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A New Approach to Solve University Course Timetabling Problem

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Abstract

University Course Time-Tabling Problem is a process of scheduling university courses for one semester by the faculties of a university, which is inherently NP-Complete problem. The main technique in the presented approach is focused on developing and making the process of timetabling common lecturers among different departments of a university scalable. This problem schedules and allocates events (lecturers/ students/ courses) to resources (time slots/ classrooms), which has two sensitive constraints including hard and soft constraints. The goal is to improve soft constraints. In this paper, the studied approaches include clustering algorithms (K-means, fuzzy C-means, and funnel), fuzzy multi-criteria decision making comparison, hybrid (local search/ genetic) and combination of clustering algorithms with fuzzy multi-criteria decision making comparison. For this, the optimization and performance comparisons of the algorithms used in this paper are thoroughly analyzed. Paper’s aims: 1) descending satisfaction of preferences and soft constraints of common lecturers among departments, 2) minimizing the loss of extra resources of each faculty. An applied dataset is based on meeting the requirements of scheduling in real world, among various departments of Islamic Azad University, Ahar Branch and the success of the results would be in respect of satisfying uniform distribution and allocation of common lecturers on extra resources among different departments.

Keywords: University Course TimeTabling (UCTTP), clustering algorithms, fuzzy multi-criteria decision making comparison algorithm, hybrid algorithm.

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Introduction

The UCTTP problem is a hybrid optimization problem in the form of hard problems that has made some issues to optimally solve this problem. This problem, which takes place at the beginning of semesters, consists of allocating events (courses, lecturers, and students) to a number of time slots and classrooms (theory and practice). The UCTTP problem must satisfy both hard and soft constraints so that the programmable time tables can be obtained after complete and correct satisfying of all hard constraints; on the other hand, the soft constraints must be satisfied to increase the quality of programmable time tables. And like hard constraints they do not necessarily need complete satisfaction. Another issue in this problem is the diversity of constraints (soft and hard) that vary from one university to another. The soft constraints considered by each solution (a timetable) are evaluated by the penalty function where this function is obtained by a sum operator. In this operator, a weight is given to each soft constraint. According to these weights, the penalty function is obtained. Then, the output of the penalty function is given into the objective function and for each solution, an objective function is calculated. After obtaining all the last solutions, timetables must be 1) without collisions (all hard constraints must be satisfied), and 2) selected in terms of the objective function of each solution that has a higher value [1-13].

Definitions

The basic definitions of UCTTP problem are as follows:

- Event: a scheduled activity such as lecturer, student and etc.
- Timeslot: a time interval; events are scheduled in time intervals. For instance, 8 am. - 9.30 pm.
- Resource: resources that are allocated by events, such as equipment, classes and etc.
- Constraint: a limitation to schedule the events, such as classrooms and given timeslots.
- People: a person (people) accompanied with events.
- Collision: when two events have a collision, for example, scheduling more than one course at the same time.

Constraints

Constraints are classified into two hard and soft types in UCTTP problem [1-13].

Hard Constraints

The hard constraints must be satisfied completely so that the obtained solutions could be programmable and without collisions. Also, the violation is not allowed in such constraints.

- There is only one class (session) for a particular course per day.
- The features of a class are considered according to the course being taught.
- Each student and lecturer can only attend one class at a time.
- Only one course is scheduled for the same timeslot and cannot be assigned to the same class.
- Lecturers should be available when their courses are scheduled.
- Some courses require a fixed number of times per week. (E.g., 3, 2, 1 time per week).
- Every course that is already scheduled is marked and those courses must be scheduled at a specific time.

Soft Constraints

These constraints are related to the objective function and the number of soft constraints should be satisfied as much as possible.

The lecturer sets a time priority for teaching.

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- Remove empty spaces in classrooms.
- The maximum continuous teaching time for a lecturer is 3 hours.
- The maximum continuous learning time for students is 4 hours.
- A subject should not be taught for more than two consecutive hours.
- An attempt to distribute events evenly among timeslots.
- Lecturers and students must have lunch hours.
- One or a group of students should not have only one specific timeslot in a day for a classroom.

Description of problems in UCTTP problem

Since timetabling is an NP-complete problem, we need to look for heuristic approaches. The reason is 1) exponential growth of this problem due to the number of changes and increasing growth of events (students); and 2) the number of constraints in this problem varies from one university to another. So, the main problem is how to satisfy the number of soft constraints in the UCTTP problem [1-13].

Related Works

The approaches that have solved the UCTTP problem include:

Operations Research Approaches

The graph coloring approach is about how to model a UCTTP problem using an undirected graph where [14] has used vertices as events, colors as timeslots and edges as constraints in a graph to solve the timetabling problem. Here, none of the two adjacent vertices should have the same color, as it represents a collision in the timetable.

Another hybrid approach to solve the UCTTP problem using genetic coloring has been proposed by [15], which reduces the cost of finding the minimum number of required colors to color a graph by this method. In [16], the IP (Integer Programming) method has been proposed for the UCTTP problem in which aim is to assign a set of courses among lecturers and groups of students as well as a set of weekly and daily time periods. [17] has presented an IP-based two-step relaxation method to produce efficient timetabling solutions where during step 1, classes requiring succession are assigned by allocating courses to specific days and times and in step 2, ensuring the succession of courses that require more than one time period for the same student groups is also performed.

Metaheuristic Approaches

In [18], a genetic algorithm is applied to sort out a university timetable with an intersection rate of 70%, however, no hard constraint is violated in the timetable and the applied constraints are more on classrooms’ occupancy and capacity. Furthermore, [19] has proposed a new GA technique to solve the UCTTP problem using a learning machine. The results of this technique include minimizing the number of violated soft constraints, more usage of the available classrooms, and reducing the lecturers’ workload. In addition, the ant colony optimization algorithm is also used by [20] for the post-registration UCTTP problem, according to the ITC-2007 dataset, where the ants assign events to classrooms and timeslots based on two types of pheromone T_{ij}^{s} and T_{jk}^{y}. This algorithm performs well on timetabling and generates good results over longer runs. Applying a hybrid ant colony system to solve the UCTTP problem has been proposed in [21]. Here are two types of hybrid ant systems: SA with AC and TS with AC. A number of ants make full allocation of courses to timeslots based on a predefined list. Timeslots probabilities selection by ants for course assignment is performed using heuristic information and indirect coordination mechanism among agents (Stigmergic) and activities in the environment. The memetic algorithm is performed by [22] to solve the UCTTP problem by

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combining the local search method in the genetic algorithm. One local search is performed on events and another one is performed on timeslots.

The Tabu search algorithm was first developed by [23] to assign students to courses and to balance the number of students in a registration group where phase 1 is to generate a set of solutions for a student, phase 2 is to combine a set of solutions and employing Tabu search with local strategies and Phase 3 is to allocate classroom and improve allocation, but without altering the initial allocation of courses to timeslots. In [24], the effect of neighborhood structures on Tabu search algorithm has been presented to solve the UCTTP problem, which tested the effect of simple and swap transfers on Tabu search operations based on neighbor structures. Here, four new neighborhood structures are used and compared. To solve the UCTTP problem, the integration of the Kempe neighborhood chain in the simulated annealing algorithm has been proposed by [25] where one of the hard constraints is reformulated by relaxation and then this constraint is created in the form of a relaxed soft constraint. The relaxation problem is analyzed in two steps: 1) To create a feasible solution, a heuristic based graph is used and 2) A simulated annealing algorithm is used to minimize the violations of soft constraints. (In step 2, a Kempe neighborhood chain based heuristic is used).

[26] Has also used a guided local search strategy within the genetic algorithm to solve the UCTTP problem, which uses a data structure to generate children that stores the extracted information from good people of previous generations. The results are satisfying with this local search integrated into the genetic algorithm. The aim is to maximize the allocations and minimize the violations of soft constraints. The Variable Neighborhood Search (VNS) algorithm has been presented by [27] to solve the UCTTP problem that proposed a basic VNS and then addressed modifications so that each solution could use an exponential Monte Carlo acceptance criterion. The main idea is to apply the Monte Carlo acceptance criterion in order to improve explorations by accepting the best possible solution to find the number of promised neighbors.

Modern Approaches

A hybrid algorithm has been proposed by [28], which has used sequential heuristics and simulated annealing to solve the UCTTP problem over ITC-2002 dataset. This method consists of three phases: Phase 1) Using a sequential heuristic to generate feasible initial timetables; Phase 2) Applying simulated annealing to minimize the number of soft constraints’ violations and Phase 3) using simulated annealing algorithm to improve the quality of the generated timetables. Recently, a multi-population hybrid genetic algorithm has been proposed by [29] to solve the UCTTP problem based on three types of genetic algorithms, FGARI, FGASA and FGATS. In this algorithm, fuzzy logic is used to measure the number violations from soft constraints in the fitness function to deal with real-world data that is ambiguous and uncertain; and random methods, local search, simulated annealing, and Tabu search methods will be useful to improve inference search to satisfy search ability.

To solve the UCTTP problem, [30] has proposed a multi-fuzzy heuristic sorting method in which the events sorting is performed by simultaneous consideration of three separate heuristics using fuzzy methods. The sequences of the three heuristics are used as follows: 1- highest degree, 2- saturation degree, and 3- registration degree, also the fuzzy weight of an event is used to represent what is the problem an event to be timetabled. The descending sorted events are assigned to the last timeslot with the minimum amount of penalty cost, while the feasibility is maintained throughout the process. A fuzzy solution based on the Memetic approach to solve the university timetabling problem has been presented by [31], where a timetable is compared with both the genetic and memetic algorithms, and the results satisfy the existing constraints within a shorter time period. The aim is to use fuzzy logic as a tool for local search in the memetic algorithm.

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[32] has proposed the fuzzy genetic heuristic to solve the UCTTP problem where the genetic algorithm is integrated using indirect representation based on events features, and the fuzzy set model is used to measure soft constraint violations in the objective function due to uncertainties and real-world data. Here, for each soft constraint, a degree of uncertainty is considered in the objective function, and this uncertainty is evaluated by formulating the violation parameter of soft constraint in the objective function using fuzzy membership functions.

Multi-Agent Systems Based Approach

To produce course timetable, [33] has utilized a distributed multi-agent architecture. Here, the UCTTP problem consists of a set of courses in constant time periods in a rotary week. The UCTTP problem is only focused on a set of university departments. Each department has a curriculum in accordance with specific rules, constraints, and goals based on their resources and resources are not shared unless the exchange of resources among departments is beneficial which will be through negotiation. To solve the problem, a market-based multi-agent timetabling system with synthetic money is considered and each department consists of three contributing agents: 1) searching for a local solution, 2) negotiating on resources with other departments, and 3) management of relevant information.

Studying the problem of distributed timetabling problem based on scheduling agents by [34], often in real-world timetabling problems includes organized parts that require creating timetables for people involved in an autonomous approach, while some global constraints are considered. Recently, departmental timetables have been combined as a result of integration and compatible solutions, and this combination itself will require the negotiation of various agents. Here, a model that contains only a double agent called CA (central agent) is examined, and the task is to coordinate the search process among all SA(s) (scheduling agents). The idea is, of course, to create feasible solutions for a network of SA(s).

Implementation of class timetabling has also done by [35] based on multi-agent systems, where the implementation process has been presented by applying the hill climbing algorithm with the steepest upward slope (up to the ancestor). CombinationGenerator and MinFinders are used to generate maximum input combinations and create a combination with the minimum value of the evaluation function for sequential examinations, respectively. Applying this proposed method will continue the initial random solution until the given optimal solution is obtained. A system model for the UCTTP problem has been proposed by [36] using mobile agents, which employed a multi-agent system to generate UCTTP problem solutions. Four types of agents 1) Course (mobile), 2- Signboard, 3- Publisher, and 4- Mediator, participate to perform the course timetabling process. The powerful advantage of this approach is to use agents' autonomy, and this autonomy is explicitly embedded in the course agent's performance. Each course agent in the system is responsible for negotiating with other course agents to find a satisfactory source class for presenting courses.

A New Approach for Solving University Courses Timetabling Problem

This section consists of three subsections, including clustering algorithms, fuzzy and hybrid multi-criteria decision making comparison.

Clustering Algorithms for Common Lecturers' Timetabling among Faculties

In this section, the way of applying clustering algorithms (K-mean, fuzzy C-mean, and funnel) for the problem of common lecturers' timetabling among faculties is studied. Clustering algorithms cluster the common lecturers' timetabling process based on their preferences (soft constraints) and their demands based on the rules for their structure. Timetabling processes are performed based on clustering

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algorithms according to the structure of each clustering algorithm. After the clustering process, these clusters (common lecturers among faculties) are mapped to resources (timeslots/classrooms).

The optimal clustering of the common lecturers is performed to map to the resources for their timetabling (common lecturers) for one semester. The fuzzy C-mean clustering algorithm will have the best performance in forming our $U^{(0)}$ matrix between two funnel and K-mean algorithms since it is based on strong mathematical rules and calculations. The data set used to simulate the clustering algorithms are: 30 lecturers, 5 faculties (computer engineering, electrical engineering, civil engineering, humanities and mathematical sciences), 7 weekly timeslots (all weekdays), 7 daily timeslots (each day starts with 8:00-9:30 timeslot, and the remaining timeslots are 10:00-11:30, 11:30-13:00, 13:00-14:30, 15:00-16:30, 17:00-18:30) and the last timeslot will be 19:00-20:30) and there are 13 classrooms per faculty (3 practical classes and 10 theory classes).

The extension and development of the fuzzy C-mean clustering algorithm for common lecturers' timetabling among faculties is given in [37] in detail. The funnel clustering algorithm outperforms over k-means algorithm since it is not based on initial random choices in the formation of the $U^{(0)}$ matrix and instead it uses the intersection rule in algebra of sets. The use of the funnel clustering algorithm has been studied in [38] for common lecturers' timetabling among faculties. The k-mean algorithm among the funnel clustering algorithms and the fuzzy C-mean algorithm yields a non-optimal performance due to the existence of random structure and the existence of only two choices of zero or one for each of the events (common lecturers) in $U^{(0)}$ matrix. The development of the k-mean clustering algorithm to solve the problem of common lecturers' timetabling among faculties is presented in [39]. Table 1 shows a comparison of clustering algorithms based on the two objectives of minimizing waste of resources and descending satisfaction of soft constraints for common lecturers among faculties.

Table (1): Comparison of Clustering Algorithms

Research goals	Standard clustering Fuzzy c- means clustering	k-means clustering	The proposed clustering The proposed funnel-shape clustering
Waste minimization Faculties additional resources	41.288 %	26.16 %	32.55 %
Descending satisfaction of common lecturers priorities	38.6 %	28.1 %	33.2 %

Fuzzy Multi-criteria Decision Making Comparative Algorithm for (common) Lecturers among Faculty(s)

This section includes the use of fuzzy comparison for two events (based on the preferences and soft constraints of the lecturers). Here, all the lecturers (common) of faculties present a list of preferences (soft constraints) and their demands in the form of a mathematical fuzzy expression and they must be scheduled so that the (common) lecturers among faculties be mapped to resources (timeslots/classrooms). In this method, the (common) lecturers are compared in a fuzzy way according to their fuzzy demands as a pair and field-wise [40] and based on the highest preference (highest weight) the process of mapping those (common) lecturers to resources is done to schedule for one semester.

Fuzzy multi-criteria decision making comparison algorithm alone does not have powerful performance in optimal timetabling of faculty (common) lecturers due to the high volume of fuzzy comparisons with fast-growing events and requires an auxiliary algorithm such as local search with genetic algorithm.

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However, in [41] a full analysis of the way of events' comparison and decision-making is illustrated by the fuzzy multi-criteria decision-making algorithm. The data set used to simulate fuzzy multi-criteria comparative decision making algorithms, local search and genetics, respectively: 50 lecturers, 1 faculty (computer engineering), 7 weekly timeslots (all weekdays), 7 daily timeslots (each day starts with 8:00-9:30 timeslot, and the remaining timeslots are 10:00-11:30, 11:30-13:00, 13:00-14:30, 15:00-16:30, 17:00-18:30) and the last timeslot will be 19:00-20:30) and there are 5 classrooms per faculty (3 practical classes and 2 theory classes).

Hybrid Algorithm (Local Search/Genetic)

This section contains two local search and genetic algorithms that are used for common lecturers timetabling among faculties. The local search algorithm, with seven random mixed neighborhood structures relocates the common lecturers timeslots among faculties in the generated solution (timetable) to provide an optimality in the preferences (soft constraints) of the lecturers (common) among faculties. It can be said that the local search algorithm is a complement to fuzzy multi-criteria decision making and clustering algorithms. However, the application of the local search algorithm in [41] is used for the timetabling of a faculty's lecturers.

Genetic algorithm improves the generated solution (timetable) in the previous steps (i.e. output of fuzzy multi-criteria comparison algorithm, clustering algorithm and local search) using the intrinsic structure of an evolutionary algorithm. The genetic algorithm used in common lectures timetabling is presented and simulated in [41]. However, in [41], the violation of each faculty lecturer's rate per algorithm is that combining fuzzy multi-criteria decision making comparison algorithms with local search has the best performance and in turn the combination of fuzzy multi-criteria decision making comparison algorithms with genetic algorithm has the worst performance.

The genetic algorithm has to spend a large number of generations to optimally generate the solution (timetable), which here due to the existence of a mutation function it performs the random process in moving the scheduled lecturers from the timetable, after the third generation the generated solution (timetable) loses its optimality and efficiency and therefore the continuation of the genetic algorithm is avoided after the third generation. Table 2 summarizes the results of applying and combining fuzzy multi-criteria decision making algorithms with local search and genetic algorithms. Table 2 presents the number of penalties for lecturers' soft constraints violations and percentages of professors' violations according to each algorithm and the combination of the algorithms.

Table (2): Number of penalties for lecturers' soft constraints violations and percentages of lecturers' violations according to each algorithm

Algorithms	The numerical penalty of lecturers' violations	The percent of lecturers' violations (%)
FMDM-LS	−19	9.3
FMDM-LS-GA	−22	10.7
FMDM-LS-GA-LS	−35	13.7
FMDM	−50	24.4

FMCDM: Fuzzy Multi Criteria Decision Making
LS: Local Search, GA: Genetic Algorithm

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Discussion, Evaluation and Comparison Results

Based on discussions of literatures related to clustering algorithms, comparing fuzzy multi-criteria decision making and combining the obtained results according to [42], the combination of local search algorithm with fuzzy C-mean clustering algorithm has optimal results for satisfying the soft constraints of common lecturers among faculties and an individual use of fuzzy multi-criteria comparative decision making algorithm is less efficient than other algorithms and their combinations. Also, the percentage of waste of resources (time slots/classrooms) among faculties has good optimality in combination with fuzzy multi-criteria decision making algorithms and fuzzy C-mean clustering algorithms. In addition, the waste of resources is lower, while the combination of three algorithms of fuzzy multi-criteria decision making, local search and K-mean clustering has a higher percentage of wasted resources and is non-optimal.

According to [42], the application of clustering algorithms in common lecturers timetabling among faculties is in this way that the performance of the fuzzy C-mean clustering algorithm is higher than the two funnel and K-mean algorithms in terms of percentage of satisfied soft constraints of common lecturers among faculties. In addition, fuzzy C-mean clustering algorithm has lower waste of resource over two funnel and K-mean clustering algorithms in terms of percentage of our resource waste among the faculties. However, the funnel clustering algorithm outperforms the K-mean clustering algorithm in terms of percentage of satisfaction of soft constraints of lecturers and the percentage of resource waste among the faculties.

Overall, it can be said that the K-mean clustering algorithm is more inefficient than the fuzzy C-mean clustering and funnel algorithms in terms of percentage of satisfaction of soft constraints of lecturers and resources among faculties.

According to [42], the application of hybrid fuzzy decision making comparison algorithms (local search/genetic) in the problem of lecturers timetabling in a faculty is such that the average percentage of violations caused by each algorithm over the preferences (soft constraints) of lecturers in a faculty has the worst performance according to the combination of fuzzy multi-criteria decision making and genetic algorithms and in turn the combination of fuzzy multi-criteria decision making comparison algorithms with local search has the best performance. Tables 3 and 4 represent the comparison of the percentage of satisfying soft constraints of common lecturers among faculties and the percentage of resource waste among faculties by each algorithm, respectively.

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Table (3): Comparison of percentage of satisfying soft constraints of common lecturers among faculties by each algorithm

Algorithms	The percent of satisfying
	Common lecturers soft constraints satisfaction percent
FMCDM- K-means clustering	24%
FMCDM- Fuzzy c-means clustering	41%
FMCDM- Funnel shape clustering	35%
FMCDM	**17.64%**
Local search	41.4%
FMCDM- Local search- K-means clustering	19%
FMCDM- Local search- Fuzzy c-means clustering	44%
FMCDM- Local search- Funnel shape clustering	37%
Local search- K-means clustering	18%
Local search- Fuzzy c-means clustering	**54%**
Local search- Funnel shape clustering	28%
FMCDM: Fuzzy Multi-Criteria Decision Making	**Max = 54%**
	Min = 17.64%

Table (4): Comparison of percentage of resources waste among faculties by each algorithm

Algorithms	The percent of waste
	The waste percent of extra resources
FMCDM- K-means clustering	18%
FMCDM- Fuzzy c-means clustering	**4%**
FMCDM- Funnel shape clustering	8%
FMCDM	15.15%
Local search	23.75%
FMCDM- Local search- K-means clustering	**29.02%**
FMCDM- Local search- Fuzzy c-means clustering	16.37%
FMCDM- Local search- Funnel shape clustering	17.51%
Local search- K-means clustering	26.91%
Local search- Fuzzy c-means clustering	26.16%
Local search- Funnel shape clustering	16.22%
FMCDM: Fuzzy Multi-Criteria Decision Making	Max = **4%**
	Min = **29.02%**

According to [43], by combining clustering algorithms of fuzzy multi-criteria decision making comparison and hybrid (local search/genetic), it can be said that increasing the soft constraints of faculty lecturers has the best performance by applying and combining three algorithms of fuzzy multi-

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criteria decision making comparison, local search, and fuzzy C-mean clustering, and in turn, applying and combining two genetic and K-mean clustering algorithms has the worst performance in terms of satisfying soft constraints and preferences of a faculty lecturers. Table 5 presents the percentages of satisfaction of soft constraints of faculty lecturers by each given algorithm.

Table (5): Percentage of satisfaction of soft constraints of a faculty lecturers by each given algorithm

Algorithms	The percent of satisfying
	Lecturers soft constraints satisfaction percent
FMCDM- k-means clustering	19.03%
FMCDM- fuzzy c-means clustering	26.10%
FMCDM- funnel shape clustering	25.75%
FMCDM	28.00%
Local search	25.00%
FMCDM- Local search	48.00%
k-means clustering	28.00%
FMCDM- Local search- k-means clustering	39.06%
FMCDM- Local search- fuzzy c-means clustering	**48.04%**
FMCDM- Local search- funnel shape clustering	46.09%
Local search- k-means clustering	19.03%
Local search- fuzzy c-means clustering	26.10%
Local search- funnel shape clustering	25.75%
Genetic	5.00%
Local search- genetic	14.00%
Local search- genetic- k-means clustering	23.00%
Local search- genetic- fuzzy c-means clustering	26.50%
Local search- genetic- funnel shape clustering	24.00%
Genetic- k-means clustering	**4.02%**
Genetic- fuzzy c-means clustering	5.04%
Genetic- funnel shape clustering	5.80%
FMCDM : Fuzzy Multi Criteria Decision Making	**Max=48.04%** **Min=4.02%**

Conclusion

It can be said that the new algorithms that have been proposed in solving the UCTTP problem in recent years can make the opportunities of new ideas for researchers and scholars. However, the structure of the UCTTP problem itself can also be analyzed by the new meta-heuristic methods to achieve remarkable and better results than traditional solutions. It can be said that the introduction of clustering algorithms (K-mean, fuzzy C-mean and funnel) along with fuzzy multi-criteria comparison algorithms and hybrid (local/genetic search) and combining these algorithms according to the published literature represent significant results and evaluations of the UCTTP problem-solving approaches. According to the simulations and obtained results from sections 3 and 4, it can be said that in applying clustering algorithms, the efficiency of fuzzy C-mean clustering algorithm is higher than funnel and K-mean clustering algorithms in minimizing resource waste (surplus) and the descending satisfaction of the common lecturers' soft constraints among faculties. However, the optimal ratio of penalties for lecturers' soft constraints violations and the percentage of lecturers' violations among the FMCDM, LS, and GA algorithms and the combination of these algorithms are related to combining two FMCDM and LS algorithms. It should be noted that in comparison of the percentage of satisfying soft constraints of common lecturers among faculties, the combination of LS algorithm with fuzzy C-mean clustering has

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the best performance and in contrast, the single application of FMCDM algorithm has the worst performance.

On the other hand, the comparison of the percentage of resource waste (surplus) among faculties has the best result due to the combination of fuzzy C-mean clustering algorithms with FMCDM and the combination of FMCDM, LS and K-mean clustering algorithms has the worst result. Finally, it can be said that the percentage of satisfaction of faculty lecturers' soft constraints using by using the combination of FMCDM, LS and fuzzy C-mean clustering algorithms is more efficient than two genetic and K-means clustering algorithms.

It is recommended that researchers and scholars of computer science and engineering test, analyze and compare their various approaches with other existing approaches for future work in the field of UCTTP problem solving with approaches of machine learning and deep learning algorithms and expert systems and knowledge engineering.

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