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Tabu Ant Colony Optimization for School Timetable Scheduling

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ABSTRACT
Ant colony optimization is an evolutionary search procedure based on the way that ant colonies cooperate in locating shortest routes to food sources. Early implementations focused on the travelling salesman and other routing problems but it is now being applied to an increasingly diverse range of combinatorial optimization problems. This paper is concerned with its application together enhanced with the tabu search algorithm to the examination scheduling problem. It builds on an existing implementation for the graph coloring problem to produce clash-free timetables and goes on to consider the introduction of a number of additional practical constraints and objectives. A number of enhancements and modifications to the original algorithm are introduced and evaluated. Results based on real-examination scheduling problems including standard benchmark data show that the final implementation is able to compete effectively with the best-known solution approaches to the problem.

KEYWORDS: combinatorial optimization, exam scheduling, tabu search, ant colony algorithms.

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I. INTRODUCTION

The exam timetabling [19], [20], [21], [22], [23], [24] problem faces the problem of scheduling exams within a limited number of available periods. As students plan to write different exams, setting up a conflict free timetable is not a trivial task due to limited resources like periods, examination rooms and teacher availability. The main objective is to balance out student's workload and to distribute the exams evenly within the planning horizon. In particular, it should be avoided that a student has to write two exams in the same period. Such situations will be referred to as conflicts of order 0 in the sequel. Additionally, as few students as possible have to attend x exams within y consecutive periods. Such conflicts can either be totally forbidden by constraints or penalized in the objective function. For example, Carter et al. proposed in [1] a cost function that imposes penalties $P\omega$ for a conflict of order ω, i.e. whenever one student has to write two exams scheduled within $\omega + 1$ consecutive periods. In the literature ω normally runs from 1 to 5 with $P1 = 16$, $P2 = 8$, $P3 = 4$, $P4 = 2$, $P5 = 1$.

Solving practical exam timetabling problems requires that additional constraints have to be considered, e.g. some exams have to be written before other exams or some exams cannot be written within specific periods. [2], [3], [4] give comprehensive lists of possible hard and soft constraints.

The exam timetabling problem can be formulated as a graph coloring problem. Each node represents one exam. Undirected arcs connect two nodes if at least one student is enrolled in both corresponding exams. Weights on the arcs represent the number of student enrolled in both exams. The objective is to find a coloring where no adjacent nodes are marked with the same color or to minimize the weighted sum of the arcs that connect two nodes marked with the same color. The exam timetabling problem is a generalization of the graph coloring problem as in the objective function also conflicts of higher orders are penalized.

To solve exam timetabling problems, several algorithms have recently been developed. In [1] applied some well-known graph coloring heuristics which they combined with backtracking. In recent time various heuristical approaches have been developed. Most of them use local search like tabu search, simulated annealing, great deluge or adaptive search methods [1], [2], [5], [6], [7], [8], [9], [10], [11]. A comprehensive survey on the literature on exam timetabling problems can be found in [4].

This research was motivated by the need for a software tool for solving a practical exam timetabling problem. As ant colony approaches have been proven to be a powerful tool for various combinatorial optimization problems (c.f. the survey in [12]), it is apparent to adapt this solution approach to the exam timetabling problem. In the literature diff erent variants of ant colony approaches have been presented. We will compare some of these strategies with respect to their suitability for our problem.

This paper is organized as follows: In section 2 a detailed problem formulation will be presented. Section 3 will give an introduction into ant colony systems. The next sections will present a solution approach and test results for some benchmark problems that were taken from the literature. Finally, section 5 summarizes the results and suggests discussion for future work.

II. PROBLEM FORMULATION

Before stating the problem formally, we introduce some notation.

Table 1: Symbol and meaning

Symbol	Meaning
R	index set of rooms
I	index set of exams
T	index set of periods
Ω	index set of order of conflicts
Krt	capacity of room r in period t
cij	number of students enrolled in exam i as well as in exam j
Ei	number of students enrolled in exam i
Pω	penalty imposed if one student has to write two exams within ω + 1 periods
yit	binary variable equal to 1 if exam i is scheduled in period t and 0 otherwise
pirt	number of students of exam i assigned to room r in period t

Using this notation, the exam timetabling problem can be formulated as follows:

$$min \sum_{\omega \in \Omega} \sum_{i,j \in I, i \neq j} \sum_{t \in T, t > \omega} P_\omega c_{ij} y_{it} y_{j(t-\omega)} \qquad (1)$$

$$\sum_{t \in T} y_{it} = 1 \quad \forall i \in I \qquad (2)$$

$$p_{irt} \leq y_{it} K_{rt} \quad \forall i \in I, \forall r \in R, \forall t \in T \qquad (3)$$

$$\sum_{r \in R} \sum_{t \in T} p_{irt} = E_i \quad \forall i \in I \qquad (4)$$

$$\sum_{i \in I} p_{irt} \leq K_{rt} \quad \forall r \in R, \forall t \in T \qquad (5)$$

$$\sum_{t \in T} c_{ij} y_{it} y_{jt} = 0 \quad \forall i, j \in I, i \neq j \qquad (6)$$

$$y_{it} \in \{0,1\} \quad \forall i \in I, \forall t \in T \qquad (7)$$

$$p_{irt} \in \mathbb{N}_0 \quad \forall i \in I, \forall r \in R, \forall t \in T \qquad (8)$$

The objective function (1) balances out students' workload by minimizing the weighted sum of all conflicts. Constraint (2) states that each exam is assigned to exactly one period. If an exam is not assigned within a period, then no seats should be reserved for that period in any room. This is imposed by constraint (3). Constraints (4) and (5) assure that the number of seats reserved for an exam will be equal to the number of students who are enrolled in that exam and that the room capacities are not exceeded. Finally, constraint (6)

avoids conflicts of order 0, i.e. that a student has to write two exams in the same period.
The exam timetabling problem is a generalization of the graph coloring problem, which is known to be NP-hard [22]. Therefore, solution approaches try to decompose the problem in order to solve it within a reasonable amount of time [30]. One way is to split up the problem into the two following sub problems, which can be solved sequentially:

Problem I: Scheduling of exams, i.e. assign exams to periods in order to balance out students' workload as pursued by the objective function (1). Instead of considering capacity constraints for the single rooms, only the total capacity of all available exam rooms within a period is considered. In the IP formulation stated above this can be accomplished by replacing the set of rooms by a artificial single room. For this problem a solution approach will be presented in the next sections.

Problem II: Room planning, i.e. distribute the exams of one period among the available examination rooms. Finding a feasible room plan is not difficult if the exams can take place in more than one room and if more than one exam can take place in one room at the same time, provided that the room capacity is not exceeded. If exams are split up into different rooms one could consider the campus layout and try to generate a room plan where these exams are only assigned to rooms not too far from each other in order to minimize walking distances. We will not consider this problem in the following.

III. ANT COLONY OPTIMIZATION

Ants live together in colonies and they use chemical cues called pheromones to provide a sophisticated communication system. An isolated ant moves essentially at random but an ant encountering a previously laid pheromone will detect it and decide to follow it with high probability and thereby reinforce it with a further quantity of pheromone. The repetition of the above mechanism represents the collective behaviour of a real ant colony which is a form of autocatalytic behaviour where the more the ants follow a trail, the more attractive that trail becomes. The above behaviour of real ants has inspired ACO which has proved to be an effective metaheuristic technique [15],[26],[27],[19] for solving many complex constraint optimization problems [21]. This technique uses a colony of artificial ants that behaves as cooperative agents in a mathematical space where they are allowed to search and reinforce pathways (solutions) in order to find the optimal ones. The features of artificial ants are: having some memory, not being completely blind and the process time is discrete.

Depending on the choice of a constructive heuristic and the way the pheromone values are used, there are different ways how this basic solution approach can be adapted to the exam timetabling problem. At each stage of the construction process in the AS approach of Costa and Hertz [7] called ANTCOL the ant chooses first a node i and then a feasible color according to a probability distribution equivalent to (c.f. section III, B, 9). The matrix τ provides information on the objective function value, i.e. the number of colors required to color the graph, which was obtained when nodes i and j are colored with the same color.

In contrast to elite strategies where only the ant that found the best tour from the beginning of the trial deposits pheromone, all ants deposit pheromone on the paths they have chosen. According to [21] this strategy is called ant cycle strategy. Different priority rules were tested as constructive heuristic. Among those chosen in each step, the node with the highest degree of saturation, i.e. the number of different colors already assigned to adjacent nodes, achieved the best results with respect to solution quality and computation times.

In [14] a pre-ordered list of events is given. Each ant chooses the color for a given node probabilistically similar to the formula (c.f. section III, B, 9). The pheromone trail τij contains information on how good the solution was, when node i was colored by color t. The constructive heuristic employed in their approach is not described.

For the exam timetabling problem the way the information in matrix τ is used in both approaches is not meaningful. Due to the conflicts of higher orders the quality of a solution does not depend on how a pair of exams is scheduled nor on the specific period an exam is assigned to. For example, assigning two exams i and j with $cij = 0$ to the same period can either result in a high or in a low objective function value as the quality of the solution strongly depends on when the remaining exams are scheduled. In the following we implemented a two-step approach.

Step I: Determine the sequence according to the exams is scheduled. Like for the TSP we assume that an ant located in a node, corresponding to an exam, has to visit all other nodes, i.e. it has to construct a complete tour. The sequence according to this ant constructs the tour corresponds to the sequence in which the exams are scheduled.

Step II: Find the most suitable period for an exam which should be scheduled. Therefore, all admissible periods are evaluated according to the given penalty function.

Following this two-step approach probabilities pvij for choosing the next node j that has to be scheduled are computed according to (c.f. section III, B, 9). Pheromone values τij the ants' paths are updated by the inverse of the objective function value.

For the heuristic value ηij the following simple priority rule for graph coloring was implemented. The exam with the smallest number of available periods is selected. A period would not be available for an exam if it caused a conflict of order 0 with another exam that has already been scheduled. This priority rule corresponds to the saturation degree rule (SD) which was tested in [1]. The value ηij is chosen to be the inverse of the saturation degree.

TABU TIMETABLE ANT COLONY OPTIMIZATION (TACO)

In the proposed TACO technique an initialisation phase takes place during which ants are positioned on different nodes (sessions) with empty tabu lists and initial pheromone distributed equally on paths connecting these sessions. Ants update the level of pheromone while they are constructing their schedules by iteratively adding new sessions to the current partial schedule. At each time step, ants compute a set of feasible moves and select the best one according to some probabilistic rules based on the heuristic information and pheromone level. The higher value of the pheromone and the heuristic information, the more profitable is to select this move and resume the search. The selected node is putted in the tabu list related to the ant to prevent to be chosen again. Heuristic information represents the nearer sessions around the current session, while pheromone level "memory" of each path represents the usability of this path in the past to find good schedules. At the end of each iteration, the tabu list for each ant will be full and the obtained cheapest schedule is computed and memorized. For the following iteration, tabu lists will be emptied ready for use and the pheromone level will be updated. This process is repeated till the number of iterations (stopping criteria) has been reached. In more details, the proposed TACO technique constructs the cheapest observation schedule for a given examination timetable using the following two stages.

SCHEDULE CONSTRUCTION STAGE

After each move, an ant leave a pheromone trail on the connecting path to be collected by other ants to compute the transition probabilities. Starting from the initial session i, an explorer ant m chooses probabilistically session j to observe next using the following transition rule:

$$P_m(i,j)=\begin{cases}\dfrac{\left[\tau_{(i,j)}\right]^{\alpha}\cdot\left[\eta_{(i,j)}\right]^{\beta}}{\sum_{k\in S_m(i)}\left[\tau_{(i,j)}\right]^{\alpha}\cdot\left[\eta_{(i,j)}\right]^{\beta}} & \text{if } j\in S_m(i)\\ 0 & \text{otherwise}\end{cases}$$

(9)

where

τ(i,j) : the intensity measure of the pheromone deposited by each ant on the path (i,j). The intensity changes during the run of the program.

α : the intensity control parameter.

η(i,j) : the visibility measure of the quality of the path (i,j). This visibility, which remains constant during the run of the program, is determined by η(i,j)=1/l(ij), where l(ij) is the cost of move from session i to the session j.

β : the visibility control parameter.

Sm(i) : the set of sessions that remain to be observed by ant m positioned at session i.

Equation 9 shows that the quality of the path (i,j) is proportional to its shortness and to the highest amount of pheromone deposited on it (i.e., the selection probability is proportional to path quality).

PHEROMONE UPDATING STAGE

Ants change the pheromone level on the paths between sessions using the following updating rule:

$$\tau_{(i,j)} \leftarrow \rho\cdot\tau_{(i,j)}+\Delta\tau_{(i,j)}$$

(10)

where

ρ : the trail evaporation parameter.

Δτ(i,j) : the pheromone level.

The amount of deposited pheromone is the mechanism by which ants communicate to share information about good paths. Stagnation may occur during the pheromone updating and this can be happened when the pheromone level is significantly different between paths connecting the observed schedule. This means that some of these paths have received higher amount of pheromone more than other and an ant will continuously select these paths and neglect the others. In this situation, ants keep constructing the same schedule over and over again and the exploration of the search stops. Stagnation can be avoided by influencing the probability for choosing the next path which depends directly on the pheromone level. To make better use of the pheromone and exploit the search space of a schedule more effectively, several ideas based on the pheromone control strategy have been implemented, tested and analysed. Some of these ideas are: additional pheromone trail limits, smoothing of the pheromone trails, re-initialization of the pheromone trial and additional reinforcement of the pheromone, etc. In the following section, different approaches based on these ideas have been proposed and implemented to effectively diverse the search space and select the best possible observation schedule for a given timetable schedule..”

ANT COLONY SYSTEM

Ant Colony System (ACS) differs from the other ACO instances due to its strategy of constructing an observation schedule [10]. An ant positioned on session i selects the session j to observe by applying the following equation:

$$p_{(i,j)} = \begin{cases} \arg\max_{k\in s_m(i)}[\tau_{(i,k)} \cdot \eta^{\beta}_{(i,k)}] & if\ q \le q_0 \\ I & otherwise \end{cases} \quad (11)$$

where

I : a random variable selected according to the probability given by Equation 1.

q : a uniformly distributed random number to determine the relative importance of exploitation versus exploration q∈[0,..,1].

q0 : a threshold parameter and the smaller q0 the higher the probability to make a random choice (0 ≤ q0 ≤ 1).

In each step of building a schedule, an ant located at session i samples the parameter q to move to session j. Using Equation 3, an ant selects the best path to reach the next session when (q ≤q0) (exploitation). Otherwise, the ant will probabilistically choose the next session to be observed using Equation 2 with a bias toward the best possible path (biased exploration). While ants build their schedules, at the same time they locally update the pheromone level of the visited paths using the local updating rule as follows:

$$\tau_{(i,j)} \leftarrow (1-\varphi)\cdot\tau_{(i,j)} + \varphi\cdot\tau_0 \quad (12)$$

where

φ : a persistence of the trail and the term (1-φ) can be interpreted as trail evaporation.

τ0: the initial pheromone level which is assumed to be a small positive constant distributed equally on all the paths of the network since the start of the survey.

The aim of the local updating rule is to make better use of the pheromone information by dynamically changing the desirability of paths. Using this rule, ants will search in wide neighbourhood of the best previous schedule. When all ants have completed their schedule, the pheromone level is updated by applying the global updating rule only on the paths that belong to the best found schedule since the beginning as follows:

$$\tau_{(i,j)} \leftarrow (1-\rho)\cdot\tau_{(i,j)} + \rho\cdot\Delta\tau_{(i,j)} \quad (13)$$

$$\Delta\tau_{(i,j)} = \begin{cases} (C_m)^{-1} & if\ (i,j) \in Global-Best-Schedule \\ 0 & oherwise \end{cases} \quad (14)$$

where

ρ : a pheromone decay parameter.

Cm : the cost of the best schedule performed from the beginning by ant m.

This rule is intended to provide a greater amount of pheromone on the paths of the best schedule, thus intensifying the search around this schedule. In other words, only the best ant that took the shortest route is allowed to deposit pheromone.

MAX-MIN ANT SYSTEM

The strategy of the MAX-MIN Ant System (MMAS) states that if the amount of the pheromone has a finite upper bound and a positive lower bound min, then ACO converges to the optimal solution [12]. The main features of MMAS algorithm for obtaining an improved performance on the basic ACO metaheuristic are as follows:

Deep exploitation to the search space of the best found schedule by allowing a single ant to add pheromone after each iteration. This ant may be the one which found the best schedule in the current iteration (iteration-best ant) or the one which found the best schedule from the beginning (global-best ant).

Wide exploration to the search space of the best found schedule by initialising the pheromone trails to max is used. Thus, in the next iteration only the paths that belong to the best schedule will receive pheromone, while the pheromone values of the other paths are only evaporated.

As shown from the above, the aim of using only one schedule is to make the paths of the best found schedule receive large reinforcements.

TACO ALGORITHM

The function of ACO algorithm with Tabu Search (TACO) is to force ants to search for a better schedule by divorcing and exploring the search space while keeping the best found schedule [22]. This can be carried out by adding extra pheromone on the unused paths during the previous iterations and this will force ants to diverse the search space and choose other new directions without repeating any bad experience and trapping again in local optimality of the schedule search space. The modified pheromone update rule in TACO is given as follows:

$$\tau_{(i,j)} \leftarrow \xi \cdot \tau_{(i,j)} + q_1 \tau_{\max}$$

(15)

where

$$\xi = \begin{cases} 1 & \text{if unused paths are evaporated} \\ \rho & \text{otherwise} \end{cases}$$

$q1 \geq 0$: a reinforcement parameter;

τ max : asymptotically the maximal value of the pheromone. This condition ($q1 \leq 1 - \rho$) must be satisfied to fulfil the above criteria of the TACO technique for updating the pheromone.

CASE STUDY

To benchmark algorithms test cases of twelve practical examination problems can be found on the site of Carter [9]. Three experiments were carried out:

1. TACO (with hill climber)
2. TACO without hill climber
3. TACO without ants

Therefore, Carter proposed weighting conflicts according to the following penalty function: P1 = 16, P2 = 8, P3 = 4, P4 = 2, P5 = 1, where $P\omega$ is the penalty for the constrain violation of order ω. The cost of each conflict is multiplied by the number of students involved in both exams. The objective function value represents the costs per student.

IV. PARAMETER ADJUSTMENT

The required parameters were specified as follows. The number of cycles was set to 50. Within each cycle 50 ants were employed to construct solutions. The candidate list contained the 20% of exams with the lowest number of available periods. Several test runs were carried out in order to determine the required parameters appropriately:

– The evaporation rate ρ was set to 0.3. Like in [14] it turned out that this parameter is quite robust, i.e. the parameter ρ does not clearly influence the performance.

– For the restrictions of the pheromone interval values to strategies were tested. Setting $\tau max = 1/\rho$ obtained slightly better results than in the case of variable τmax and τmin as proposed in [14].

– Diff erent values for the weighting factors α and β were tested. It turned out that the approach performed best when α was set to one and β was chosen high. Best results were obtained for β equal to 24. But the diff erence was on the average less than one percent when β was bigger than eight. A high β forces that exams which can be scheduled, due to zero order conflicts, only in a few remaining periods are scheduled first as they are given a much higher probability in (c.f. section III, B, 9). Remember that ηij is the inverse of the saturation degree. Thus, a high β value has the same eff ect like a candidate list. This could be a reason why the use of the candidate list did not improve the solutions. Whereas, for small values of β, i.e. values lower than 5, solutions with zero order conflicts could not always be avoided.

– As the approach is non-deterministic each test case was solved twenty times. After determining the parameters in such a way, it turned out that less than 2 % of the solutions were generated more than once. Thus, stagnation that is caused by the fact that many ants generate almost the same solutions could not be observed.

V. TEST RESULTS

Table 2 displays the results for diff erent approaches. For each approach the minimal objective function value and the average result after twenty test runs are given. Results of the proposed TACO approach are given in the second column.

In order to find out how much the hill climber contributes to the solution the TACO approach was also tested without making use of the hill climber. Comparing the results in the second and in the third column it is obvious that the hill climber considerably improves the solutions.

Thus, one could ask how much the ants contribute to the solution or if solutions of the same quality could also be achieved by applying only the hill climber on a random starting solution. Therefore a third version of the TACO approach was implemented where each ant constructs an exam timetable without interacting with the other ants, i.e. the matrix τ is not updated at all. This approach can be seen as a randomized greedy heuristic. As in TACO with 50 ants and 50 cycles 2500 exam timetables were generated. The best solutions of this approach are displayed in the last column of table 1. As the TACO approach without ants generates the worst solutions it is obvious, that the ant colony has a positive impact on the diversification of the solution space, i.e. the ants guide the search process into promising regions of the solution space where the hill climber can find good solutions. Increasing the number of ants and the number of cycles to 100 in the TACO approach did not result in achieving better solutions. Neither the average value of all twenty iterations was improved nor was better solutions found during the twenty iterations.

Table 2: Results for three diff erent variants of the TACO approach for twenty test runs

	TACO		TACO without hill climber		TACO without ants	
test case	best	avg	best	avg	best	avg
car-f-92	4.8	4.9	7.4	8.2	10.9	13.5
car-s-91	5.7	5.9	9.2	9.6	11.6	13.8
car-f-83	36.8	38.6	49.9	53.6	48.6	61.3
hec-s-92	11.4	11.6	14.8	15.2	11.3	15.2
kfu-s-93	15.1	15.4	23.8	24.6	19.3	22.5
lse-f-91	12.1	12.7	19.2	19.5	16.8	25.6
pur-s-03	504	5.6	12.2	12.5	11.5	14.5
rye-s-93	10.2	10.4	18.1	18.5	12.1	15.2
sta-f-83	155.3	157.5	160.3	161.3	157.6	158.2
tre-s-92	8.8	9.1	12.5	12.8	9.6	13.2
uta-s-92	3.8	3.8	6.2	6.5	8.5	9.8
ute-s-92	27.7	28.6	33.8	32.5	27.5	31.2
yor-f-83	39.6	40.3	50.23	51.9	62.8	75.2

VI. CONCLUSION

In this paper different strategies for solving exam timetabling problems were tested. Ant colony approaches are capable of solving large real world exam timetabling problems. The implemented algorithms generated comparable results like other high performance algorithms from the literature. Unlike for other combinatorial optimization problems like the TSP or the QAP for the exam timetabling problem the variants of the TACO approach did not outperform the simpler strategies. Of course, it goes without saying but proper adjusting parameters can improve the performance of an algorithm considerably. A self-evident extension would be to incorporate additional constraints and requirements like e.g. scarce room resources or precedence constraints between exams. For future work, dynamic optimization will be searched for improving the use of space technology in other real life applications (e.g., ambiguity resolution). These applications require powerful dynamic optimization tools that account for the uncertainty present in a changing school environment. This will provide the state of the art and latest research on how dynamic metaheuristic algorithms may be applied to effectively and efficiently solve and optimize this kind of complex problems.

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