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An Automated Task Assignment System for University Lecturers

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ABSTRACT

The aim of this research study was to develop an automated course assignment system for university lecturers using Mixed-Integer Linear Programming (MILP) with the objective of maximizing the planning score, which is derived from satisfaction scores and the total number of lecturers for all subjects. The study was conducted at the Faculty of Logistics, Burapha University, The study compared the model with the current approach over a period of two semesters. Three indicators were used to evaluate the performance: accuracy of allocation, teaching workload in credit allocation, and planning time. The results showed that the model outperformed the current approach in terms of accuracy of allocation and teaching workload in credit allocation. Specifically, it reduced workloads exceeding the minimum requirements by 2.92% and 14.78% per semester, respectively. Moreover, the model provided faster answers, with each iteration taking only 0.5-1 minute. The usability and satisfaction derived from using the model might not be explicitly clarified, but the model's results adhere to university regulations while also considering satisfaction as an important element within the objective function. Finally, this study successfully developed a model that effectively allocates tasks and reduces excessive workloads for university lecturers.

Keywords: Human Resource Allocation Problem; Task Assignment Problem; Mixed Integer Linear Programming; Optimization; Lecturer

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Introduction

Human resource management (HRM) is drastically essential in every organization, especially in this era. All companies are impacted by high competition and rapid changes in globalization. The Human Resource Allocation Problem (HRAP) [1] is one of the main problems affecting the company particularly within the service sector. Several research works from the last decade have studied this problem and implemented some analytical tools to analyze and make better decisions for HRM.

Teaching load and course schedule assignment is one of HRAP problems that is frequently used in universities. The challenging point is how to balance workload between lecturers and courses based on the resource limitation in each faculty or school. Additionally, load balancing should be appropriate and competitive with other schools. For example, the Faculty of Logistics at Burapha University revised the curriculum courses and subjects more than ten courses in year 2022, which is five more than in 2017, to serve all business and government sectors. This improvement impacts the human resource allocation of lecturers and subjects in the faculty. We can see that more than 120 subjects are required to allocate for 46 lecturers and 1,471 students with 26 groups in one semester. This problem is one of the hardest problems [1] to solve and defines an optimal solution.

Under the current assignment approach, the staff is responsible for assigning subjects for each semester and conducting surveys to gauge the preferences of lecturers regarding their subjects. Subsequently, the staff arranges meetings with all lecturers to confirm the subject assignments for each of them. However, it has been observed that the outcomes of this approach do not align with the university's policies for certain lecturers. This can result in assignments that exceed or lower requirements, ultimately leading to lower levels of lecturer satisfaction.

Furthermore, the current approach consumes a significant amount of time. Meetings often remain inconclusive because the outcomes do not always align with the preferences of lecturers, necessitating the scheduling of additional meetings to resolve issues. Observations indicate that these meetings typically last more than one hour each.

Regarding all mentioned problems above, we propose an automated task assignment system for university lecturers to fix the HRAP problem in the lecturer and subject load balancing context. This system will not only increase the efficiency of human resource allocation; it will also be the first modular system for other faculties in the university to manage their lecturer and subject loads.

Research Methodology

This research study focuses on the human resource allocation problem (HRAP) and aims to provide a comprehensive literature review on this subject. By exploring the HRAP and its main resolution approaches, literature review, and methodology, this research aims to contribute to the understanding of HRAP and provide insights into more effective allocation strategies. The study seeks to advance knowledge in this area and identify potential avenues for future research in human resource allocation.

1.Human Resource Allocation Problem

The Human Resource Allocation Problem (HRAP) has been extensively studied in the field of operations research and management science. Various approaches and techniques have been proposed to address this complex assignment problem, considering different objectives and constraints. This literature review [1] provides a comprehensive overview of the existing research on HRAP, focusing on both mono-objective and multi-objective formulations. The distinction between these methods is based on their respective objectives. The mono-objective approach primarily aims to minimize the cost incurred when assigning each job to a worker. Conversely, the multi-objective approach not only seeks to minimize costs, like the mono-objective approach, but also places emphasis on maximizing profit. The equation representing this objective trade-off is presented below.

Indices

i = Index of job (i = 1,2,...,n)

j = Index of the worker (j = 1,2,...,m)

Parameters

X = Set of jobs

Y = Set of workers

n = Total number of jobs

m = Total number of workers

c_{ij} = Cost of job i when worker j is assigned

p_{ij} = Profit of job i when worker j is assigned

Decision variables

x_{ij} = 1, if worker j is assigned to job i

or

x_{ij} = 0, otherwise

1.1. Mono-Objective

$$\min \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij} x_{ij} \quad (1.1.1)$$

Subject to

$$\sum_{j=1}^{m} x_{ij} = 1 \qquad \forall i \in X \quad (1.1.2)$$

$$\sum_{i=1}^{n} x_{ij} = 1 \qquad \forall j \in Y \quad (1.1.3)$$

$$x_{ij} = 0 \text{ or } 1 \qquad \forall i \in X, j \in Y \quad (1.1.4)$$

(1.1.1) The objective function for minimizing the total cost of all jobs when assigning them to workers.

(1.1.2) The constraints for each job need one worker.

(1.1.3) The constraints for each worker need one job.

(1.1.4) The decision variable is binary.

1.2. Multi-Objective

$$\min \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij} x_{ij} \quad (1.2.1)$$

$$\max \sum_{i=1}^{n} \sum_{j=1}^{m} p_{ij} x_{ij} \quad (1.2.2)$$

Subject to

$$\sum_{j=1}^{m} x_{ij} = 1 \qquad \forall i \in X \quad (1.2.3)$$

$$\sum_{i=1}^{n} x_{ij} = 1 \qquad \forall j \in Y \quad (1.2.4)$$

$$x_{ij} = 0 \text{ or } 1 \qquad \forall i \in X, j \in Y \quad (1.2.5)$$

(1.2.1) The first objective function for minimizing the total cost of all jobs when assigning them to workers.

(1.2.2) The second objective function for maximizing the total profit of all jobs when assigning them to workers.

(1.2.3) The constraints for each job need one worker.

(1.2.4) The constraints for each worker need one job.

(1.2.5) The decision variable is binary.

From sections 1.1 and 1.2, the main formulation of both methods shows that the structure of the formulations does not differ significantly. The clear distinction between them is based on the objective function. In the case of the mono-objective approach, there is only one objective, which is to minimize the cost (1.1.1). On the other hand, the multi-objective approach also seeks to minimize costs (1.2.1) but additionally includes another objective, which is to maximize profit (1.2.2). However, the main formulations do not differ in terms of the constraints.

2.The main resolution approaches for human resource allocation problem

In the literature [1], various methods from the fields of operational research and computer science have been proposed to address the HRAP problem. These methods can be categorized into several types, including Exact Methods, Heuristic Algorithms, Metaheuristic Methods, and Hybridization Methods, each aiming to find an optimal solution in different ways. In the subsequent discussion, highlighting the key literature that is most relevant to the HRAP.

2.1. Exact Methods

The exact method aims to find the best solution for the problem, making it particularly suitable for small-scale problems with a limited number of variables. However, the effectiveness of this solution can be influenced by the complexity of the problem. In a research study [2], the Hungarian method was employed to provide a solution for assigning teachers to different courses within the HRAP. Linear programming can be used to formulate HRAP, as discussed in another research study [3], which explores the generalization of a linear programming model for various human resource problems. Additionally, the goal programming method is utilized in a study [4] that specifically addresses the teacher assistant-task assignment problem within the HRAP.

2.2. Heuristic Algorithms

Heuristic algorithms are utilized in cases where the exact method fails to provide a solution or becomes impractical due to extensive computation time. These algorithms offer approximate solutions that are considered acceptable, even though they may not guarantee optimality. They are particularly useful in situations where finding the best solution is difficult or time-consuming. Furthermore, heuristic methods have been successfully employed to address larger instances of the assembly line worker assignment and balancing problem (ALWABP) in various studies [5-7]. In one study [7], the objective function aims to maximize the cumulative throughput rates of each assembly line.

2.3. Metaheuristic Methods

Metaheuristic methods offer a practical approach to tackling highly complex problems within reasonable time constraints. These methods have gained widespread recognition in numerous research studies as they provide solutions that are close to optimal or sufficiently good for practical purposes.

One prominent metaheuristic algorithm is simulated annealing (SA), which draws inspiration from the annealing process of solids. SA employs hill-climbing moves to escape local optima and search for global optima. In the context of the HRAP, a study [8] focused on balancing the workload by assigning teachers to courses and course sections. The SA method was used and compared with tabu search. Another study [9] introduced a modified simulated annealing algorithm (MSA) that aimed to converge faster by incorporating a parabolic exponential temperature decrease function instead of the traditional linear exponential temperature decrease function.

The ant colony optimization algorithm, inspired by the behavior of ants, is designed to find optimal paths through graphs. In a research study [10] addressing timetabling course problems, variants of ant colony optimization known as the best-worst ant system (BWAS) and the best-worst ant colony system (BWACS) were proposed. These variants were integrated into an ant colony-based timetabling (ANCOT) tool specifically developed for solving timetabling problems.

Tabu search (TS), a metaheuristic algorithm, utilizes local search to address optimization problems. It overcomes the challenge of local optima by incorporating a memory mechanism called the tabu list. The tabu list records the search history and visited solutions, preventing the algorithm from revisiting them in subsequent iterations. Tabu search has been applied to various HRAP-related problems. For instance, a study [11] employed TS to solve the timetabling problem, while another study [12] utilized it in the context of a production system with parallel machines and multi-skilled workers for assignment purposes.

Particle Swarm Optimization (PSO), inspired by swarm intelligence observed in bird and fish flocks, is another popular metaheuristic used to address the HRAP. A study [13] aimed to assign m workers to n jobs, maximizing benefits while minimizing total costs. They employed a modified binary particle swarm optimization (mBPSO) algorithm and compared the solutions obtained with those derived from ant colony optimization (ACO) and hybrid genetic algorithms (hGA), showcasing the performance and effectiveness of these methods.

2.4. Hybridization Methods

Hybridization is a methodology that combines different tools and techniques from various approaches to enhance the efficiency of finding solutions in human resource management. By leveraging the strengths of multiple methods, hybrid algorithms offer increased flexibility, adaptability, and effectiveness. For instance, in a specific study [14], the hybridization of Ant Colony Optimization (ACO) with the Simplex method improved task allocation among multi-project staff with varying skills. Another study [15] combined Ant Colony Optimization and Genetic Algorithms to address resource allocation in project management, demonstrating competitive results compared to using the individual metaheuristics separately. Additionally, research [16] proposed a hybrid approach that integrated the Constraint Satisfaction Problem with the Backtracking Search Algorithm for efficient human resource allocation in healthcare systems. Overall, hybridization provides a powerful approach to tackle human resource management challenges, offering enhanced efficiency and effectiveness in finding optimal solutions.

3.Literature review

3.1. Resource allocation

The first research [[17studied about the task assignment problem of employees in the healthcare industry. This problem came from varied customer demands and the uncertain number of employees, including the priority of different works. In addition, Mixed Integer Linear Programming (MILP) was implemented to solve this problem considering weight score of the most popular task, task schedule with sufficient hours and lowest standard deviation, and balance with task schedule during holidays. Scholars conducted experiments using the method in the healthcare industry in Belgium. The results showed that MILP could propose an optimal solution of task assignment.

The second research [18] studied the human resource assignment problem for developing software. This problem impacted directly to the successful rate of the project such as on-time product launching, or product's quality. Even though there were several solutions to solve this problem, some factors were not considered to fix the problem. Therefore, the solution was not optimal or suitable with the real situation. Moreover, Integer Linear Programming (ILP) was formulated to solve this problem. The objective function was the maximum customer satisfaction level with some relevant constraints such as lowest total cost, highest efficiency level with and without consideration of budget. The results showed that an ILP model can discover an optimal solution of human resource assignment for developing software.

These existing works demonstrate that resource allocation has been studied in various domains. One interesting aspect is the implementation of resource allocation to discover optimal allocation solutions for high-skilled labor.

3.2. High-Skilled Labor Resource Allocation

The first research [[19studied the workforce optimization problem, which involves matching highly skilled individuals to available positions. This problem can lead to issues such as understaffing, underqualification, or overqualification of the workforce. Constraint programming was utilized as the tool to address this problem, and the results demonstrated that it effectively handled all the constraints and provided solutions close to the optimal solution. The model employed two types of work: prioritized matching, where recommended jobs were approved by candidates, and assignment, where the best job was automatically selected. The study utilized the IBM dataset, which comprised 24,480 candidates and 703 jobs, and the calculation time required was 146 seconds.

The second research [20] studied the medical staff allocation problem in an uncertain environment. The challenges were various factors, such as number of work hours, shift type, the medical staff skill and number of patients. This paper designed a two-stage method combining Linear Programming (LP) and Analytic Hierarchy Process (AHP) to resolve integrated staff allocation and scheduling problems in a case study. The experiment was separated into 2 steps. The first step had objective functions regarding minimizing the number of medical staff, then bringing an answer to manage and find the best schedule in the second step. This paper used an AHP for weighting all factors that affected this problem. The results showed that a model can find an optimal solution and reduce planning time from the manual process by around 1-2 days.

The study highlights that high-skilled labor resource allocation is a complex issue due to the involvement of various job types, employee categories, and skill sets. The field of education also faces this challenge. Effectively assigning tasks to employees necessitates careful consideration of both cost and qualifications simultaneously.

3.3. Staff Allocation in Education Field

The first research [21] studied the Teacher Assignment Problem (TAP) in the school of Industrial Engineering of Barcelona, Universitat Politècnica de Catalunya. The objective function was balancing teachers' teaching load and maximizing teachers' preferences. This problem is challenging because the School of Industrial Engineering is the largest school in this university. So, all the data for this model is huge and complex. This paper identified two main components of this problem: subjects and teachers were analysed. This paper used Mixed Integer Linear Programming (MILP) to solve this problem. The first answer involved balancing teachers' loads by minimizing the standard deviation of the TAP assignment, and the second answer was adjusting the weight of each parameter to maximize teachers' preferences. The results showed that a MILP model could discover an optimal solution, but this model was suitable for problems that have ten or more teachers and around 40-20 subjects. In the case of fifty or more teachers, this model couldn't discover an optimal solution.

The second research [22] studied the Tutor Allocation Problem (TAP) in the school of mathematics, University of Edinburgh. The objective involves assigning a set of tutors and a set of workshops to maximize tutors' preferences. Various tutors' preferences, students and workshops affect the complexity of this problem. This paper applied Integer Linear Programming (ILP) to solve this problem and conducted an experiment into three parts. The first part, an ILP model solved this problem with tutors' preference equal to 60 percent and increasing from the current solution equal to 29 percent. However, this experiment highlighted the challenge of balancing tutors' preferences between satisfied and unsatisfied tutors. The second part was focused on balancing tutors' preferences and discovering a good answer. And the third part, a conflict arose between tutors' preferences and the quantity of workload. Finally, the data was simulated in this paper to measure the performance of an ILP model, which could solve problems involving 1,500 tutors and 600 workshops.

Based on the literature review, this study identified a gap and developed the mathematical model for solving the high-skilled labor resource allocation in the Thai education field. In the related research on resource allocation techniques, it was found that both integer programming models [18] and mixed integer models [17] have been utilized. However, the objective considered in these models was maximizing satisfaction without considering cost objectives. Regarding research on high-skilled labor resource allocation, it was observed that the models used in the studies [20] also considered a mono objective, such as minimizing the number of personnel, rather than incorporating cost considerations. Finally, in the research related to education resource allocation, it was found that models were developed using linear programming techniques. Some studies [21] considered multiple objective functions, including minimizing total cost, and minimizing standard deviation of differences among the minimum workloads. These studies concluded that both objectives lead to the highest satisfaction. This study suggests that this gap in the literature can be addressed by incorporating lecturer satisfaction as part of the objective function, aligning with the preferences and needs of the lecturer.

This study seeks to incorporate credits received from subject assignments into the model, as workload balancing in the Thai education field takes credit into account.

Table 1 presents a condensed overview of the literature reviewed in this research, highlighting crucial aspects such as the research field, methodology, and the number of objective functions employed in each study.

Table 1 Summary of the literature review

Author	Field		Method	Objective Function	
	Education	Other		Mono-Objective	Multi-Objective
(Naveh et al., 2007)		✓	Constraint Programming		✓
(Fikri et al., 2011)		✓	Hybridization Method ,Ant Colony Optimization, Simplex Method	✓	
(Gunawan & Ng, 2011)	✓		Metaheuristic Method ,Simulated Annealing		✓
(Ammar et al., 2012)		✓	Metaheuristic Method ,Tabu Search	✓	
(Costa Filho et al., 2012)		✓	Hybridization Method, Constraint Satisfaction Problem, Backtracking Search	✓	
(Moreira et al., 2012)		✓	Heuristic Algorithms	✓	
(Xian-Ying, 2012)	✓		Exact Method, Hungarian Method	✓	
(Azimi et al., 2013)		✓	Exact Method, Linear Programming	✓	
(Fan et al., 2013)		✓	Metaheuristic Method,Particle Swarm Optimization		✓

Table 1 Summary of the literature review (continue)

Author	Field		Method	Objective Function	
	Education	Other		Mono-Objective	Multi-Objective
(Kyriklidis et al., 2014)		✓	Hybridization Method, Ant Colony Optimization, Genetic Algorithms		✓
(Swangnop & Chaovalitwongse, 2014)	✓		Metaheuristic Method, Tabu Search	✓	
(Thepphakorn et al., 2014)	✓		Metaheuristic Method ,Ant Colony Optimization	✓	
(Araujo et al., 2015)		✓	Heuristic Algorithms	✓	
(Güler et al., 2015)	✓		Exact Method, Goal Programming	✓	
(Moreira et al., 2015)		✓	Heuristic Algorithms	✓	
(Odeniyi et al., 2015)	✓		Metaheuristic Method, Simulated Annealing, Tabu Search	✓	
(Chen et al., 2016)		✓	Exact Method, Linear Programming , Analytic Hierarchy Process (AHP)	✓	
(Domenech & Lusa, 2016)	✓		Exact Method, Mixed-Integer Linear Programming		✓
(Ağralı et al., 2017)		✓	Exact Method, Mixed-Integer Linear Programming	✓	

Table 1 Summary of the literature review (continue)

Author	Field		Method	Objective Function	
	Education	Other		Mono-Objective	Multi-Objective
(Chiang & Lin, 2020)	✓		Exact Method, Integer Linear Programming	✓	
(Caselli et al., 2022)		✓	Exact Method, Integer Linear Programming	✓	

4. Methodology

This research aims to investigate various aspects related to the allocation of human resources at the Faculty of Logistics, Burapha University. The study focuses on the following key objectives:

1) Understanding the criteria and policies used to determine workload allocation in the faculty's case study.

2) Identifying factors significantly associated with the allocation of human resources.

3) Developing a mathematical model that effectively optimizes resource allocation.

4) Exploring the current resource allocation process within the faculty and designing an efficient and accurate system, including a streamlined workflow for staff involved.

5) Utilizing Mixed-Integer Linear Programming (MILP) to create a suitable mathematical model for resource allocation.

6) Evaluating the developed model based on three performance indicators include accuracy of allocation, proximity to minimum teaching workload in credit allocation, and reduced planning time.

These objectives will guide the research and contribute to a comprehensive understanding of resource allocation in the Faculty of Logistics, Burapha University.

4.1. Factors Related to Teaching Resource Allocation

Teaching resource allocation is a complex and challenging problem that involves maintaining a balance in workload allocation. Additionally, it requires considering the expertise and satisfaction of teachers. The following factors are identified as relevant to teaching resource allocation:

1) Number of teachers: The number of teachers is a crucial factor that affects the allocation of teaching resources, particularly in terms of individual workload. Sufficient

teacher-to-subject ratios lead to more balanced workloads. Conversely, a shortage of teachers compared to the number of subjects can result in excessive workloads, leading to decreased satisfaction among teachers and reduced teaching effectiveness.

2) Teacher expertise: Teacher expertise refers to their proficiency or experience in different subjects, which may come from educational background, work experience, academic achievements, or teaching experience. It is assumed that allocating teachers according to their expertise enhances their satisfaction and improves teaching effectiveness. However, this factor requires regular evaluation and clear criteria for assessing expertise in each subject.

3) Teaching workload per semester: The teaching workload per semester for each teacher is a condition that influences the allocation of teaching resources. For example, teachers with administrative responsibilities may have lighter teaching loads compared to those without administrative duties. The teaching workload per semester should meet the minimum required allocation for each teacher, considering the credit units. It is crucial to avoid excessive teaching workloads that could negatively impact teacher satisfaction.

4) Number of subjects in each curriculum: In different programs may have varying sequences and numbers of subject. This factor also affects the allocation of teaching resources. If the number of subjects does not align with the number of teachers, it may lead to an improper allocation of teaching workload.

5) Number of students in each curriculum: The number of students enrolled in each program directly impacts the subject and the number of student groups. Some subjects may have limitations on the number of students per class, requiring the formation of multiple teaching groups. This factor affects the calculation of teaching workload.

In addition to the mentioned factors, other elements such as joint teaching workload in the same subject can also influence teaching resource allocation. Therefore, to develop an effective mathematical model to address this issue, it is essential to consider a comprehensive set of factors related to teaching workload allocation.

4.2. Teaching Resource Allocation in Case Study

Based on the study conducted on the allocation of teaching resources in Faculty of Logistics, Burapha University, the following findings can be summarized:

1. Faculty Members

- In the academic year 2022, the faculty had a total of 57 members, including 32 full-time faculty and 25 contract members. There are 26 available full-time lecturers for this academic year. The unavailable members are on leave for studying and cannot teach during this academic year.

- The minimum workload for all full-time members per semester is 240 credits, ranging from 3 to 9 credits per person.

2. Course Information

- In the academic year 2022, the first semester had 74 subjects with 351.90 credits and the second semester had 99 subjects with 400 credits.
- Each course specifies the lecturers who are capable of teaching. However, the satisfaction score is derived from the survey conducted before the start of the new semester, as explained in the forthcoming section of the mathematical model. parameter $\mathbf{S_{ij}}$, represents the satisfaction score of subjecti when lecturer j is assigned.

3. Curriculum and Section

- Faculty of Logistics offers a total of 40 sections, categorized by curriculum and academic year level.
- The total number of students in this faculty is 2,291.

4. Calculation of Teaching Workload and Credits Received

- In general, each subject has no more than 3 persons, except for some courses taught by a team of faculty members.
- The teaching workload calculation is divided into 3 categories: a subject taught by 1 person receives 100% workload, a subject taught by 2 persons receives 50% workload per person, and a subject taught by 3 persons receives 33.33% workload per person.
- The teaching workload carries significant implications for the credits that each lecturer will receive from each subject, as explained in the forthcoming section of the mathematical model. The parameter $\mathbf{C_{ij}}$, representing the credits of subject i when assigned to lecturer j, is calculated using the following solution.

Regarding the calculation of credits received, there are 4 different scenarios based on the inclusion or exclusion of groups and the number of students:

- In the case of excluding groups and less than or equal to 40 students:

Credits received per person = Total credits * Workload percentage received

- In the case of excluding groups and more than 40 students:

Credits received per person = [Total credits * (Number of students / 40)] * Workload percentage received

- In the case of including groups and less than or equal to 40 students:

Credits received per person = (Total credits * Workload percentage received) * (Number of students / Total number of students in all groups)

- In the case of including groups and more than 40 students:

Credits received per person = [(Total credits * (Number of students / 40)) * Workload percentage received] * (Number of students / Total number of students in all groups)

4.3. Mathematic Model

Indices

i = Index of subject (i = 1,2,...,n)

j = Index of the lecturer (j = 1,2,...,m)

Parameters

X = Set of subjects

Y = Set of lecturers

n = Total number of subjects

m = Total number of lecturers

M= Coefficient of satisfaction score

t = Minimum ratio

$\mathrm{p_i}$ = Minimum lecturers of subject i

$\mathrm{q_i}$ = Maximum lecturers of subject i

$\mathrm{u_j}$ = Minimum credits of lecturer j

$\mathrm{v_j}$ = Maximum credits of lecturer j

$\mathrm{s_{ij}}$ = Satisfaction score of subject i when lecturer j is assigned

$\mathrm{c_{ij}}$ = Credits of subject i when lecturer j is assigned

Decision variables

$\mathrm{k_{ij}}$ = 1, if lecturer j is assigned to subject i

or

$\mathrm{k_{ij}}$ = 0, otherwise

$\mathrm{r_{ij}}$ = the ratio of workload that lecturer j is assigned to subject i

Objective Function

$$\max \sum_{i=1}^{n} \sum_{j=1}^{m} s_{ij} r_{ij} - \sum_{i=1}^{n} \sum_{j=1}^{m} k_{ij} \quad (1)$$

Subject to

$$\sum_{j=1}^{m} k_{ij} \geq p_i \qquad \forall i \in X \quad (2)$$

$$\sum_{j=1}^{m} k_{ij} \leq q_i \qquad \forall i \in X \quad (3)$$

$$k_{ij} \leq Ms_{ij} \quad \forall i \in X, j \in Y \tag{4}$$
$$k_{ij} \geq r_{ij} \quad \forall i \in X, j \in Y \tag{5}$$
$$\sum_{j=1}^{m} r_{ij} = 1 \quad \forall i \in X \tag{6}$$
$$r_{ij} \geq t \quad \forall i \in X, j \in Y \tag{7}$$
$$\sum_{i=1}^{n} c_{ij} \geq u_j \quad \forall j \in Y \tag{8}$$
$$\sum_{i=1}^{n} c_{ij} \leq v_j \quad \forall j \in Y \tag{9}$$
$$k_{ij} = 0 \text{ or } 1 \quad \forall i \in X, j \in Y \tag{10}$$
$$r_{ij} \leq 1 \quad \forall i \in X, j \in Y \tag{11}$$

(1) The objective function for maximizing the total assigning score with two components, the satisfaction score of all subjects when assigning them with ratio to lecturers and the number of assigning lecturers.

(2) The constraints for each subject need minimum lecturers.

(3) The constraints for each subject need maximum lecturers.

(4) The constraints for each subject need an available lecturer who can teach.

(5) The constraints for each subject can identify the ratio when this subject was selected.

(6) The constraints for each subject need a total ratio equal to 1 or 100%.

(7) The constraints for each subject need a minimum ratio per lecturer.

(8) The constraints for each lecturer need minimum credits.

(9) The constraints for each lecturer need maximum credits.

(10) The decision variable is binary.

(11) The ratio constraints. The ratio must be less than or equal to one.

In Equation 1, there are two main components: the first component is the satisfaction score, calculated based on the workload ratio, and the second component is the total assigned lecturers. The objective is to minimize the total number of selected lecturers, leading to a proportional allocation that is deemed necessary. This approach is especially relevant when dealing with situations where multiple lecturers may be assigned to teach a single subject, which adds complexity to the management process compared to assigning only one lecturer per subject. If the focus is only on maximizing satisfaction, the model may opt to allocate multiple lecturers to a subject to maximize the score according to the objective function.

The constraints governing the number of lecturers for each subject are outlined in Equations 2 and 3. This model allows for the establishment of both minimum and maximum lecturer counts prior to problem-solving. Equation 4 introduces a constraint that links the decision variable (k_{ij}) to the satisfaction score (s_{ij}). Specifically, the decision variable can only assume a value of one when the satisfaction score is greater than zero, signifying lecturer satisfaction in that subject.

This model effectively simulates real-world scenarios. In instances involving multiple lecturers within a single subject, Equation 3.5 serves as a constraint for each subject's ratio when selected. Furthermore, the total ratio in each subject must sum to 1 or 100%, as dictated by Equation 6. In cases involving multiple lecturers, Equation 7 can establish a minimum ratio per lecturer, ensuring a fair distribution of the workload.

University regulations stipulate minimum and maximum credit requirements for each lecturer per semester, with values varying based on workload considerations, such as managerial responsibilities. If a lecturer serves on the faculty management board, the minimum teaching credits are set lower than those for general lecturers. To address this, our model incorporates two constraints, as specified in Equations 8 and 9, ensuring compliance with all requirements.

For the preparation of lecturer satisfaction data, this research has received approval from the academic department of the Faculty of Logistics at Burapha University. The teaching history data for all regular lecturers, covering a total of 4 semesters, including Semester 1 of the academic year 2021, Semester 2 of the academic year 2021, Semester 1 of the academic year 2022, and Semester 2 of the academic year 2022 , were collected. The satisfaction scores will range from 0 to 1, resulting from the transformation of various satisfaction levels. A score of 1 indicates that the lecturer is highly satisfied with teaching that subject, while a score of 0 means the lecturer is least satisfied or not satisfied at all. In cases where multiple lecturers gave the same satisfaction score for the same subject, the model allocated them randomly, considering the highest total satisfaction score under all constraints.

4.4. Evaluation

The research aims to compare the efficiency of the model with the current method of resource allocation in teaching. The evaluation criteria include accuracy of allocation, proximity to minimum teaching workload in credit allocation, and reduced planning time. The study assesses the model's performance in these aspects to determine its effectiveness compared to the current method.

For the usability model, this research has compared the different processes between the current approach and the model, but it has not included criteria for this aspect. The satisfaction score from the model cannot be directly compared and evaluated with the current approach because the current approach has not collected satisfaction scores from the assignment plan. However, the satisfaction score is an important element and part of this model. Therefore, the assignment results from the model will be planned with the objective function of maximizing the total satisfaction score of all subjects when assigning them in relation to lecturers and considering the lecturer's satisfaction.

4.5. Tools

OpenSolver [23] is an open-source tool for solving linear, non-linear, and integer optimization problems. It has the advantage of integration with spreadsheet software such as Microsoft Excel and Google Sheets. It is capable of handling large-scale problems with a high number of variables and constraints, and it is also free to use.

This research chose OpenSolver as the tool for developing an automated teaching resource allocation system because of its strong compatibility with Microsoft Excel, which is used for storing data related to teachers, courses, and subjects in the traditional allocation process.

4.6. Approach for Developing an Automated Task Assignment System for University Lecturers

This research designed a new process for planning the teaching resource allocation. The process is as follows:

1) Survey and collect all necessary data for model processing, including lecture information.

2) Identify the expertise of lecturers or create a list of lecturers qualified to teach specific courses.

3) Identify lecturers' satisfaction levels score for each different subject.

4) Process the teaching resource allocation using OpenSolver.

5) Validate the allocation result with all constraints, such as minimum teaching workload requirements.

6) If the allocation meets the constraints, utilize the results to create a teaching timetable.

7) In cases where the allocation does not meet the constraints, repeat steps 2 and 3, potentially refining the data for specific lecturers or subjects.

8) The output will be a list of courses that each lecturer is assigned to teach in each semester.

Results and Discussion

This research involved testing a mathematical model with real allocation data from Faculty of Logistics, Burapha University during two semesters: the first semester of the academic year 2022 and the second semester of the academic year 2022. The selection criteria were as follows:

1) Only subjects under Faculty of Logistics, Burapha University, were considered.

2) Only subjects that had a full time lecturer from Faculty of Logistics, Burapha University, during the first semester of the academic year 2022 to the second semester of the academic year 2022 were selected.

Based on these criteria, a total of 136 subjects met the requirements, with 74 subjects in the first semester of the academic year 2022 and 62 subjects in the second semester of the academic year 2022.

For the preparation of lecturer satisfaction data, the research obtained approval from the academic department within the Faculty of Logistics at Burapha University. The teaching history of twenty-six full-time lecturers for four semesters was compiled, which included the first semester of the academic year 2021, the second semester of the academic year 2021, the first semester of the academic year 2022, and the second semester of the academic year 2022. This research focuses solely on the twenty-six full-time lecturers available for assignment during these semesters. It does not include the unavailable lecturers on study leave, nor does it account for the contract lecturers, who are subject to different regulations as stipulated by the university. As explicit satisfaction scores were not recorded, the research converted this information into scores, assigning a value of 1 if the instructor had previously taught the subject and 0 if the instructor had not. It's worth noting that this model can accommodate various scales of satisfaction scores in the future with more reliability. It is not limited to computing solely from historical data and transforming them into a standardized 0 to 1 scale. In cases where instructors selected the same subject, the model randomly allocated subjects while considering the highest total allocation score and adhering to specified conditions.

The study compared three performance indicators include accuracy of allocation, proximity to minimum teaching workload in credit allocation, and reduced planning time. The results of the testing are as follows:

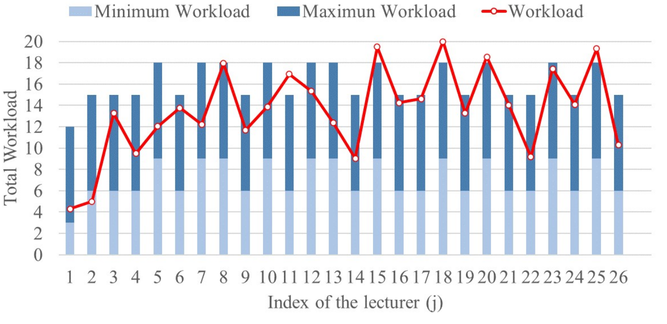

Figure 1 The total credits by the current approach, Semester 1, Academic Year 2022

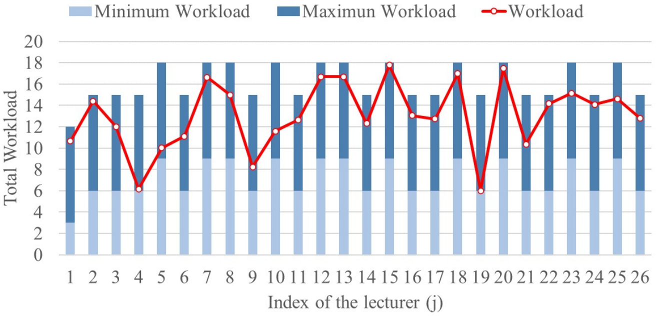

Figure 2 The total credits by the model, Semester 1, Academic Year 2022

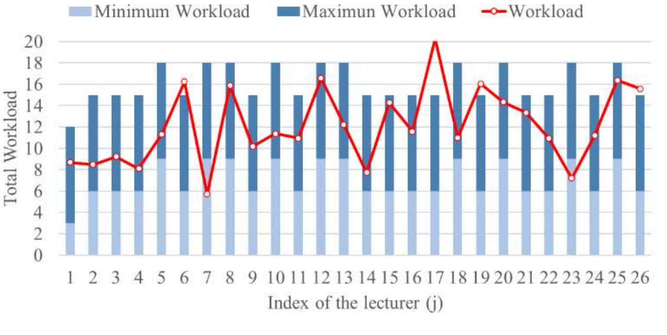

Figure 3 The total credits by the current approach, Semester 2, Academic Year 2022

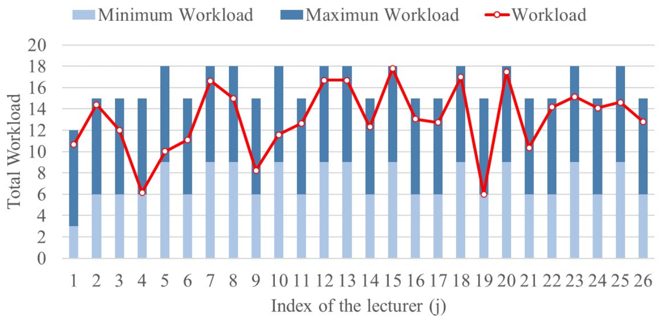

Figure 4 The total credits by the model, Semester 2, Academic Year 2022

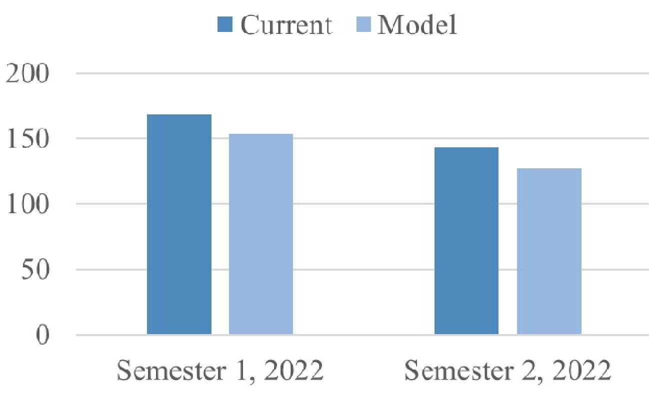

Figure 5 The total credits over the requirement by the current approach and the model, Academic Year 2022

1) Accuracy of Allocation

Each member is assigned a minimum and maximum workload, and this indicator assesses the accuracy of the workload allocation. Each member should be allocated a workload within the specified range, neither below nor above the target workload. The results indicate that the model successfully allocated subjects accurately in both semesters.

When we examine the total number of members whose workload fell below or exceeded the requirements, as shown in Figures 2 and 4, the model ensured that no member received an allocation below or above the target workload. However, when we look at Figures 1 and 3, the current approach failed to allocate subjects correctly according to all criteria, resulting in 6 members in both semesters not being allocated in accordance with the requirements. For instance, in Figure 1, Lecturer No. 2 has a minimum credit requirement of 6 credits, but the current approach assigns only 5 credits for this semester. Similarly, Lecturers No. 8, 11, 15, 18, 20, and 25 do not meet the university regulations, as they are either assigned fewer credits than the specified minimum or higher credits than the specified maximum. When considering Figure 3, it is observed that in this semester, 6 members do not meet the requirements: Lecturers No. 6, 7, 17, 19, 23, and 26. However, the model's results show that all requirements are met for both semesters.

In terms of accuracy, the model achieved a perfect score of 100 percent, surpassing the current approach, which had an accuracy rate of 79.62 percent.

2) Teaching Workload in Credit Allocation

The minimum workload for each lecturer is contingent on the regulations and administrative workload for each semester, spanning from 3 to 9 credits. Consequently, the allocated credits should closely align with the minimum workload of each member, with any surplus credits being categorized as additional teaching workload.

Figure 5 illustrates that the model successfully achieved a workload allocation that closely matched the minimum requirements of each member in both semesters, surpassing the performance of the current approach. In the first semester, the minimum credit that require equal to 186 credits. The model allocated a total of 153.50 credits above the requirement, while the current system allocated 167.90 credits, indicating a reduction of 14.40 credits. When we compare the percentage of total credits exceeding the requirement, the model achieved 85.14%, whereas the current approach achieved 88.06%, reflecting a decrease of 2.92%.

In the second semester, the minimum credit that require equal to 183 credits. The model allocated 126.89 credits above the requirement, whereas the current system allocated 143.07 credits, resulting in a reduction of 16.18 credits. The percentage of total credits exceeding the requirement for the model was 68.36%, in contrast to 83.14% in the current system, signifying a decrease of 14.78%.

It's important to note that some lecturers may experience variations in their total workload compared to the current approach. Although this model does not possess a direct parameter for workload balancing, it operates based on an assignment plan that aligns with the university's regulations.

3) Planning Time

In the current approach, the allocation process requires meetings with all professors, typically held 1-3 times per semester and 1-2 hours each. In contrast, the model can allocate workload within 0.5-1 minute per session, depending on the number of lecturers and total subjects. However, data preparation for the model also takes a reasonable amount of time. Each lecturer needs to specify the subjects they are interested in and can teach, along with their previous teaching history provided by the faculty staff. Therefore, if we only measure the processing time, the model provides faster results. However, if consider the entire process, there is no clear answer as to which method is faster. This aspect requires real-world testing and comparison with the current approach.

In the model's output, all lecturers receive a subject list that has been assigned to them for each semester. Tables 2 and 3 display the subject lists for Lecturer No.6 in the same semester, but through different approaches.

Table 2 The current approach result of Lecturer No.6, The second semester of the 2022 academic year.

Lecturer No.6		
Subject	Percentage of Workload	Credits Received
Operation Management Section 1	100.00	5.93
Logistics Inspiration	12.00	0.98
Freight Transport and Distribution Section1	100.00	8.18
Preparation for Careers	15.53	1.15
Total Credits Received		16.24
Managerial Credits Received		3.00
Total Gross Credits Received		19.24

In the current approach for Lecturer No.6 in the second semester of the 2022 academic year (Table 2), it was found that Operations Management Section 1 was assigned with a workload percentage of 100%. This indicates that Lecturer No.6 was the single lecturer, and the total credit allocated was 5.93. Furthermore, Logistics Inspiration was assigned with a workload percentage of 12%, signifying that Lecturer No.6 co-taught the subject, with a total of 0.98 credits. Additionally, Freight Transport and Distribution Section 1 had a workload percentage of 100%, indicating that Lecturer No.6 was the single lecturer, with a total of 8.18 credits. Lastly, Preparation for Careers had a workload percentage of 15.53%, meaning that Lecturer No.6 co-taught the course, with a total of 1.15 credits. Therefore, when combined with the managerial workload of 3 credits, this lecturer would have a total workload of 19.24 credits, which does not align with the university's regulation.

Table 3 The model result of Lecturer No.6, The second semester of the 2022 academic year.

Lecturer No.6		
Subject	Percentage of Workload	Credits Received
Quantitative Methods for Logistics Management Section1	100.00	7.58
Warehousing and Inventory Management Section 2	100.00	5.40
Total Credits Received		12.98
Managerial Credits Received		3.00
Total Gross Credits Received		15.98

While the model approach for Lecturer No.6 in the second semester of the 2022 academic year (Table 3), it was found that Quantitative Methods for Logistics Management Section 1was assigned with a workload percentage of 100%. This indicates that Lecturer No.6 was the single lecturer, and the total credit allocated was 7.58. Lastly, Warehousing and Inventory Management Section 2had a workload percentage of 100%, meaning that Lecturer No.6 single-taught the course, with a total of 5.40 credits. Therefore, when combined with the managerial workload of 3 credits, this lecturer would have a total workload of 15.98 credits, which does align with the university's regulation.

The model provides a range of assignments for each lecturer, which can fluctuate from the current approach. It has the flexibility to align with the university's regulations. As observed in Table 2, it's evident that the subject list for Lecturer No.6 does not meet the specified requirements. An essential aspect of this model is its endeavor to seek a solution that effectively balances lecturer satisfaction with all the necessary requirements.

Indeed, the results from the model might include subjects that align with or differ from the current approach. However, these outcomes are contingent on the satisfaction scores associated with each subject and each lecturer. The model strives to identify the optimal solution based on the available data, considering these satisfaction scores to determine the most suitable assignments.

In addressing the limitations of the model, this research conducted experiments to solve five problem sizes by simulating new data sets containing 2,000 decision variables, 5,000 decision variables, 10,000 decision variables, 20,000 decision variables, and 100,000 decision variables. The tests were performed on a private laptop equipped with an AMD Ryzen 9 5900HX processor with Radeon Graphics clocked at 3.30 GHz and 16.0 GB of RAM.

Microsoft Excel 365 and OpenSolver Version 2.9.3 were used for the experiments. The results of the testing are as follows:

Table 4 Experiment Results for Optimization Model.

Number of Decision Variable	Number of Subject	Number of Lecturer	Set Up Time (Second)	Process Time (Second)	Optimal Solution
2,000	50	20	10	0.05	Yes
5,000	50	50	33	0.25	Yes
10,000	100	50	115	0.38	Yes
20,000	100	100	406	2.13	Yes
100,000	500	100	9,514	16.44	Yes

Table 4 illustrates the outcomes of a series of experiments conducted to evaluate the performance of an optimization model across various problem sizes. As depicted in the table, the experiments encompassed different scales of the problem, ranging from 2,000 to 100,000 decision variables. These variables represent the elements the optimization model considers when making decisions.Consider the following example where 2,000 decision variables originate from 50 subjects and involve 20 lecturers. This model encompasses two types of decision variables, namely $k_{ij}$and r_{ij}, representing the assignment of subject i to lecturer j and the ratio of the workload assigned to lecturer j for subject i. Consequently, the total number of decision variables in this experiment amounts to 2,000.

One of the most significant observations from the experiments is that for every configuration tested, the optimization model successfully arrived at an optimal solution. This implies that even when dealing with a substantial number of decision variables, subjects, and lecturers, the model was able to find the best possible solution, demonstrating its robustness and reliability.

An intriguing trend observed in the results is the increase in both Set Up Time and Process Time as the number of decision variables, subjects, and lecturers increased. This is a common characteristic in optimization problems - as the complexity of the problem grows, the time required to set up and solve it also increases. Notably, even for the most complex scenario with 100,000 decision variables, the model successfully found an optimal solution within a reasonable time frame, as indicated by the Process Time.

In summary, the results confirm the effectiveness of the optimization model across a range of diverse and complex problem sizes. In this case study, the problem size involved several decision variables ranging between 2,000 and 5,000. This demonstrates the model's ability to efficiently solve general problems within this range.

Conclusions

The focus of this research study was on maximizing the highest level of satisfaction in task assignment while minimizing the workload exceeding the minimum requirement. The results showed that the model was able to accurately allocate tasks according to all conditions and reduce the excessive workload in each semester by 2.92% and 14.78% respectively. Additionally, the model required a processing time of only 1-2 minutes per iteration, depending on the size of the data used for computation.

In conclusion, this research focuses on comparing the efficiency of the proposed model with the existing method of resource allocation in teaching. The evaluation criteria encompass the accuracy of allocation, proximity to the minimum teaching workload in credit allocation, and reduced planning time. Through a rigorous assessment, the model's performance in these areas was analysed to gauge its effectiveness when compared to the current method.

In terms of usability, the research examined the different processes between the current approach and the model. However, it's important to note that specific criteria for this aspect were not included in the evaluation. Notably, the satisfaction score from the model cannot be directly compared with the current approach, as the latter does not collect satisfaction scores from the assignment plan. Nevertheless, satisfaction score constitutes a vital component of this model. Consequently, the assignment results from the model were optimized with the objective function of maximizing the total satisfaction score of all subjects. This optimization process considers the relationship between subjects and lecturers, while also considering lecturer satisfaction.

By addressing these critical evaluation criteria and incorporating user satisfaction as a fundamental element, this research provides valuable insights into the potential effectiveness and user-friendliness of the proposed model in the context of teaching resource allocation.

In terms of cost, the model does not definitively conclude that the assignment plan decreases expenses, as it exclusively focuses on full-time lecturers. To address the cost issue comprehensively, it is imperative to incorporate contract lecturers into the model. By expanding its scope, the model has the potential to be developed to account for this aspect. However, it is noteworthy that costs related to full-time lecturers can be reduced. This reduction stems from the decreased total credit hours, which fall below the minimum requirement in both semesters. Consequently, the faculty can achieve cost savings for this reason.

The future challenge in developing this model is incorporating other significant factors into the model, particularly regarding the cost of task allocation. If there is an excessive workload, the cost that the faculty must pay to each lecturer needs to be calculated. Another aspect to consider is the integration of contract lecturers with full-time lecturers, which have different costs. Including these factors in the model will lead to more comprehensive and realistic results.

The current evaluation method for lecturer satisfaction in subject assignments lacks flexibility and requires significant data preparation time. By incorporating a recommendation system, specifically for subjects that are similar or sequential in nature, the process of assigning lecturers can be optimized, ensuring that experienced instructors are matched with relevant subjects and reducing the likelihood of non-feasible solutions from the model.

References

[1] Bouajaja, S., & Dridi, N. (2017). A Survey on Human Resource Allocation Problems and its Applications. *Operational Research*, 17(2), 339-369.

[2] Xian-Ying, M. (2012). Application of Assignment Model in PE Human Resources Allocation. *Energy procedia*, 16, 1720-1723.

[3] Azimi, M., et al. (2013). Optimal Allocation of Human Resources by using Linear Programming in the Beverage Company. *Universal Journal of Management and Social Sciences*, 3(5), 48-54.

[4] Güler, M. G., et al. (2015). On Teaching Assistant-Task Assignment Problem: A Case Study. *Computers & Industrial Engineering*, 79, 18-26.

[5] Moreira, M. C. O., et al. (2012). Simple Heuristics for the Assembly Line Worker Assignment and Balancing Problem. *Journal of heuristics*, 18, 505-524.

[6] Moreira, M. C. O., et al. (2015). Model and Heuristics for the Assembly Line Worker Integration And Balancing Problem. *Computers & Operations Research*, 54, 64-73.

[7] Araujo, F. F., et al. (2015). Balancing Parallel Assembly Lines with Disabled Workers. *European Journal of Industrial Engineering*, 9(3), 344-365.

[8] Gunawan, A., & Ng, K. M. (2011). Solving the Teacher Assignment Problem by Two Metaheuristics. *International Journal of Information and Management Sciences*, 22(1), 73-86.

[9] Odeniyi, O. A., et al. (2015). Development of a Modified Simulated Annealing to School Timetabling Problem. *International Journal of Applied Information Systems*,

8(2), 16-24.

[10] Thepphakorn, T., et al. (2014). An Ant Colony Based Timetabling Tool. *International Journal of Production Economics,* 149, 131-144.

[11] Swangnop, S., & Chaovalitwongse, P. (2014). A Two-Step Tabu Search Heuristic for Multi-Period Multi-Site Assignment Problem with Joint Requirement of Multiple Resource Types. *Engineering Journal*, 18(3), 83-98.

[12] Ammar, A., et al. (2012). Resolution of Multi-Skilled Workers Assignment Problem using Simulation Optimization: A Case Study. In *2012 IEEE International Conference on Computer Science and Automation Engineering* (p. 748-754). 25-27 May, 2012, Zhangjiajie, China.

[13] Fan, K., et al. (2013). An Effective Modified Binary Particle Swarm Optimization (mBPSO) Algorithm for Multi-Objective Resource Allocation Problem (MORAP). *Applied Mathematics and Computation*, 221, 257-267.

[14] Fikri, M., et al. (2011). Assignment Staff with Dynamic Competencies in Multi-Projects & Multi-Periods: Modeling and Solving by a Hybridization of Ant Colony Algorithm. *International Journal of Computer Science and Network Security*, 11(3), 227.

[15] Kyriklidis, C., et al. (2014). Hybrid Nature-Inspired Intelligence for the Resource Leveling Problem. *Operational Research*, 14, 387-407.

[16] Costa Filho, C. F. F., et al. (2012). Using Constraint Satisfaction Problem Approach to Solve Human Resource Allocation Problems in Cooperative Health Services. *Expert Systems with Applications*, 39(1), 385-394.

[17] Ağralı, S., et al. (2017). Employee Scheduling in Service Industries with Flexible Employee Availability and Demand. *Omega*, 66, 159-169.

[18] Chiang, H. Y., & Lin, B. M. (2020). A Decision Model for Human Resource Allocation in Project Management of Software Development. *IEEE Access*, 8, 38073-38081.

[19] Naveh, Y., et al. (2007). Workforce Optimization: Identification and Assignment of Professional Workers using Constraint Programming. *IBM Journal of Research and Development*, 51(3.4), 263-279.

[20] Chen, P. S., et al. (2016). A Two-Stage Method to Determine the Allocation and Scheduling of Medical Staff in Uncertain Environments. *Computers & Industrial Engineering*, 99, 174-188.

[21] Domenech, B., & Lusa, A. (2016). A MILP Model for the Teacher Assignment Problem Considering Teachers' Preferences. *European Journal of Operational Research*, 249(3), 1153-1160.

[22] Caselli, G., et al. (2022). Integer Linear Programming for the Tutor Allocation Problem: A Practical Case in a British University. *Expert Systems with Applications*, 187, 115967.

[23] Mason, A. J. (2011). Opensolver-An Open Source Add-In to solve Linear and Integer Progammes in Excel. In *International Conference on Operations Research* (p.401-406), 30 August - 2 September, 2011, Zurich, Switzerland.