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Optimal Faculty Staffing Using Depth-First Search

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Abstract

Scheduling at academic departments is a challenging issue as it involves assigning courses to faculty based on their availability and qualifications while avoiding double allocation of classrooms and lectures.

In this paper, we tackle the problem of allocating faculty to courses for an academic year across multiple terms. The aim is to assign instructors to courses in an efficient and effective manner, considering all constraints, and giving priority to highly qualified and interested instructors. We use a Depth First Search algorithm that considers factors such as faculty availability, subject matter expertise, and class modality.

The optimal staffing problem is not only prevalent in academia but is also faced in various other industries where limited resources must be matched to available time slots. Automating the process of scheduling nurses in a hospital, for instance, can improve resource utilization significantly. Thus, the course staffing optimization solution presented in this paper can also be applied to other industries in critical situations such as the recent Covid-19 pandemic, allowing for effective and efficient utilization of resources like doctors, nurses, and lab technicians.

Keywords: *Course Scheduling, Faculty Staffing, Schedule Optimization, Backtracking, Depth First Search.*

1. Introduction

Academic institutions often spend long hours trying to manually find an optimal schedule for staffing faculty to classes based on their preferences and availability while avoiding conflicts caused by duplicate staffing, faculty unavailability, or even faculty assignment to a class outside their domain of expertise. This manual process becomes more difficult with an increase in the number of faculty, classes, and constraints. As academic institutions increasingly depend on pools of adjunct instructors to teach classes, the staffing process is likely to become more challenging. This situation is further complicated due to adjunct faculty with limited availability in terms of time and modality to teach.

In this paper, a solution using the Depth First Search algorithm is proposed for solving the faculty staffing problem. The work presented in this paper is a continuation of the research published in [1] where a solution to the staffing problem was proposed and formulated using 0/1 integer programming. The integer programming solution considered many hard and soft constraints such as faculty qualification and interests in topics, as well as their availability and preference in teaching onsite or online classes. The 0/1 integer programming solution had elegant constraint formulations and provided flexibility for the inclusion of complex constraints. However, the complexity of the problem rapidly grows with an increase in the number of variables of the problem. This prompted the investigation into alternative solution approaches that can effectively handle practical problems with a greater number of faculty members, courses, and concurrent programs to be scheduled.

Scheduling and staffing in general have been studied in various papers and different application domains. Authors in [2] proposed a new algorithm for staffing optimization in multi-skill call centers, using logistic regression and Linear Programming. Authors in [3] examined a decision support system with the VIKOR ranking method based on multiple criteria including verbal abilities, voice intonation, English proficiency, memorization power, and entrance test scores of call center staff to optimally assign them to service calls. A hierarchal modeling process of patient flow in emergency departments based on Petri Nets was developed in [4]. Authors in [5] used renewal reward theorem and fractional programming to solve optimal staffing for ticket queues. A solution for optimal call center forecasting and staffing based on a two-stage model was proposed in [6]. A solution based on mixed-integer optimization was proposed in [7] for multi-period planning of home-care services under uncertainty. Authors in [8] proposed a Particle Swarm Optimization (PSO) based approach for class scheduling allowing instructors with day of the week and consecutive lecture periods flexibility. A Genetic Algorithm was introduced in [9] for Optimum Broadcast Scheduling (OBS). In [10], a model for assigning employees to engineering-to-order production based on available knowledge (i.e., equivalent to faculty qualification in academic scheduling problems) was considered. The Hungarian method and Linear interactive and discrete optimization techniques were used in [11] to solve the staff-subject allocation problem.

Like many important problems in science and engineering, optimal faculty staffing requires searching for a solution with a given special property in a large domain that grows exponentially with the problem size. This is typically seen in combinatorial optimization problems where one is seeking to find an element in the domain that maximizes or minimizes some characteristics in the problem such as a path length in the traveling salesman problem or the cost of job assignment in the job assignment problem. An exhaustive search of the domain for the optimal solution might be the only option in case of large instances of such difficult combinatorial problems. But there are algorithm techniques such as backtracking and Depth First Search that help solve some instances of these large combinatorial problems. Typically, these algorithms build a partial solution to the problem step-by-step, one component at a time. At each step, a choice is made from among all available choices that add a component to the partial solution. The new partial solution is evaluated to ensure all constraints are satisfied. At any step along the construction of the solution if a partially constructed solution fails to satisfy any of the constraints, then the remaining components of the partial solution are not generated [12]. In these algorithms, a tree node represents a selection of a particular component of the solution. During the state-space tree construction, if it is realized that a tree node cannot be further built to extend to a full solution, then the node is terminated and the search for a full solution along the outgoing edges of this node is stopped. The Depth First Search algorithm is used in optimization problems where at each step (or the tree node) the algorithm approximates an upper bound for the given objective function prescribed for the problem. The upper bound gives the potential value of the objective function if the current partial solution is built to completion.

2. Problem Definition

The staffing assignment is similar to the well-known job assignment problem. We have a set "T" consisting of instructors t_i and another set "C" of classes c_i to be offered over a full academic year. The goal is to staff classes with the available instructors under given constraints while maximizing a certain objective function. While it is not necessary to have all instructors assigned to a class, it is required to staff all classes.

There are a few constraints attached to the staffing assignment studied in this paper:

1) *One class per month:* Classes are offered monthly, and each instructor can only teach one class per month.
2) *Online and onsite modality:* The instruction mode is either online (OL), or onsite (S). It is assumed that onsite instructors can teach online as well. However, online instructors must only be staffed in classes with online modality only.
3) *Availability:* Instructors must be available to teach in the months they are staffed to teach a class. So, the instructors must only be staffed to teach in the months they are available.
4) *Class Staffing:* Each class must be staffed by one instructor only.

The objective is to assign instructors to courses for which they have the highest level of interest and expertise in the topic while meeting all the constraints for the instructors and courses. Instructors are given a quality score for each class that ranks their subject matter expertise and their interests in teaching that class. The quality scores range between 0 and 3. A score of 0 means that the instructor does not have the background or interest to teach the class and a max quality score of 3 indicates that the instructor is among the most qualified and interested to teach the class. The optimal staffing solution should maximize the overall quality score of all assigned classes to ensure student satisfaction, in addition to satisfying the constraints of the problem.

Assuming that we have n classes to staff and there are m_i instructors to choose from to assign to the ith class (where $i = 1, 2, \ldots, n$), then the state-space tree will have $\sum_{i=0}^{n-1} \prod_{j=i}^{i+1} m_j$ nodes, where $m_0 = 1$ and a total of $\prod_{i=1}^{n} m_i$ end nodes representing complete solutions to the staffing of n classes. Assuming $m_i > 1$, we have a search domain that grows exponentially with the number of classes to be staffed.

3. Depth First Search for Optimal Faculty Staffing

We use Depth First Search traversal with a heuristic to construct an optimal solution to the staffing problem while satisfying all problem constraints. The algorithm starts from the root of the tree by staffing one class at a time. All classes in the starting month of the academic year are staffed first. The algorithm then continues to staff the remaining classes in the following months consecutively until reaching the last class in the last month. Figure 1 shows an example of a partial state-space tree generated by this algorithm while staffing five classes labeled *A* through *D*. The algorithm takes a random unstaffed class from the initial month and assigns it an instructor that satisfies all the problem constraints discussed earlier. Next, another class from the current month is selected and staffed, this step-by-step process of constructing the solution continues in a Depth First Search (DFS) manner. The DFS search format can be seen in Figure 1, where at level 1 of the state-space tree, instructor t_1 is staffed in class *A*. This instructor has a quality score of 3, which is placed on the tree edge. At level 2, instructor t_2 with a quality score of 1 is assigned to class *D*. The algorithm tracks the overall quality of the partial solutions by combining the quality score of the individual instructors assigned to the classes. This overall quality score, which is the sum of the quality scores of each individual instructor, is the staffing problem objective function that is to be maximized. It can be seen in Figure 1 that the overall quality score for this two-level partial solution is 4.

The state-space tree generated by the search has two types of leaf nodes. The *end* leaf nodes where the last class in the schedule is staffed and the *termination* leaf nodes where either a partial solution cannot be completed due to unsatisfied constraints, or a partial solution cannot lead to a complete solution with a better overall quality score (or the objective function value) than a solution found earlier in the search.

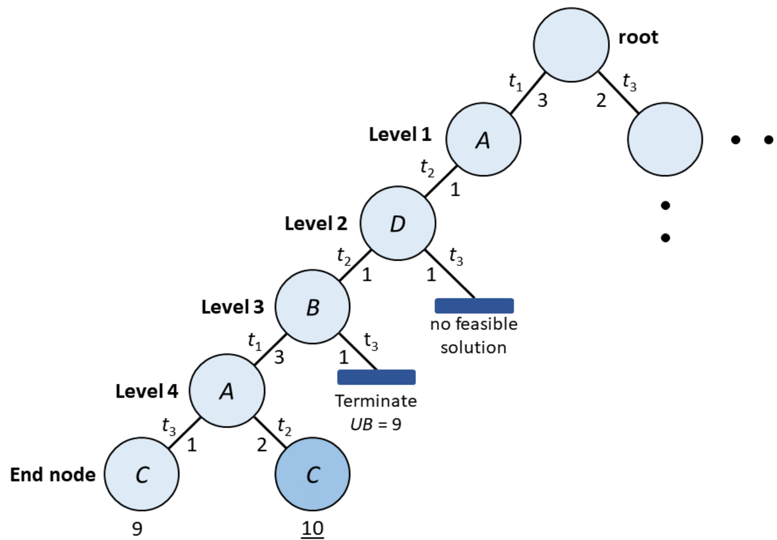

Figure 1: Partial State Space Tree

At each node, the algorithm uses a simple heuristic to estimate an upper bound (*UB*) for the overall quality of the completed solution along the current node. The upper bound is obtained by assuming that the remaining unstaffed classes in the current partial solution are staffed with instructors with quality score of 3, which is the highest.

$$UB = \textit{quality score at the current node} + 3 \times \textit{number of classes left to staff}$$

The far-left tree branch in Figure 1, which starts from the root and goes down to the end leaf node represents a complete solution to the staffing problem with an overall quality score of 9. The partial solution at the right child of the level 3 node is terminated since the best it can do is to achieve an overall quality score of 9, which has already been discovered. If desired, we can generate all staffing solutions with the same overall quality score rather than producing the first solution found, which is done here. Figure 1 shows a second terminating leaf node at level 2, where there is no instructor to be staffed in class B while satisfying all the constraints.

4. Course Staffing Optimization Using Depth First Search

The case study considers staffing of the Master's in Computer Science program at the National University. The program is offered in an accelerated format where each course is completed within four weeks. The graduate program consists of 13 courses, as shown in Table 1, and is offered three times a year, twice a year in an online format, and once a year in an onsite format. Each of the 13 courses is abbreviated with lowercase letters *a*, *b*, *c*, …, *m*. Table 2 shows the offering of courses for each month from January to December each year, the same pattern is repeated every year. The courses that are listed with "*OL*" are offered in the online format. For example, in the month of February four courses are offered. Course *f* is offered in the onsite format while courses *a*, *h*, and *m* are offered in the online format.

Table 1: MSCS Course and corresponding abbreviation.

Courses	Abbr.
CSC600 Advanced Programming	*a*
CSC603 Software Engineering Fundamentals	*b*
CSC605 Software Architecture Principle	*c*
CSC606 Modern Operating Systems	*d*
CSC607 Security in Computing	*e*
CSC670 User Interface Engineering	*f*
CSC675 Database Design and Impl	*g*
CSC678 Advanced Database Programming	*h*
CSC680 Database Web Interface	*i*
CSC685 Topics in Computing	*j*
CSC686 Computer Science Project I	*k*
CSC687 Computer Science Project II	*l*
CSC688 Computer Science Project III	*m*

Table 2: Course offering monthly schedule for the graduate program.

Month	Courses			
January		*g (OL)*	*e*	*l (OL)*
February	*a (OL)*	*h (OL)*	*f*	*m (OL)*
March	*b (OL)*	*i (OL)*	*g*	
April	*c (OL)*	*j (OL)*	*h*	
May	*d (OL)*	*k (OL)*	*i*	
June	*e (OL)*	*l (OL)*	*j*	
July	*f (OL)*	*m (OL)*	*k*	*a (OL)*
August	*g (OL)*		*l*	*b (OL)*
September	*h (OL)*	*a*	*m*	*c (OL)*
October	*i (OL)*	*b*		*d (OL)*
November	*j (OL)*	*c*		*e (OL)*
December	*k (OL)*	*d*		*f (OL)*

There are 12 instructors who teach these 13 courses offered in the program. Table 3 shows the availability of different instructors to teach in a particular month and their willingness to teach an onsite class. The second column in this table shows the months (0 is for the month of January and 11 is for the month of December) for which an instructor is not available to teach. The values 1 and 0 in column three represent the availability and non-availability of instructors to teach onsite, respectively. Table 3 displays the availability of 12 instructors to teach 13 courses in the program.

The second column represents the months (0-11) when instructors are unavailable to teach. Column three displays the availability (1) and non-availability (0) of instructors for onsite teaching.

Table 3: The availability of instructors in different months and their availability to teach onsite classes.

Instructor	Months Not Available	Available to Teach Onsite
A	2, 7, 9, 10, 11	1
B	0, 1, 3, 4, 6, 10,11	1
C	0, 1, 2, 4, 6, 9, 11	1
D	0, 2, 4, 5, 6, 7, 8, 9, 11	1
E	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 11	1
F	0, 1, 3, 4, 5, 7, 8, 10, 11	1
G	2, 3, 7, 8, 9, 10	0
H	0, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11	0
I	0, 1, 3, 4, 5, 9, 10, 11	1
J	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10	0
K	0, 1, 2, 3, 5, 6, 7, 8, 10	1
L	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11	0

Each instructor is given a weighted score which denotes the instructor's overall experience and preference to teach a course. The score has an integer value between 0 and 3 and is a measure of interest, experience, and preference of instructor *A* in teaching a course. A score of 0 indicates that an instructor lacks experience and interest, while a score of 3 indicates high interest and proficiency in teaching a course. Table 4 provides a description of the scores. The preference is to staff classes with the most interested and experienced instructors. Table 5 shows instructors teaching in the graduate program and their respective weighted scores for each course in the program.

Table 4: Description of the instructor's weight scores.

Score	Description
0	Lacks experience and has no interest in teaching the course
1	Lacks direct experience but has an interest in teaching the course
2	Experienced but has low interest in teaching the course
3	Experienced and interested in teaching the course

Table 5: Instructor’s weight scores for the graduate program.

Instructor \ Course	*a*	*b*	*c*	*d*	*e*	*f*	*g*	*h*	*i*	*j*	*k*	*l*	*m*
A	3	2	2	1	1	0	3	3	1	0	3	3	3
B	0	3	2	0	0	0	3	3	0	3	0	0	0
C	0	3	3	0	0	0	0	0	0	0	2	2	2
D	0	0	0	3	0	3	1	0	0	3	0	0	0
E	0	0	0	0	3	0	0	0	0	0	0	0	0
F	2	0	0	0	0	3	1	0	3	0	0	0	0
G	0	0	0	0	0	0	3	3	2	0	3	3	3
H	0	0	0	0	0	0	3	3	2	0	0	0	0
I	0	3	3	0	0	0	0	0	0	0	3	3	3
J	0	0	0	0	0	3	0	0	0	0	0	0	0
K	0	0	0	3	3	0	0	0	0	0	0	0	0
L	0	0	0	0	0	0	3	2	0	0	0	0	0

The objective is to optimally staff classes in such a way that satisfies the constraints and maximizes the total sum of the staffing weight scores by assigning courses to highly qualified and interested instructors. The test run presented an optimal solution as shown in Table 6.

Table 6: Final staffing solution for the graduate program.

Month	(Courses, Instructor, Score)			
January	('*g*', *L*', 3)	('*e*', '*A*', 1)	('*l*', '*G*', 3)	
February	('*a*', '*A*', 3)	('*h*', '*H*', 3)	('*f*', '*D*', 3)	('*m*', '*G*', 3)
March	('*b*', '*I*', 3)	('*i*', '*F*', 3)	('*g*', '*B*', 3)	
April	('*c*', '*C*', 3)	('*j*', '*D*', 3)	('*h*', '*A*', 3)	
May	('*d*', '*K*', 3)	('*k*', '*G*', 3)	('*i*', '*A*', 1)	
June	('*e*', '*A*', 1)	('*l*', '*G*', 3)	('*j*', '*B*', 3)	
July	('*f*', '*F*', 3)	('*m*', '*G*', 3)	('*k*', '*I*', 3)	('*a*', '*A*', 3)
August	('*g*', '*B*', 3)	('*l*', '*I*', 3)	('*b*', '*C*', 3)	
September	('*h*', '*B*', 3)	('*a*', '*A*', 3)	('*m*', '*I*', 3)	('*c*', '*C*', 3)
October	('*i*', '*F*', 3)	('*b*', '*B*', 3)	('*d*', '*K*', 3)	
November	('*j*', '*D*', 3)	('*c*', '*C*', 3)	('*e*', '*E*', 3)	
December	('*k*', '*G*', 3)	('*d*', '*K*', 3)	('*f*', '*J*', 3)	

The scheduling result shown in Table 6 provides information about courses, the month each course is offered, instructors staffed for the courses, and the experience/interest scores for the instructors. For example, for course *g* offered in March, instructor *B* with a score of 3 is assigned. The total max score that could be achieved for scheduling all 39 courses is 117 if all the courses are staffed with an instructor with a score of 3.

The solution achieved using the proposed Depth First Search approach has resulted in a total score of 111. The algorithm is successful in optimally staffing 36 courses with instructors of score 3, and only three courses have a score of 1 for the staffed instructors. For example, for the month of January, course "*e*" is staffed with a faculty having a score of 1, which means the faculty lacks previous experience but is interested in teaching the course. We often face situations like this when the most qualified and experienced instructor is not available for a course, and we must staff a faculty who has expressed interest in teaching the class rather than either not staffing the class or staffing it with faculty who has no interest in teaching the class. The results obtained from the test run matched exactly with the schedule that was prepared manually by applying all the constraints.

5. Conclusion

A Depth First Search algorithm was presented in this study to optimally staff classes for a multi-semester program. The main objective was to allocate courses to instructors who possess the necessary qualifications and are highly interested in teaching the subject matter. The proposed method was applied to the Master of Science in Computer Science (MSCS) program at National University and was successful in generating schedules that adhered to the constraints and favored highly qualified instructors by maximizing their total weight scores.

The method introduced in this paper can be extended and applied to a variety of staffing and optimal scheduling problems. For example, we can use a similar Depth First Search approach to determine the optimal number of nurses and doctors required for a hospital at different times of a day and week to ensure that patients receive adequate care. Similarly, we can use the same approach to determine an optimal schedule for buses, trains, and subways to maximize ridership while minimizing wait times and operating expenses. Manufacturing workforce scheduling, airline crew scheduling, project management resource allocation are examples of other problem domains the proposed approach can be applied to.

6. References

[1] Wyne, M., Farahani, A., Atashpaz-Gargari, E., & Zhang, L., *"Multi-Semester Course Staffing Optimization"*, In the proceedings for 2022 ASEE Annual Conference & Exposition, June 26-29, Minneapolis, MN, 2022.

[2] T. A. Ta, T. Mai, F. Bastin and P. L'Ecuyer, "*A Logistic Regression and Linear Programming Approach for Multi-Skill Staffing Optimization in Call Centers*" 2022 Winter Simulation Conference (WSC), Singapore, 2022, pp. 3087-3098, doi: 10.1109/WSC57314.2022.10015281.

[3] Darmanto, E., Siregar, M. , Hayadi, B., Renwarin, J., Asfar, D., Sulissusiawan, A., Anam, S., and Fatmawati, I., "*Decision Support System for Staff Assignment Using VIKOR Algorithm*", Journal of Physics Conference Series, March 2021.

[4] J. Wang, "*Patient Flow Modeling and Optimal Staffing for Emergency Departments: A Petri Net Approach*" in IEEE Transactions on Computational Social Systems, 2022, doi: 10.1109/TCSS.2022.3186249.

[5] Xiao, L., Xu, S.H., Yao, D.D. et al. "*Optimal staffing for ticket queues*". Queueing Syst 102, 309–351 (2022). https://doi.org/10.1007/s11134-022-09854-8

[6] Ding, S., & Koole, G. (2022). "*Optimal call center forecasting and staffing. Probability in the Engineering and Informational Sciences*", 36(2), 254-263. doi:10.1017/S0269964820000595

[7] Naderi, Bahman, et al. "*A novel and efficient exact technique for integrated staffing, assignment, routing, and scheduling of home care services under uncertainty*" Omega 116 (2023): 102805.

[8] Der-Fang Shiau, "*A hybrid particle swarm optimization for a university course scheduling problem with flexible preferences*", Expert Systems with Applications Vol. 38, pp. 235–248, 2011.

[9] Christy Jackson J, Rekha D, Vijayakumar V, and Surya Prasath V B, "*Broadcast Scheduling Problem in VANETs: A Discrete Genetic Algorithm Approach*", International Journal of Recent Technology and Engineering (IJRTE), Vol. 7, Issue-6S2, pp. 360-366, April 2019.

[10] Roblek, M., Zajec, M., and Urh, B., "*Knowledge-Based Assignment Model for Allocation of Employees in Engineering-to-Order Production*", In Knowledge Management Strategies and Applications, Edited by Mohiuddin, M., Halilem, N., Kobir, SM., and Cao, Y., November 2017.

[11] Kabiru, S., Saidu, B., Abdul, A., and Ali, U., "*An Optimal Assignment Schedule of Staff-Subject Allocation*", *Journal of Mathematical Finance*, **7**, pp. 805-820, 2017.

[12] Anany Levitin, "*Introduction to the Design and Analysis of Algorithms"*, 3rd Edition, Pearson Publishing, 2014.

[13] David Figlio and Morton Schapiro, *"Staffing the Higher Education Classroom"*, Journal of Economic Perspective, Vol. 35 (1), pp. 143–162, 2021.