined by the head of the department? For the lessons with the same score from different professors, the head of the department determines which lesson has more priority than the other.

The priorities for class hours are:

- 8 a.m. to 10 a.m.
- 10 a.m. to 12 p.m
- 1 p.m. to 3 p.m.
- 3 p.m. to 7 p.m.
- 5 p.m. to 7 p.m.

After prioritizing the hours, the professors were asked about their preference for class days. The days of specialized courses are considered according to university regulations. For example, course X can only be on one of the following days: Saturday-Sunday, Saturday-Monday, Sunday-Tuesday, or Sunday-Wednesday.

Then, in order to complete the time constraints, the professors are asked about the times that they are not available to teach and the reason why, if it's possible to mention. Then, to distinguish the courses with higher priority, the opinion of the head of the department is asked, and according to his/her opinion, the final prioritization is determined.

Based on the questionnaire and professors' preferences, integer linear programming is used to maximize the objective function.

4.8. Integrated Planning

This case considers the optimal value of modeling by minimizing the energy cost and maximizing the quality of education. The main problem is that the objective functions do not have the same unit and dimension .The quality of education is a dimensionless qualitative parameter, while the cost of energy is a quantitative parameter. To solve this problem, it is assumed that the current educational planning has a minimum quality of education, and quality of education shouldn't be less than this in the suggested planning .The new defined constraint can be expressed as $\sum_k \sum_j C_{ijk} x_{ijk} \geq b_i$. Where b_i is the value of the current desirability. By adding this constraint to the problem, it is possible to maintain the quality of education and obtain the minimum energy cost by using the minimum energy cost objective function.

5. Results

The semester date and class temperature are two key parameters that influence the timetable and the objective function. The early semester date can reduce energy consumption. As the ambient temperature is the same as comfort temperature in late summer, there will be no need to use the cooling or heating system. The ideal class temperature in the cold seasons is between 23 and 25.5 degrees Celsius, and in the hot seasons between 20 and 23.5 degrees Celsius. Therefore, the range of temperature changes in this study is considered from 20 to 26 degrees Celsius. Subsequently, the cost of energy for holding the classes within this range has been calculated and compared. In this section, the obtained results from modeling are analyzed. For each scenario, the graphs and timetables are presented. Then, the best class temperature and semester date are suggested. For clarity, it should be emphasized that throughout the figures and analyses, the label "without timetabling" corresponds to the Conventional timetabling case, while the label "with timetabling" denotes the Proposed timetabling approach. Likewise, the term "Unchanged Semester Date" has been interpreted as the Conventional baseline scenario.

5.1. Scenario 1

The first scenario has been investigated to minimize the cost of energy consumption in three cases:

- If the semester date is unchanged
- If the semester date is held one week earlier.
- If the semester date is held two weeks earlier.

According to Figure 1, consistently advancing the start of the term reduces energy consumption by about 2.6 to 4.2%, indicating improved thermal coordination with outdoor conditions. Higher indoor temperatures lead to higher energy demand, especially at the start of the term without change (up to 69.80 kWh at 26°C). This trend shows that energy consumption in unscheduled use of the building is sensitive to both indoor temperature and the academic calendar. In conventional timetabling, energy management lacks time optimization and makes the system more vulnerable to thermal inefficiencies.

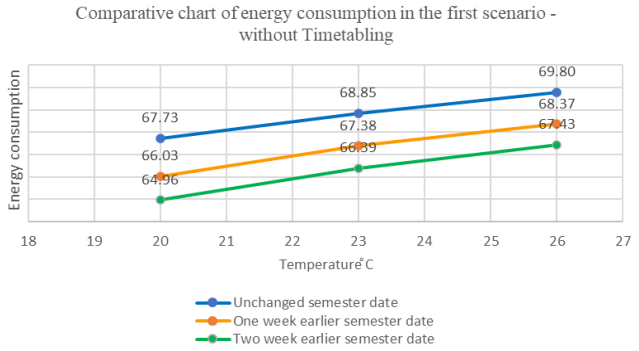

Fig. 1. The proposed timetables: a)Conventional, b) Semester date one week earlier, c) Semester date two weeks earlier

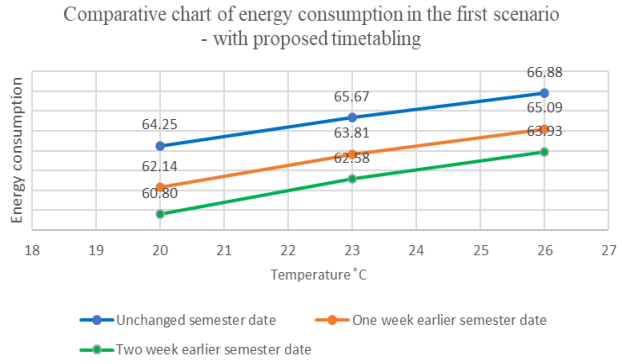

Fig. 2. Energy consumption in different semesters for the first scenario: a) unchanged timetable, b) proposed timetable

Figure 2 compares energy consumption (kWh) at three indoor temperature settings, 20°C, 23°C, and 26°C, under three term scheduling conditions: Advancing the start of the term consistently by 1 or 2 weeks reduces total energy consumption, with a maximum saving of 6.08% at 20°C when starting 2 weeks earlier. The maximum energy consumption is observed at 26°C with unchanged scheduling, totaling 66.88 kWh.It appears that earlier term scheduling coordinates occupancy with milder weather conditions, allowing for less energy required for space heating or cooling.

Figure 3 highlights the intensity of class scheduling across five daily time blocks and two weekday groups (Saturday-Monday and Sunday-Thursday) in Scenario 1: 10-12 and 15-13 in both weekday sets, each host 14 classes, indicating peak instructional usage in the late morning and early afternoon hours.19-17 and 10-8, each with only 1 scheduled class, confirming minimal instructional usage in the early morning and late evening hours.This distribution indicates a strong preference for mid-day teaching, consistent with theories of cognitive function and institutional scheduling norms.

5.2. Scenario 2

Figure 4 shows that the quality of instruction with a timetable remains constant at 960°C across all temperatures (20–26°C), indicating resistance to temperature changes. In contrast, the quality without a timetable remains consistently higher at 1564°C, indicating a significant difference in baseline. The presence of a timetable appears to reduce the quality of instruction by approximately 604 units (1564–960) compared to the absence of a timetable, regardless of temperature.

Figure 5 presents a structured timetable model designed for Scenario 2, showing the frequency of scheduled classes in defined time slots and two weekday groups: Saturday-Monday and Sunday-Thursday. This diagram serves as a planning tool to optimize the delivery of education while supporting the strategic management of energy and space in university campuses.

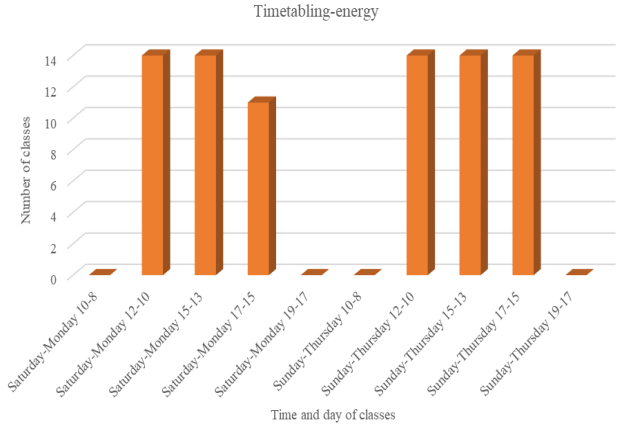

Fig. 3. Quality of education in different class temperatures

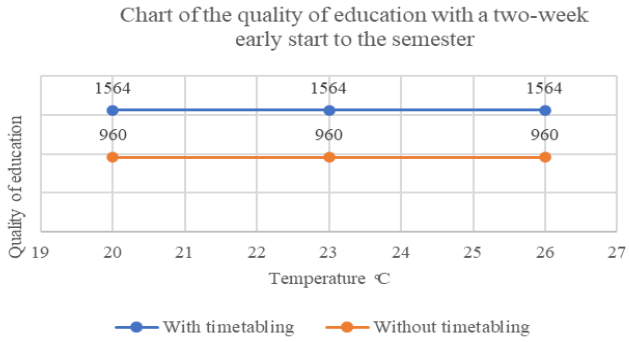

Fig. 4. the quality of education in different class temperatures for the second scenario

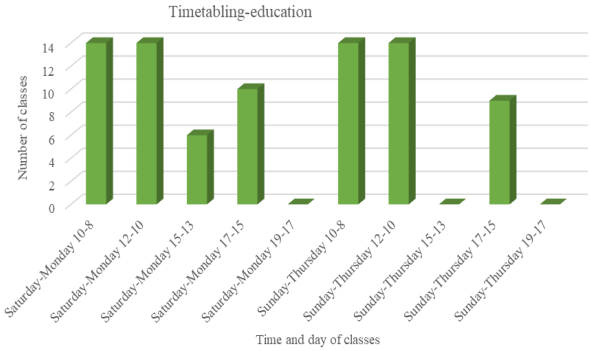

Fig. 5. The proposed timetable for the second scenario

Peak educational periods are consistently observed in the morning time slots (10-8 and 12-10) with 14 classes in both weekday groups.Afternoon sessions (15-13 and 17-15) show more activity on Saturday-Monday (6 and 10 classes) compared to Sunday-Thursday where only 1 and 10 classes are scheduled.Evening time slots (19-17) are minimized in both weekday groups - only one class per class, indicating low academic engagement in the late hours.

5.3. Scenario 3

The third scenario aims to achieve a solution that maximizes the quality of education while the energy consumption is lower than its value in the usual schedule. However, it is not necessary to reach the lowest amount of energy consumption .

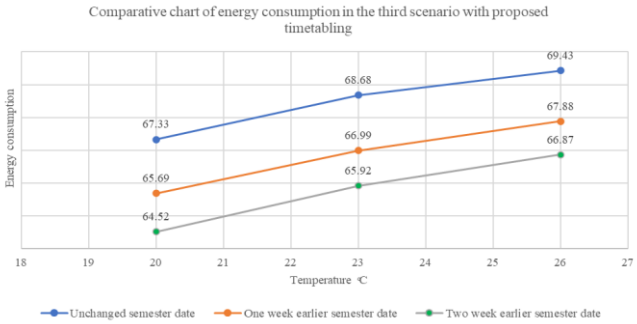

Fig. 6. The energy consumption for the third scenario: a) conventional, b) one week earlier semester date, c) two weeks earlier semester date

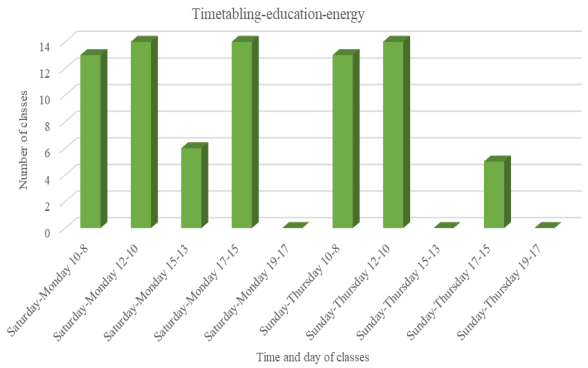

Fig. 7. The proposed timetable for the third scenario

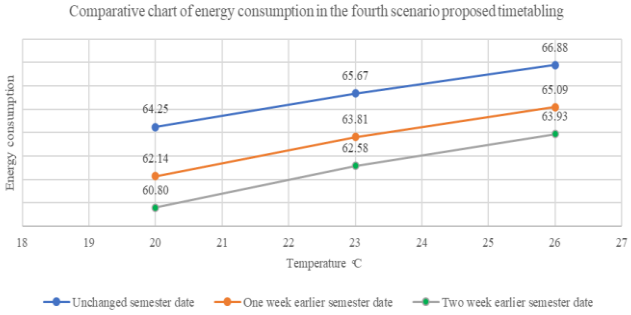

Fig. 8. The energy consumption for the fourth scenario, one week earlier semester date

Figure 6 shows that all three scenarios show an overall increase in energy consumption with an increase in temperature from 20°C to 26°C, indicating a positive correlation between temperature and energy consumption, likely due to an increase in cooling demand. The unchanged term date consistently shows the highest energy consumption across all temperatures, peaking at 69.43 at 26°C. The term date one week earlier shows a moderate decrease, peaking at 67.88 at 26°C. The term date two weeks earlier has the lowest energy consumption, peaking at 66.87 at 26°C, indicating a potential energy saving benefit from earlier scheduling. Shifting the term date one or two weeks earlier reduces energy consumption, with the two-week shift offering the greatest savings. This can be attributed to cooler ambient conditions that reduce the need for artificial cooling.

Figure 7 shows that the highest class density is observed in the time slots 10–8 and 12–10: In the afternoon slots (15–13 and 17–15), the number of classes decreases significantly, especially on Sunday–Thursday, when only 1 class is held in the 15–13 slot. The 17–19 slot also has only 1 class in both groups of days, indicating minimal educational utilization in the late hours of the day. The class pattern indicates a concentration of educational activities in the early hours of the day, which psychologically reinforces high alertness at times. This pattern could lead to the development of energy-saving policies in universities, such as reducing heating or air conditioning during the low-consumption evening slots. A comparison between Saturday–Monday and Sunday–Thursday shows that standard workdays accommodate a greater volume of educational activities.

5.4. Scenario 4

The aim of this scenario is to achieve the minimum energy consumption while maintaining the minimum quality of education. According to Figure 16, if the start date is unchanged, by using the represented timetable in Figure 8, energy consumption will be 64.25 at 20 degrees, which is lower than its value in the case not provided with the best schedule.

According to Figure 8, at 20°C, energy consumption is lowest for the two-week early term (around 60.8), followed by one-week early (62.14) and the unchanged term (64.25). This pattern is consistent at 23 and 26°C, with energy consumption increasing with increasing temperature in all cases, but consistently lower for earlier term start dates. For example, at 26°C, energy consumption for the unchanged term is around 66.88, for one-week early it is 65.09 and for two-week early it is 63.93, representing an improvement of around 4.5% for the two-week early start compared to the unchanged case.The linear increase in energy consumption with temperature indicates a positive correlation between ambient temperature and energy demand, which is likely to indicate the load on the air conditioning system.Moving the start date forward reduces overall energy consumption across all temperature settings, reinforcing the scheduling strategy as an effective lever for energy management in educational institutions. The consistent energy savings from starting one or two weeks earlier suggests that spreading academic activities across a longer or modified calendar helps reduce peak energy loads and improves operational efficiency.

Importantly, the differences observed when moving from no change to one week earlier and then to two weeks earlier show a gradual increase, indicating diminishing returns that must be weighed against the flexibility of the academic calendar and stakeholder acceptance.

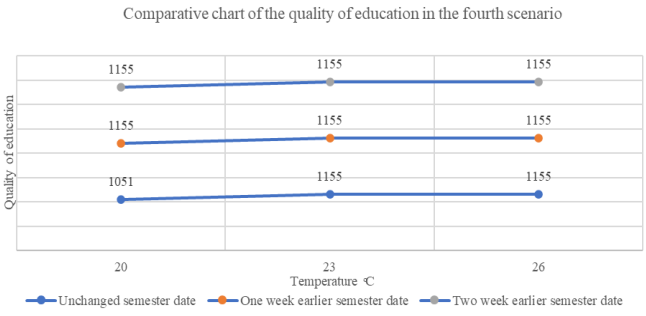

Fig. 9. The energy consumption for the fourth scenario, two weeks before earlier semester date

Figure 9 shows the teaching quality scores at three temperature levels: 20°C, 23°C, and 26°C. For the unchanged term date, the teaching quality score increases from approximately 1051 at 20°C to 1155 at 23°C, and remains constant at 26°C. In contrast, term dates one week earlier and two weeks earlier maintain a stable and higher quality score of 1155 at all temperatures, indicating no significant change in temperature. These data suggest that advancing the start of the term by one or two weeks, independent of ambient temperature, results in consistently high teaching quality scores, while not changing the start of the term only shows a significant improvement

when the temperature increases from 20°C to 23°C.

Advancing the start date of the semester appears to stabilize instructional quality across temperature changes, eliminating the temperature sensitivity observed in the unchanged semester schedule. This suggests that an earlier start may reduce the adverse effects of lower temperatures on instructional outcomes.

Instructional quality is highest and most stable (1155) when the semester starts earlier, suggesting that adjustments in academic scheduling can serve as a non-physical intervention to maintain or enhance learning effectiveness regardless of environmental conditions. The small increase in instructional quality with increasing temperature in the unchanged semester scenario may reflect the inherent effect of environmental comfort on student performance. However, this dependence is eliminated with an earlier start, likely through better alignment of classroom conditions with optimal learning environments. These findings support the comprehensive approach of the study and show that scheduling manipulation not only contributes to energy efficiency, but also positively affects educational quality and promotes resilience to environmental variables. The constant score of 1155 in the early semester scenarios indicates a constant level of quality, indicating potential limitations beyond which scheduling adjustments alone may not improve educational outcomes and indicating the need for complementary strategies such as improving the classroom environment or educational settings.

In summary, Figure 10 quantitatively confirms that early semester starts stabilize and maximize educational quality under different temperature conditions, while qualitatively highlighting the strategic advantage of academic calendar adjustments to enhance educational resilience and efficiency. This emphasizes the value of integrated environmental planning and management policies in educational institutions with the aim of creating sustainable and effective learning ecosystems.

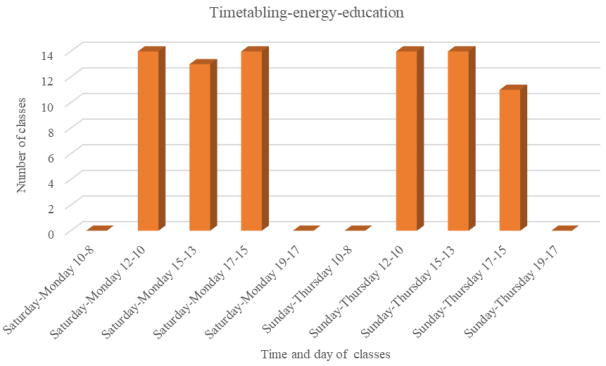

Fig. 10. The proposed timetable for the fourth scenario- two weeks earlier semester date

Figure 10 shows the distribution of class sessions across different time slots in two sets of days: Saturday-Monday and Sunday-Thursday. The peak class occupancy is observed in the time slots 12:00-14:00 (12-10) and 15:00-17:00 (15-13) in both sets of days, with up to 14 classes scheduled in each time slot. No classes are scheduled in the earlier (10:00-08:00) and later (19:00-17:00) time slots for either set of days, as indicated by the zero height in those columns. The time slot 17:00-19:00 (17-15) on Sundays through Thursdays has slightly fewer classes (12 sessions) than the midday time slots. By avoiding early morning and late evening classes, this schedule reduces the need for long-term heating/cooling during periods when the temperature difference with the outside is greatest – thus maximizing energy savings. This is in line with the goal of Scenario 4 of minimizing energy consumption without compromising educational quality.

Educational quality and satisfaction: Mid-day scheduling is generally beneficial for student and staff alertness and engagement, and prevents fatigue caused by classes that start too early or late. Such scheduling has been shown in the scientific literature to increase learning effectiveness and engagement. Implementing a two-week earlier start time, as demonstrated in this scenario, spreads energy demand over a larger time frame, potentially reducing peak loads, and providing operational flexibility. The intentional elimination of some time slots (notably 8:00-10:00 and 17:00-19:00) across all days highlights the priority of optimization not only to save energy, but also to maintain or even enhance the quality of teaching and learning. This optimal scheduling meets both of the objectives stated in the study – reducing energy costs and improving educational quality, by revealing explicit, data-driven trade-offs in class distribution.

The results show that the quality of education is independent of temperature change for all cases, except for the case of the conventional, which is decreased between 20-23. In this scenario, the lowest energy consumption is related to the early start date of the semester for two weeks by using the suggested timetables. According to the 4 scenarios mentioned in this study, in each scenario, one can witness a reduction in energy consumption or an increase in the quality of education or satisfaction of both functions. According to the first scenario, which only tries to minimize the amount of energy consumption per hour, the goal of the function is achieved by providing an appropriate schedule. In a case where the schedule is provided in accordance with the modeling and the academic semester has started on time, reducing the temperature from 26 degrees Celsius to 23 degrees Celsius reduces the amount of energy consumption by 1.8%, and if the temperature is reduced to 20 degrees Celsius, this reduction in energy consumption will reach 3.9%. If the academic term starts one week earlier, reducing the temperature from 26 to 23 and 20 degrees Celsius will result in a reduction in energy consumption of 2% and 4.47%, respectively. With an early start of the academic term for two weeks, this reduction will reach 2.11% and 4.9%.

To examine the effect of changing the start time of the term at 26 degrees Celsius, starting the academic term early by one week will result in a reduction in energy consumption of 2.7% and 4.4% for two weeks. This amount will reach 2.8% and 4.7% at 23 degrees Celsius and 3.3% and 5.4% at 20 degrees Celsius. Finally, in the case where the optimal scheduling table is presented, reducing the temperature from 26 to 20 and also starting the academic term early for two weeks will reduce energy consumption by 9%. Table (4) presents the reduction in energy consumption compared with the regular course scheduling mode under the conditions considered in the first scenario.

Table 4. Energy consumption reduction between the normal lesson scheduling mode and when the first scenario is considered

	Regular start of the semester	A week earlier	Two weeks early
26 C	5.2%	4.8%	4.2%
23 C	5.7%	5.3%	4.6%
20 C	6.4%	5.9%	5.1%

Finally, it can be said that by providing an optimal schedule and reducing the temperature of the class to 20 degrees Celsius and starting the academic semester early for 2 weeks, the energy consumption will be reduced by 13%. The optimal timetable obtained for the first scenario is presented in Table (5). The table shows the distribution of classes across the five available time intervals for the two weekday combinations considered in the model.

In the second scenario, the objective function is to maximize the quality of education. According to the data obtained from the results, the quality of education will not change with changing the

temperature and the time of starting the academic semester, and fundamental changes in the quality of education are achieved by providing a schedule.

Table 5. Optimal scheduling table for the first scenario

Class day combination	8:00–10:00	10:00–12:00	13:00–15:00	15:00–17:00	17:00–19:00
Saturday–Monday	14	14	6	10	0
Sunday–Tuesday	14	14	0	9	0

Table 6. Optimal scheduling table for the second scenario

Class day combination	8:00–10:00	10:00–12:00	13:00–15:00	15:00–17:00	17:00–19:00
Saturday–Monday	12	14	14	0	0
Sunday–Tuesday	13	14	14	9	0

Table 7. Energy consumption reduction between the normal lesson scheduling mode and when the third scenario is considered

	Regular start of the semester	A week earlier	Two weeks early
26 C	0.5%	0.7%	0.8%
23 C	0.24%	0.57%	0.7%
20 C	0.59%	0.51%	0.67%

Table 8. Optimal scheduling table for the third scenario

Class day combination	8:00–10:00	10:00–12:00	13:00–15:00	15:00–17:00	17:00–19:00
Saturday–Monday	14	14	4	14	0
Sunday–Tuesday	14	14	2	5	0

In the cases of starting the academic semester normally and with an early start of two weeks during temperatures of 26, 23 and 20 degrees Celsius, and in both cases with a schedule and without a schedule, the quality of education remained unchanged. In the case of starting the academic semester two weeks earlier than the scheduled date, the quality level is constant in both cases with and without a schedule at temperatures of 26 and 23 degrees Celsius, but when a schedule is provided, the quality level in this case decreases by 22.5% at a temperature of 20 degrees Celsius. This means that in this scenario, with the provision of a schedule, it is better not to implement the schedule at a temperature of 20 degrees Celsius and in the case of starting the academic semester 2 weeks earlier, but in other cases, the quality level does not depend on the temperature and the start time of the semester.

In this case, the quality level of education with a schedule increased by 63% compared to the initial case, and in the exception case of a temperature of 20 degrees and starting the academic semester 2 weeks earlier, it increased by 24.7%. Overall, the quality of education improves through the implementation of the proposed timetable. The optimal timetable obtained for the second scenario is presented in Table (6). It illustrates the number of classes assigned to each available time interval for the two weekday combinations. The third scenario is to achieve the highest quality of education in a situation where energy consumption does not exceed the normal state. According to the results obtained, in this case, the quality of education will not change with changes in temperature and the start time of the semester, and only by providing a schedule, the quality of education will increase by 63%. To provide the best schedule, the amount of energy consumption will be examined. In this scenario, by providing an optimal schedule according to the usual start of the academic semester and by reducing the temperature from 26 degrees Celsius to 23 and 20 degrees Celsius, the amount of energy consumption reduction will be 1.1% and 3%, respectively. By starting the academic semester earlier for one week and reducing the temperature from 26 to 23 and then 20 degrees Celsius, the amount of energy consumption reduction will be 1.3% and 3.2%. In the case where the academic semester starts 2 weeks earlier, this reduction will reach 1.4% and 3.5%. Then, the effect of the start time of the academic semester is examined. At a temperature of 20 degrees, the reduction in energy consumption from starting the academic semester one week and two weeks earlier than normal is 2.4% and 4.2%, respectively. At a temperature of 23 degrees Celsius, this reduction reaches 2.5% and 4%, and at a temperature of 26 degrees Celsius, it reaches 2.2% and 3.7%. Table (7) summarizes the energy consumption reductions achieved under the third scenario compared with the normal lesson scheduling mode. The reduction in energy consumption achieved by using the proposed timetable is also compared with the case in which the optimal timetable is not implemented. Based on the results, the most suitable condition for holding the academic semester is at a temperature of 26°C, with the semester starting two weeks earlier and the proposed timetable being implemented. The optimal timetable obtained for the third scenario is presented in Table (8).

In general, in this scenario, energy consumption decreases by 0.83%, while the quality of education increases by 63%. The fourth scenario is to achieve the lowest energy consumption in a situation where the quality of education is not lower than the situation without the optimal schedule. Initially, the energy consumption in this scenario is examined with changes in temperature and the start time of the semester.

Since the first objective is the function of minimizing energy, the results of this scenario are the same as the first scenario, but since there is also another objective function called educational quality, it is also necessary to analyze the education quality data to provide the best schedule. In this case, the quality of education at all times and temperatures increased with the use of the schedule compared to the absence of the schedule, but in each case (with and without the schedule), there was no change in the increase in the quality of education with changes in temperature and semester start time. However, at a temperature of 20 degrees Celsius and the usual start time of the semester, the percentage of growth in the quality of education with the schedule was lower than at other temperatures and times and was equal to 8.6%, but in other cases it was equal to 16.9%. It is better not to hold classes at a temperature of 20 degrees and the usual start time of the semester in this scenario so that this scenario achieves its goal, and finally the proposed schedule will be as shown in Table (9).

Table 9. Optimal scheduling table for the fourth scenario

Class day combination	8:00–10:00	10:00–12:00	13:00–15:00	15:00–17:00	17:00–19:00
Saturday–Monday	13	13	14	0	0
Sunday–Tuesday	12	14	14	9	0

6. Discussion

The research findings correspond with international energy policy trends that prioritize energy efficiency, decarbonization, and sustainable building operations, as detailed in the 2023 Global Status Report for Buildings and Construction. The building sector accounts for approximately 30% of total final energy consumption and about 15% of direct CO_2 emissions, with indirect emissions nearly doubling this effect. The study's emphasis on educational buildings,

characterized by high occupancy and substantial heating, ventilation, and air-conditioning (HVAC) requirements, is particularly noteworthy in light of these statistics. Educational institutions offer an ideal environment for testing low-cost, energy-saving strategies that can be applied to other public and commercial structures. The modeling results of this study demonstrate that operational strategies, particularly class scheduling, can lead to significant energy savings. Numerical findings indicate that shifting the semester start date forward by two weeks and maintaining classroom temperatures at 20°C can decrease energy consumption to 60.80 kWh, as determined in Scenario 1, compared to 67.73 kWh for the original semester schedule. Integrating an optimized timetable consistently reduces energy consumption, yielding savings of 3–5% compared to traditional scheduling methods. The findings align with international efforts focused on demand-side energy management, which aim to reduce energy consumption by optimizing operational schedules and user behavior, rather than relying solely on expensive infrastructure retrofits. The results indicate that energy optimization can be achieved without compromising educational quality. In Scenario 2, the quality of education, measured by normalized performance scores, increased from 960 (traditional scheduling) to 1,564 with optimized timetabling, while energy consumption remained stable within the 20–26°C temperature range. Scenario 3, which integrates educational quality with energy conservation, demonstrates that initiating the semester two weeks earlier at 20°C is the most effective approach, yielding both decreased energy consumption and enhanced academic outcomes. Scenario 4, designed to minimize energy consumption while maintaining a baseline quality of education (1115 units in normalized terms), demonstrates that early scheduling interventions can achieve optimal trade-offs.

The findings highlight the relationship between energy policy and operational efficiency. Global energy strategies emphasize the integration of digital optimization tools, cost-effective scheduling algorithms, and user-centric methodologies to achieve energy reductions. This study employs linear optimization and the Anagram thermal model, illustrating the role of digital modeling and data-driven decision-making in advancing international objectives. The proposed framework emphasizes operational measures, thereby circumventing the substantial initial costs associated with structural retrofits. This approach is especially pertinent for developing countries, where capital-intensive solutions may be impractical. The study demonstrates that intelligent scheduling can yield energy savings of up to 10.2% (67.73 → 60.80 kWh), directly supporting the International Energy Agency (IEA) Net Zero by 2050 roadmap, which identifies energy efficiency as essential for decarbonization. By integrating the proposed scheduling approach with additional measures, such as those in Table 2, including HVAC optimization and green building design, universities can create a replicable blueprint for substantial, scalable energy reductions worldwide. These results underscore not only the transformative potential of operational strategies but also set the stage for future research and implementation, advancing global sustainability targets across diverse educational settings. The important point is that if we compare this model with the model presented in [3], which is a more complex model, there is no effect between the presented model and the anagram, and the authors confirm that we can easily reach the answer with the anagram model, and the advantage of the anagram model is that the computational burden of this model is also low.

6.1.Sensitivity analysis

6.1.1.Sensitivity and Robustness Analysis

The robustness of the proposed optimisation framework was evaluated by examining the model outputs across different combinations of the key decision variables considered in this study, namely indoor comfort temperature (20, 23, and 26 °C) and semester start date (unchanged, one week earlier, and two weeks earlier). The results consistently show that these parameters influence the magnitude of energy consumption but do not change the overall behaviour of the optimisation model. The most influential parameter was the indoor temperature. Lower set-point temperatures always reduce heating energy demand across all scheduling scenarios. Similarly, shifting the semester starting date by one or two weeks led to systematic reductions in energy consumption by combining academic activities with more favourable outdoor climatic conditions. The total energy demand varied, but the optimal scheduling strategy was identical across all investigated cases, with the same general distribution of class periods and all scheduling constraints satisfied. This consistency indicates the stability of the proposed optimisation framework within the considered range of operating conditions. The absolute values of the predicted energy consumption may be affected by remaining uncertainties, e.g., year-to-year weather variations, occupancy variations, professors' preferences, and simplifications inherent to the deterministic Anagram thermal model, but these are not expected to affect the relative performance of the evaluated scheduling scenarios. Thus, the primary findings of this study are robust for the range of conditions considered.

Table 10-Sensitivity Analysis of Key Variables and Their Impact on Energy Consumption

Variable	Variation	Effect on energy
Indoor temperature	±3°C	High
Semester start date	±2 weeks	High
Building heat-loss coefficient	±10%	Moderate
HVAC efficiency	±10%	Moderate
Professor preference weight	±20%	Low

The most sensitive of all the variables studied was indoor comfort temperature. An increase in the set-point from 20°C to 26°C increased heating energy demand by about 8-10%, while advancing the semester by two weeks decreased total energy consumption by about 4-6%. In contrast, moderate changes in HVAC efficiency and educational preference weights led to relatively small changes in the optimal timetable, indicating that the proposed scheduling framework is governed primarily by climatic conditions rather than subjective scheduling preferences.

6.2.Uncertainty analysis

The proposed model is subject to uncertainties, including year-to-year weather variability, classroom occupancy fluctuations, instructor scheduling preferences, and assumptions underlying the deterministic Anagram thermal model.

Sensitivity and uncertainty analyses revealed that indoor comfort temperature and semester start date are the most important factors affecting building energy consumption. The largest difference in heating demand was due to changes in indoor temperature, and the minimum energy consumption across all scenarios studied was recorded when the academic calendar was adjusted. Conversely, moderate changes in HVAC efficiency, professor preference weights, and building thermal parameters had relatively minor effects on the optimal scheduling solution. Furthermore, the optimal timetable was found to be largely invariant for all the investigated combinations of parameters, thereby confirming the robustness and stability of the proposed optimisation framework. These results show that the primary findings of this study are not dependent on a single set of assumptions, but are valid over a realistic range of operating conditions.

Climatic variables govern the heating energy demand of educational buildings. It has been further proven that outdoor

temperature is the main driver across climates. Other parameters (solar gains, wind, humidity) affect loads based on the envelope, ventilation, and occupancy [33]Several studies have shown that temperature is the most important predictor, whereas the influence of wind speed and solar radiation varies with climate and building stock [33].

Based on Fathi et al.[34], the effectiveness of optimal educational scheduling as an energy-saving strategy for climate change is evaluated across various operational scenarios. Climate-driven heating estimates rely on local or high-resolution weather data (and future scenarios when considering climate change), the integration of climate inputs into building energy models, and the clear statement of climate context (climate zone, HDD/CDD, scale) to allow generalization. The choice of weather data (AMY, TMY, or site-specific) has a major impact on heating loads, especially under changing climate conditions. Multi-decade simulations with realistic weather data improve robustness [34].

The case-study building mentioned in Fathi et al. al was simulated in several cities across Iran's major climate zones to assess the robustness of the proposed educational scheduling framework under varying climate conditions. The analysis evaluates the effects of variations in climatic conditions and indoor heating temperature setpoints on the optimal classroom schedule within the optimization framework. In particular, the effect of changes in climate or temperature setpoints on the scheduling solution with minimum heating energy consumption is studied.

The energy demand of buildings was investigated under different climatic conditions using a geographically representative dataset of 2,700 locations in Iran. The simulation results show that the highest heating energy demand occurs during the 18:00–19:30 interval at most analysed locations. This result contradicts the one reported by Fathi et al. [35], who found a different interval as the peak-demand period. However, the predicted heating energy demand during 07:30-09:00 and 18:00-19:30 is quite similar. The difference between the two time periods is marginal, as shown in Fig. 11[34].

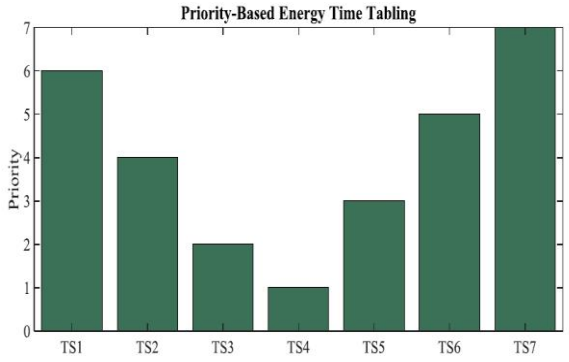

Fig. 11. Prioritising each instructional hour to reduce energy consumption in educational planning [34]

Figure 11 Normalized priority weights of each teaching period based on the objective of minimizing the demand for heating energy. The weighting factors were individually normalized for each climate zone to enable comparison across climatic regions. However, the absolute magnitude of heating energy demand is strongly affected by variations in indoor temperature setpoints and climatic conditions. In contrast, the relative priority of the teaching periods is little affected[34].

Figure 12 shows that the 18:00-19:30 teaching session consistently has the lowest priority weight across all climate zones, indicating that this is the least favorable time slot for minimizing heating energy demand. The magnitude of the weighting factor varies across climatic zones because of differences in ambient temperature profiles and heating demand. However, the relative rank order of this time slot is not altered. The weighting factor is larger in colder climate zones to compensate for the higher heating-energy penalty of late-evening occupancy, and smaller in warmer climates because of lower heating demand. However, the relative order of instructional periods is the same for all climatic scenarios. This means that climatic variability affects the magnitude of energy consumption and not the order of optimal scheduling[34].

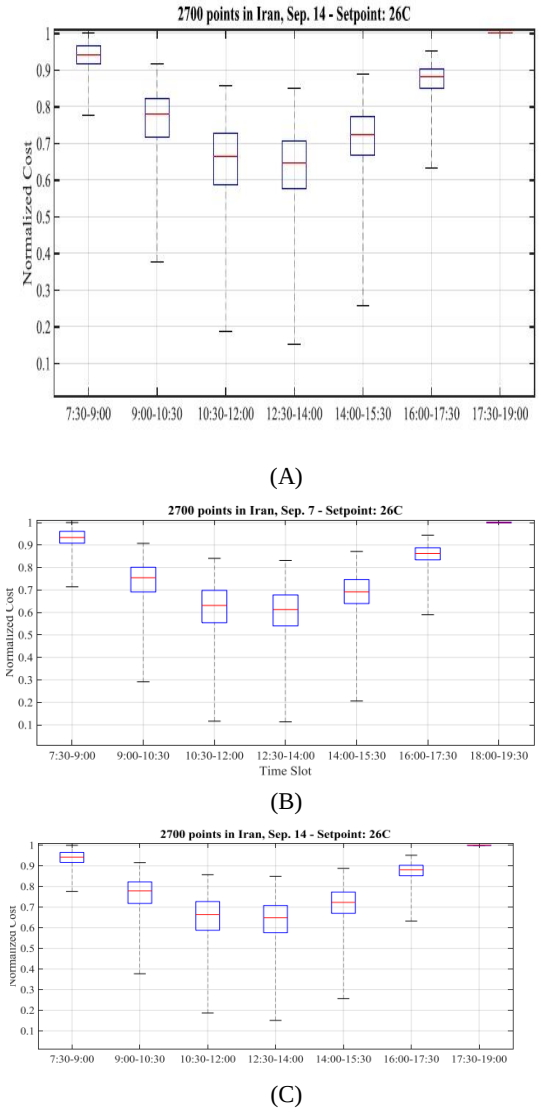

Fig. 12. Normalized coefficients of climate class designation in each climate zone under three wet-start time periods (A – wet start on August 31, B – wet start on September 7, and C– wet start on September 14) [34]

The results indicate that the proposed scheduling strategy reduces heating energy demand across all climates, but the magnitude of the savings varies by climate. In cold and glacial climates, space heating is the dominant component of building energy use, and the largest absolute reductions are achieved there. In contrast, in temperate and warm climates, comparatively smaller reductions are achieved because of lower seasonal heating requirements [34].

Furthermore, the proposed scheduling framework need not rely

on highly accurate temperature forecasts during the academic semester, because the optimal order of instructional periods is invariant to variations in outdoor climatic conditions and indoor temperature setpoints. Rather, climatic variability affects the scale of heating energy demand but has minimal impact on the optimal scheduling hierarchy[34].

7. Conclusion

This study presented a comprehensive model for energy-efficient scheduling in university buildings by aligning academic timetables with environmental and infrastructural constraints. Given the significant share of educational facilities in total building energy consumption, integrating energy-saving strategies into operational planning, such as course timetabling, presents a promising and underutilized solution. The primary goal of the research was to minimize energy consumption without compromising educational quality. To this end, a linear programming-based scheduling model was proposed that integrates multiple constraints, including limited classroom availability, avoidance of schedule overlap for professors, symmetrical class timings, and faculty unavailability. These constraints were translated into mathematical formulations and evaluated across different scheduling scenarios. The study also innovatively integrated climate data specific to the fall semester in Tehran to guide schedule optimization.

Results from model implementation indicate that the optimized scheduling approach reduced total energy demand by approximately 10% compared to conventional timetables. Specifically:

- Morning classes were shifted to cooler hours to lower cooling loads.
- Simultaneous sessions were grouped to minimize building operation hours.
- Courses requiring ventilation or lab access were strategically placed during low-humidity periods.

The model improved the consistency and predictability of the academic schedule, enhancing satisfaction among students and faculty. It also supported sustainable campus goals by aligning educational planning with energy policy objectives. This work contributes to the literature by offering a multi-objective, data-driven, and implementable scheduling framework for higher education institutions.

Future studies could extend this model to include renewable energy forecasts, adaptive learning algorithms, or apply it in hybrid in-person/online settings.

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