

Scheduling Technicians and Tasks in a Telecommunications Company

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Abstract

This paper proposes a construction heuristic and an adaptive large neighborhood search heuristic for the technician and task scheduling problem arising in a large telecommunications company. This problem was solved within the framework of the 2007 challenge set up by the French Operational Research Society (ROADEF). The paper describes the authors' entry in the competition which tied for second place.

Keywords: Heuristics, simulated annealing, large neighborhood search, scheduling, manpower planning.

1 Introduction

This paper proposes a construction heuristic and an adaptive large neighborhood search heuristic for the technician and task scheduling problem (TTSP) in a large telecommunications company. These tasks can be maintenance, installation or construction jobs. The TTSP is a difficult real-life problem, introduced as the subject of the 2007 challenge set up by the French Operational Society (ROADEF) in collaboration with France Télécom. This challenge is organized on a different theme every second year. Challengers are given the definition of a hard optimization problem arising in practice and are asked to develop an algorithm for its solution. Several data sets are provided by the organizers for testing purposes but new data are used at the final stage of the competition. In 2007, 31 teams entered the challenge and 11 made it to the final stage. This paper describes the authors' entry in the competition which tied for second place.

The TTSP is defined in Dutot et al. [2006]. We are given a set of tasks $N = \{1, \dots, n\}$ and a set of technicians $\mathcal{T} = \{1, \dots, m\}$. Each technician is proficient in a number of *skill domains*. There are q skill domains and a technician's level of proficiency in a given domain is described by an integer from 0 to p , where 0 means that the technician has no skill in the associated domain. We can express each technician's skills by a q -dimensional *skill vector* in which the l^{th} entry indicates the technician's skill level in the l^{th} skill domain.

The tasks vary in difficulty and some require more than one technician. The number of technicians required and the difficulty of a task i are described by a $p \times q$ *skill requirement matrix* ($s_{\alpha\beta}^i$). The columns in the matrix correspond to skill domains and the rows correspond to proficiency levels. The entry $s_{\alpha\beta}^i$ indicates the number of technicians with a level of at least α in domain β that are necessary to perform task i . Note that a requirement for a high skill level carries over to the lower skill levels. An example of a skill requirement matrix with four domains and three skill levels is given below:

$$\begin{pmatrix} 1 & 2 & 0 & 2 \\ 0 & 1 & 0 & 2 \\ 0 & 1 & 0 & 2 \end{pmatrix}.$$

In this example the task requires one technician with a proficiency of at least 1 in domain 1. It requires two technicians to be proficient in domain 2: one must be at least a level 1 technician and the other must be at least level 3. No skilled technician in domain 3 is needed and two technicians with skill level 3 in the fourth domain are necessary.

Similarly, we represent the skills of technician j as a matrix ($v_{\alpha\beta}^j$). The skill matrix of a technician with skill vector (2,1,1,3), $p = 3$ and $q = 4$ is

$$\begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \end{pmatrix}.$$

Technicians are grouped into teams in order to perform the tasks. If two technicians have skill vectors $(2, 1, 1, 3)$ and $(1, 3, 2, 3)$, then a team consisting of these two technicians would be able to serve a task with the above skill requirement matrix. The team would be overqualified for the task, but this is allowed. Usually it is impossible to perform all tasks of a TTSP instance in a single day and the tasks are performed over several days. A team must stay together on a given day, but can be broken up on the following day. A task can always be completed in a single day and the execution of a task cannot be interrupted nor split over several days. Technicians can be unavailable on specific days due to holidays or training. We will denote the set of technicians available on day k by \mathcal{T}_k .

Apart from the skill requirement matrix, each task $i \in N$ is characterized by a duration $d_i \in \mathbb{Z}^+$, an outsourcing cost $c_i \in \mathbb{Z}^+$, a set π_i of predecessor tasks, a set σ_i of successor tasks, and a priority level $p_i \in \{1, \dots, 4\}$. The set π_i contains the tasks that must be completed before i starts and the set σ_i contains the tasks that cannot be started before task i is finished. It is assumed that $j \in \pi_i \Leftrightarrow i \in \sigma_j$ for all $i, j \in N$. The duration d_i states how long it takes to perform task i . This duration is constant and remains the same no matter how many technicians are assigned to the task.

The priority p_i of a task is used in the objective function of the problem, which is a weighted makespan of each priority type. More precisely we minimize the function $w_1 t_1 + w_2 t_2 + w_3 t_3 + w_4 t_4$, where t_i is the ending time of the last task of priority type $i \in \{1, 2, 3\}$ and t_4 is the ending time of the last task under consideration. The weights w_i are defined in Dutot et al. [2006] as $w_1 = 28, w_2 = 14, w_3 = 4, w_4 = 1$. One sees that it is important to serve priority 1 tasks as early as possible.

A budget C is available to outsource tasks. A set of tasks A can be outsourced if $\sum_{i \in A} c_i \leq C$ and $\sigma_i \subseteq A, \forall i \in A$. Outsourcing tasks is not penalized in the objective.

Figure 1 depicts an example of a solution to a TTSP instance with 20 tasks, no precedence relations, seven technicians, and $C = 0$. The solution is displayed as a Gantt chart and spans three days. Each task is shown as a rectangle whose width corresponds to the duration of the task. The shade of the rectangle encodes the priority of the task (lighter rectangles correspond to more important tasks). Each row in the figure corresponds to a team; the technicians in the team are displayed on the left. The x -axis shows the time (each day is divided into 120 time units). The horizontal placement of each task shows its starting and ending times. The figure illustrates that although priority 1 tasks are the most important, it is not always best to first serve the tasks in order of decreasing importance. In the example, priority 2 tasks are finished quickly as there only are a few of these tasks. The cost of the solution is $28 \cdot 300 + 14 \cdot 120 + 4 \cdot 360 + 1 \cdot 360 = 11,880$.

The problem under study belongs to the class of multi-skill project scheduling problems with hierarchical skill levels, investigated by Bellenguez and Néron [2005] and Bellenguez-Morineau and Néron [2007]. To our knowledge, the exact problem considered in this paper has not been previously addressed. In particular, we are the only ones to minimize a weighted

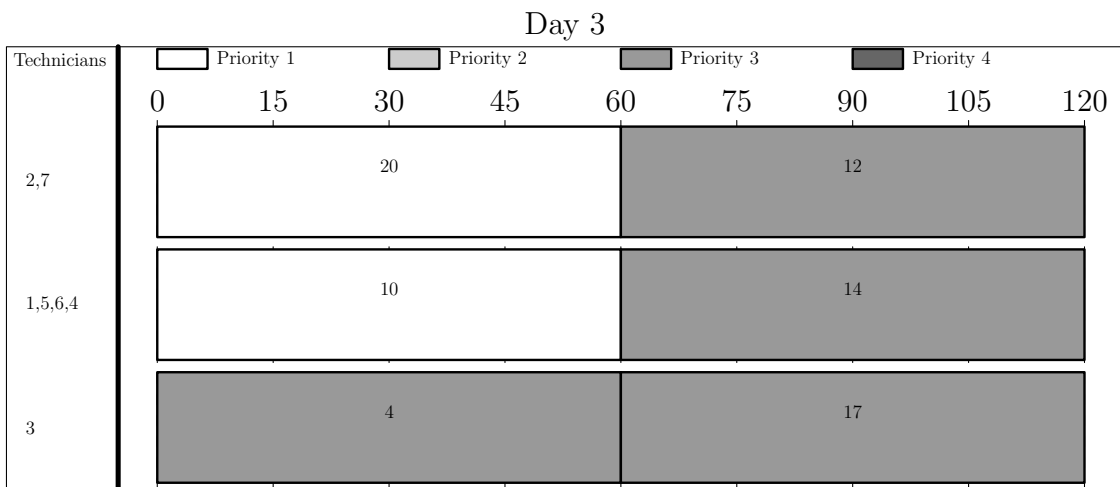
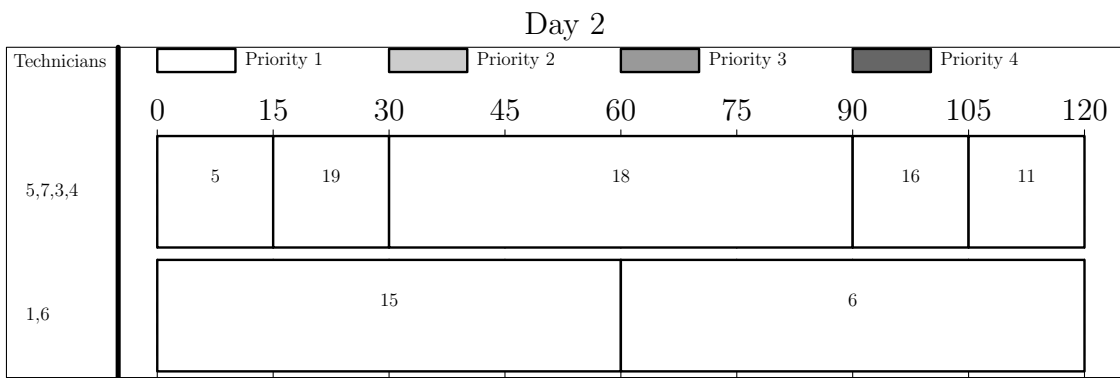
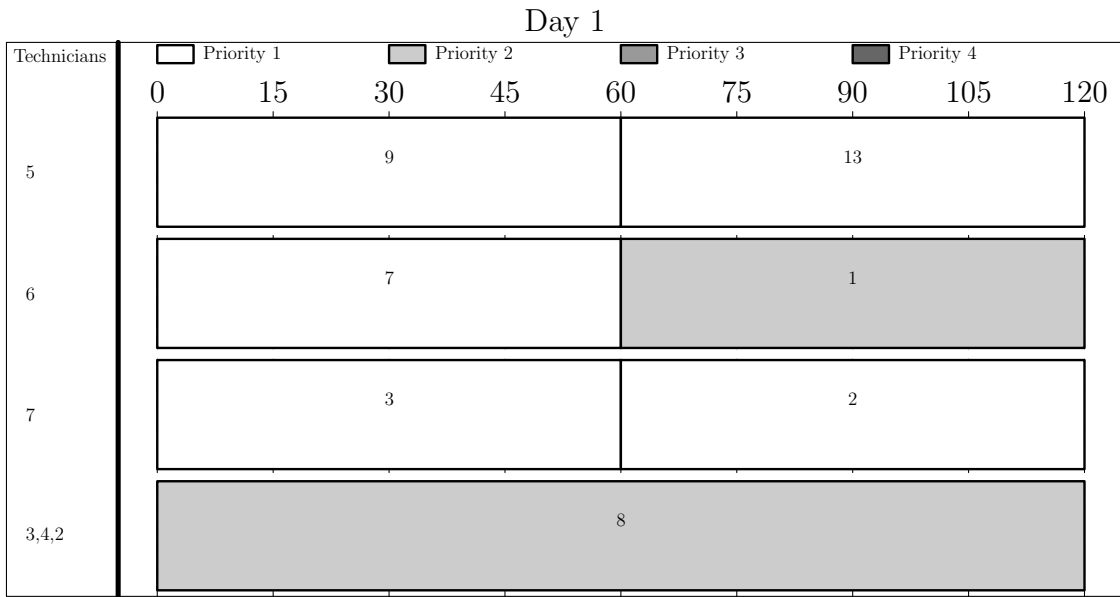


Figure 1: Solution of an instance with 20 tasks and seven technicians.

prioritized objective. Our paper, like those of Caramia and Giordani [2008], Bellenguez and Néron [2005] and Bellenguez-Morineau and Néron [2007], does not consider routing costs between tasks. In these three references this is only natural because tasks are assigned to fixed resources like machines. All other references we are aware of (Begur et al. [1997], Weigel and Cao [1999], Eveborn et al. [2006], Bertels and Fahle [2006]) handle skill levels, as we do, as well as routing costs. No other study considers outsourcing. Like us, Eveborn et al. [2006], Bellenguez and Néron [2005] and Bellenguez-Morineau and Néron [2007] assign several technicians of different skills to the same task, while most other studies assign a single technician to a task. With the exception of Bellenguez and Néron [2005] and Bellenguez-Morineau and Néron [2007] who have developed lower bounds and an exact branch-and-bound algorithm, all authors have proposed heuristics: classical heuristics (Eveborn et al. [2006], Begur et al. [1997]), metaheuristics (Bertels and Fahle [2006], Weigel and Cao [1999], Caramia and Giordani [2008]) or heuristic constraint programming (Caseau and Koppstein [1992]). Overall, the paper that most resembles ours is that of Caseau and Koppstein [1992] which considers routing costs and maximizes the number of tasks that can be completed within a preset time limit.

The remainder of this paper is organized as follows. In Section 2 we provide a mathematical model for the problem. Sections 3 and 4 describe our construction heuristic and our adaptive large scale neighborhood search heuristic, respectively. Computational results follow in Section 5.

2 Mathematical model

This section presents a mathematical model to precisely define the problem. We introduce further notation. Let N_p denote the set of tasks with priority p , N^σ the set of tasks with successors, and K the index set of all days. There is no imposed upper bound on the number of days used to schedule all tasks, but by using an upper bound u on the objective function value, one can derive a limit on the number of days: since an optimal solution can use at most $\lceil u/120 \rceil$ days, $K = \{1, \dots, \lceil u/120 \rceil\}$. In the following, M denotes a large number and setting $M = 120|K|$ is sufficient.

Our model uses binary variables $x_{jkr} \in \{0, 1\}$ equal to 1 if and only if technician j is assigned to team r on day k , and $y_{ikr} \in \{0, 1\}$ equal to 1 if and only if task i is assigned to team r on day k . We also use continuous variables $b_i \geq 0$ for the start time of task i and $e_p \geq 0$ for the ending time of the latest task of priority p for $p \in \{1, 2, 3\}$ and the latest task overall for $p = 4$. Binary variables $z_i \in \{0, 1\}$ take value 1 if and only if task i is outsourced. Finally, binary variables $u_{ii'} \in \{0, 1\}$, $i, i' \in N$, $i \neq i'$ take value 1 if and only if task i finishes before task i' starts. These are used to ensure that two tasks served by the same team on the same day do not overlap. Using this notation, the TTSP can be modeled as follows:

$$\text{minimize } \sum_{p=1}^4 w_p e_p \quad (1)$$

subject to

$$e_p \geq b_i + d_i \quad \forall p \in \{1, 2, 3\}, \forall i \in N_p \quad (2)$$

$$e_4 \geq b_i + d_i \quad \forall i \in N \quad (3)$$

$$\sum c_i z_i \leq C \quad (4)$$

$$|\sigma_i| z_i \leq \sum_{i' \in \sigma_i} z_{i'} \quad \forall i \in N^\sigma \quad (5)$$

$$\sum_{r=1}^m x_{jkr} \leq 1 \quad \forall k \in K, \forall j \in \mathcal{T}_k \quad (6)$$

$$\sum_{r=1}^m x_{jkr} = 0 \quad \forall k \in K, \forall j \in \mathcal{T} \setminus \mathcal{T}_k \quad (7)$$

$$z_i + \sum_{k \in K} \sum_{r=1}^m y_{ikr} = 1 \quad \forall i \in N \quad (8)$$

$$y_{ikr} s_{\alpha\beta}^i \leq \sum_{j \in \mathcal{T}_k} v_{\alpha\beta}^j x_{jkr} \quad \forall i \in N, \forall k \in K, \forall r \in \{1, \dots, m\},$$

$$\forall \alpha \in \{1, \dots, p\}, \forall \beta \in \{1, \dots, q\} \quad (9)$$

$$b_i + d_i \leq b_{i'} + M z_i \quad \forall i \in N^\sigma, \forall i' \in \sigma_i \quad (10)$$

$$120(k-1) \sum_{r=1}^m y_{ikr} \leq b_i \quad \forall i \in N, \forall k \in K \quad (11)$$

$$120k \sum_{r=1}^m y_{ikr} \geq b_i + d_i \quad \forall i \in N, \forall k \in K \quad (12)$$

$$b_i + d_i - (1 - u_{ii'})M \leq b_{i'} \quad \forall i, i' \in N, i \neq i' \quad (13)$$

$$y_{ikr} + y_{i'kr} - u_{ii'} - u_{i'i} \leq 1 \quad \forall i, i' \in N, i \neq i', \forall k \in K, \forall r \in \{1, \dots, m\} \quad (14)$$

$$x_{jkr} \in \{0, 1\} \quad j \in \mathcal{T}, \forall k \in K, \forall r \in \{1, \dots, m\} \quad (15)$$

$$y_{ikr} \in \{0, 1\} \quad i \in N, \forall k \in K, \forall r \in \{1, \dots, m\} \quad (16)$$

$$z_i \in \{0, 1\} \quad i \in N \quad (17)$$

$$u_{ii'} \in \{0, 1\} \quad i, i' \in N, i \neq i' \quad (18)$$

$$e_p \geq 0 \quad \forall p \in \{1, 2, 3, 4\} \quad (19)$$

$$b_i \geq 0 \quad i \in N. \quad (20)$$

Inequalities (2) and (3) define the ending times used in the objective, and inequality (4) enforces the outsourcing budget. Inequalities (5) ensure that if a task is outsourced then so

are all its successors. Inequalities (6) ensure that a technician is used at most in one team per day, and inequalities (7) mean that unavailable technicians are not used. Inequalities (8) ensure that every task is either performed or outsourced, while inequalities (9) state that each task is performed by a team with the appropriate skills (if it is not outsourced), and inequalities (10) enforce the precedence constraints. Inequalities (11) and (12) set lower and upper bounds on the starting time of each task based on which day the task is performed. Inequalities (13) set the $u_{ii'}$ variables correctly relative to the starting times of task i and i' , while (14) guarantee that task i and i' do not overlap if they are performed by the same team on the same day: if two distinct tasks i and i' are served by the same team r on the same day k , then $y_{ikr} + y_{i'kr} = 2$ and either $u_{ii'}$ or $u_{i'i}$ must be equal to 1 for the inequality to be satisfied. Constraints (15)–(20) define the domains of the decision variables.

3 Construction heuristic

This section describes a construction heuristic for the TTSP. This heuristic can reasonably quickly provide a feasible solution to the problem and is used as an important component in the metaheuristic described in Section 4. It plans one day at a time, using a two-phase approach. In the first phase teams are constructed and a single task is assigned to each of them, while in the second phase more tasks are assigned to the already constructed teams.

The precedence constraints are cumbersome to handle and we have therefore chosen a simple strategy to ensure that they are satisfied by the solution produced by the construction heuristic. The strategy prevents tasks having unplanned predecessors from being inserted by the construction heuristic. As soon as all predecessors of a task have been inserted, the task becomes available for the construction heuristic and it can then be inserted in a position that satisfies the precedence constraint.

3.1 Phase 1: constructing teams

The heuristic constructs teams by selecting an unserved task and constructing a team for it. We call such a task a *seed task*. Seed tasks are selected based on three criteria: *criticality*, *difficulty* and *similarity*. The first criterion measures how important it is to serve the task early, depending on the priority and duration of the task and of its successors. More precisely, we define the criticality α_i of a task i as

$$\alpha_i = w_{p_i} d_i + \sum_{j \in \sigma_i} w_{p_j} d_j.$$

Recall that p_i is the priority of task i and w_j is the weight used in the objective for priority j . One sees that high priority tasks and tasks with many successors are considered critical.

The second criterion, difficulty, is a measure of how difficult it is to create a team for the task. It is based on the skill matrix of the task. We define the difficulty β_i of a task i as

$$\beta_i = \sum_{k=1}^p \sum_{l=1}^q (s_{kl}^i)^\delta,$$

where δ is a weight that can be used to make tasks requiring several technicians more difficult. This difficulty measure reacts to tasks that require highly skilled technicians. For example, assume that $\delta = 1$. If a task requires precisely one level 1 technician in a single domain its difficulty score is 1. If a task requires precisely one level 5 technician in a single domain its difficulty score is 5 because the task's skill matrix would have $s_{kl} = 1$ for $l = 1, \dots, 5$ for the particular domain k . Such a task would seem much more difficult.

The last criterion, similarity, measures how similar a task is to the tasks already chosen as seed tasks. We want the seed tasks to be different from each other in order to be able to serve a variety of tasks on a given day and not just a small subset of the tasks. We define the similarity γ_{ij} between two tasks i and j as

$$\gamma_{ij} = \sum_{k=1}^p \sum_{l=1}^q |s_{kl}^i - s_{kl}^j|.$$

This similarity measure is defined in terms of the difference in the skill requirements of the two tasks. We also define the similarity γ_{iS} of a task i , relative to a set of already chosen seed tasks S as

$$\gamma_{iS} = \sum_{j \in S} \gamma_{ij}.$$

The three measures are used to construct a score for each unassigned task i as follows:

$$f(i, S) = w_\alpha \alpha_i + w_\beta \beta_i + w_\gamma \gamma_{i,S},$$

where S is the set of existing seed tasks and w_α, w_β and w_γ are parameters that determine the importance of each measure. The task with the highest score is chosen as a possible seed task. If it is possible to perform it with the technicians available on the current day, then this task is declared a seed task and the corresponding team is created (the process will be explained later). If this is impossible, then the algorithm proceeds with the next best task based on the $f(i, S)$ score until a task that can be served has been found or all tasks have been considered. Each time a team has been constructed, the number of unassigned technicians is checked. If fewer than $\theta |\mathcal{T}_k|$ technicians are unassigned then the construction of teams is stopped. Here $\theta \in [0, 1]$ is a *safety stock* parameter on day k , introduced to ensure that some technicians are left unassigned for the second phase of the heuristic where tasks are assigned to the existing teams. These remaining technicians can be used to adjust existing teams when a team lacks a few skills in order to serve a certain task.

When constructing teams the algorithm follows a greedy approach. Initially an empty team is created. Technicians are then added one at a time to the team until it is able to

serve the task, or when it is determined that the task cannot be served by the available technicians. The algorithm always adds the technician who is able to *cover* most of the demanded skills not already covered by the other technicians in the team. To illustrate the concept of covering skill requirements we use the following example. Consider the skill requirement matrix used in Section 1:

$$A = \begin{pmatrix} 1 & 2 & 0 & 2 \\ 0 & 1 & 0 & 2 \\ 0 & 1 & 0 & 2 \end{pmatrix},$$

and three technicians with skill vectors $(2, 1, 1, 3)$, $(1, 3, 2, 3)$ and $(1, 1, 0, 0)$. We can express these skill vectors as the three matrices B , C and D :

$$B = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \end{pmatrix}, C = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 \\ 0 & 1 & 0 & 1 \end{pmatrix}, D = \begin{pmatrix} 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}.$$

The formula for calculating by how much a technician with skill matrix $Y = (y_{kl})$ covers a task with skill requirement matrix $X = (x_{kl})$ is

$$\sum_{k=1}^p \sum_{l=1}^q \min\{x_{kl}, y_{kl}\}.$$

In this example the covering scores for the three technicians are 5, 7 and 2, respectively. The greedy heuristic would consequently chose the second technician, after which the skill requirement matrix is updated since some skills have been covered. We construct a new skill requirement matrix $X' = (x'_{kl})$ from the prior skill requirement matrix X and the technician skill matrix Y by setting $x'_{kl} = \max\{0, x_{kl} - y_{kl}\}$, $k = 1, \dots, p, l = 1, \dots, q$. The updated skill requirement matrix A' in the example is

$$A' = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \end{pmatrix},$$

and the covering scores by using matrix B and D are 4 and 1, respectively. The greedy algorithm would choose to add the first technician to the team and the resulting team could then perform the task.

If several technicians have the same covering score, a second criterion is then used to break ties. It measures the amount of skills *wasted* by assigning the technician to the task and team. If the technician's skill matrix is Y and the skill requirement matrix is X then the score for wasted skills is

$$\sum_{k=1}^p \sum_{l=1}^q \max\{0, y_{kl} - x_{kl}\}.$$

The skill requirement matrix A and the skill matrices B, C and D result in the waste scores 2, 2 and 0 respectively. Further tie breaking is done by selecting the technician with lowest index.

The first phase of the construction heuristic is outlined in Algorithm 1. The function $\text{makeTeam}(i, M')$ creates a team for task i using technicians from the set M' as described above. The function returns the set of technicians on the team. If it is impossible to create a team for the task then the empty set is returned. The function $\text{addteam}(k, U)$ adds the team consisting of the technicians in the set U to the current plan on day k .

Algorithm 1 Phase 1: Team construction

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1: input:  $k$  (day),  $T$  (unassigned tasks);
2:  $S = \emptyset$ ;  $M' =$  available technicians on day  $k$ ;
3: repeat
4:   repeat
5:      $i' = \arg \max_{i \in T} \{f(i, S)\}$ ;
6:      $T = T \setminus \{i'\}$ ;
7:      $U = \text{makeTeam}(i', M')$ ;
8:      $M' = M' \setminus U$ ;
9:   until  $U \neq \emptyset \vee T = \emptyset$  ;
10:  if  $U \neq \emptyset$  then
11:     $\text{addTeam}(k, U)$ ; assign  $i'$  to new team;  $S = S \cup \{i'\}$ ;
12:  end if
13: until  $|M'| \leq \theta m_k \vee T = \emptyset$ 

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3.2 Phase 2: assigning tasks

In the second phase of the construction of a day in the schedule, the algorithm assigns tasks to the teams constructed in phase 1. The core of the second phase is a score $g(i, u)$ that measures how promising it is to assign task i to team u . This score is composed of three weighted terms: 1) the criticality α_i of task i as defined in Section 1, 2) the number of technicians $h_1(i, u)$ that must be added to team u so that it can perform task i , and 3) the skills $h_2(i, u)$ wasted by assigning task i to team u after team u has been extended to be capable of serving i (if necessary). The term $h_1(i, u)$ is calculated by using the algorithm for constructing teams outlined in Section 1 and by using the skill requirement matrix that remains after covering the requirement matrix of task i with the technicians in team u . Of course, only the remaining free technicians can be used to extend the team. The term $h_2(i, u)$ is calculated for the extended team found when calculating $h_1(i, u)$ and only takes into account the skills wasted when serving task i , not the skills wasted while serving the

other task assigned to team u . The formula for calculating $g(i, u)$ is

$$g(i, u) = w_\kappa h_1(i, u) + w_\lambda h_2(i, u) - w_\mu \alpha_i,$$

where w_κ , w_λ and w_μ are parameters. If task i cannot be served by team u , even after adding extra technicians, then we set $g(i, u) = \infty$. Obviously low scores are preferred.

Having defined $g(i, u)$ the rest of phase 2 is simple. We scan all teams and all unassigned tasks and choose the task and team for which $g(i, u)$ is lowest. The selected task i is inserted into the selected team u and technicians are added to team u if necessary. This process stops when no more tasks can be inserted into any team on the current day. When that happens the algorithm checks whether some technicians are still unassigned. If this is the case, then one of these technicians is chosen and a team consisting of only that technician is formed. The algorithm then attempts to insert tasks into this team using the $g(i, u)$ score. The team can be extended with more technicians if possible and necessary. We continue adding teams in this fashion until all technicians have been assigned to a team and no more tasks can be inserted. If there still are unassigned tasks left after finishing phase 2 we start on a new day and repeat phases 1 and 2.

3.3 Further details and improvements

This section describes details and features of the construction algorithm. Section 3.3.1 explains how the algorithm selects the tasks that should be outsourced and Section 3.3.2 discusses the parameters of the construction algorithm.

3.3.1 Outsourcing tasks

In the description of the construction algorithm we have not explained how the algorithm deals with the opportunity to outsource tasks. Since there is no penalty in the objective function for outsourcing tasks, as long as the budget is respected, the algorithm should take advantage of this opportunity.

We select the tasks to outsource before the construction starts. We assign a score $\chi(p_i)d_i\nu_i/c_i$ to each task i , where $\chi(p_i) = (w_{p_i})^2$ (recall that w_{p_i} is the objective weight of the priority class of task i) and ν_i is a lower bound on the number of technicians needed to perform task i . This value is determined as $\nu_i = \max_{k \in \{1, \dots, p\}, l \in \{1, \dots, q\}} \{s_{kl}^i\}$. The score expresses a preference to outsource tasks that take a long time, have an important priority and need many technicians but are cheap to outsource. Tasks are sorted according to a decreasing score and are outsourced by processing the sorted list as long as the budget allows it. When we encounter a task that cannot be outsourced because of insufficient budget we skip it and try the next one. We take care not to remove tasks that have non-outsourced successor tasks in order to avoid infeasible solutions.

3.3.2 Setting parameters

The construction heuristic is controlled by many parameters, which is usually undesirable. We can, however, use the parameters to our advantage to create a diversification effect. This is done by setting the parameters randomly within certain intervals. The parameters are $\delta, w_\alpha, w_\beta, w_\gamma$ and θ (parameters used in first phase of construction algorithm), w_κ, w_λ and w_μ (parameters used in the second phase of the construction algorithm). The default values of the parameters are $\delta = 1, w_\alpha = 0.1, w_\beta = 1, w_\gamma = 1, \theta = 0.2, w_\kappa = 5, w_\lambda = 1$ and $w_\mu = 0.025$. In the randomizing process, the values of the parameters are chosen randomly within the following intervals $\delta = 1, w_\alpha \in [0; 1], w_\beta \in [0; 10], w_\gamma \in [0; 10], \theta \in [0; 0.5], w_\kappa \in [1; 20], w_\lambda \in [0.5; 2]$ and $w_\mu \in [0; 0.2]$. The parameter values and intervals were calibrated by performing a limited number of tests.

In Section 4 it will become clear how the different versions of the construction heuristic are used within the adaptive large neighborhood search algorithm.

4 Adaptive large neighborhood search

Adaptive large neighborhood search (ALNS) is an extension of the *large neighborhood search* (LNS) metaheuristic proposed by Shaw [1998] and is related to the *ruin and recreate* (RR) heuristic of Schrimpf et al. [2000]. It was introduced by Ropke and Pisinger [2006a] and has been successful in solving many variants of the vehicle routing problem (see Pisinger and Ropke [2007], Ropke and Pisinger [2006b]). The basic idea behind the LNS and RR heuristics is to improve an initial solution by repeatedly *destroying* and *repairing* the solution. In the destroy step, a part of the solution structure is broken down and the solution is reconstructed in the repair step. The combination of these two steps hopefully lead to a better solution. In our problem, a solution is destroyed by removing a subset of the tasks from the solution and the solution is repaired by reinserting these tasks using the construction heuristic described in Section 3.

The ALNS heuristic extends LNS by applying several destroy and repair methods. The performance of each method is recorded and the heuristic adapts to the current instance by favoring methods that have so far performed well. Algorithm 2 shows the pseudo-code for the ALNS algorithm. Five variables are maintained by the algorithm. The variable x^* is the best solution observed during the search, x is the current solution and x' is a temporary solution that can be discarded or promoted to the status of current solution. The variables ρ^d and ρ^r are vectors with a component for each destroy and repair heuristic, respectively. A component is a weight that measures how well the corresponding removal or repair heuristic has performed during the search. In line 2 the global best solution is initialized and the vectors containing the scores of the destroy and repair methods are initialized (initially all methods are given equal weight). In line 4 the heuristic selects a destroy and repair method

Algorithm 2 Adaptive Large Neighborhood Search

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1: input: a feasible solution  $x$ 
2:  $x^* = x$ ;  $\rho^d = (1, \dots, 1)$   $\rho^r = (1, \dots, 1)$ 
3: repeat
4:   Choose a destroy method  $d$  and a repair method  $r$  by roulette wheel selection using
      $\rho^d$  and  $\rho^r$ ;
5:    $x' = r(d(x))$ ;
6:   if  $\text{accept}(x', x)$  then
7:      $x = x'$ ;
8:   end if
9:   if  $f(x') < f(x^*)$  then
10:     $x^* = x'$ ;
11:  end if
12:  update  $\rho^d$  and  $\rho^r$ ;
13: until stop criterion is met
14: return  $x^*$ 
```

based on the current score vector. This selection process is described in detail in Section 4.3. In line 5 the heuristic first applies the chosen destroy heuristic and then the chosen repair heuristic to obtain a new solution x' . The destroy and repair heuristics are described in Sections 4.1 and 4.2 respectively. In line 6 the new solution is evaluated, and the heuristic determines whether this solution should become the new current solution (line 7) or whether it should be rejected. In our implementation we use a simulated annealing criterion as in Ropke and Pisinger [2006a]. The new solution x' is always accepted if $f(x') \leq f(x)$, and accepted with probability $e^{-(f(x')-f(x))/T}$ if $f(x') > f(x)$. Here $f(x)$ denotes the objective of solution x and $T > 0$ is the current *temperature*. The temperature is initialized at $T_0 > 0$ and is decreased at each iteration by performing the update $T_{new} = \zeta T_{old}$, where $0 < \zeta < 1$ is a parameter. Because of the acceptance criterion, the metaheuristic proposed in this paper can also be viewed as a standard simulated annealing algorithm with a complex neighborhood definition. Details about simulated annealing algorithms can be found in Kirkpatrick et al. [1983]. Line 9 checks whether the new solution is better than the best known solution, which is then updated in line 10. In line 12 the score-vectors are updated based on the performance of the destroy and repair heuristics chosen at the current iteration. In line 13 the termination condition is checked. The heuristic stops if a certain number of iterations have been performed or if the allocated running time is exhausted (see Section 4.4 for details). In line 14 the best known solution is returned.

4.1 Destroy heuristics

This section describes the five destroy heuristics. A solution is destroyed by removing a set S of tasks, while ensuring that $i \in S \Rightarrow \sigma_i \subseteq S$, which makes it easier to repair the solution. To illustrate the difficulties we would encounter if we did not remove successors, consider an example. If a task i is removed but a successor $i' \in \sigma_i$ is not, then it becomes more difficult to reinsert i . Either we would have to impose a deadline on when i can be served, or we would have to relocate i' if i were inserted too late. Removing i' together with i removes these difficulties. In practice we check the successors of i every time a task i is added to the set S of tasks to be removed. As stated above this is done for all removal heuristics and we do not describe this common step in the detailed descriptions of the heuristics below.

When a number of tasks have been removed it is often possible to *trim* the teams, that is to remove redundant technicians. An extreme example is when all tasks assigned to a team are removed, in which case all technicians can be removed from the team and the team itself can be discarded. The heuristic always performs such a trimming procedure when a task removal has been performed. This ensures that we are able to move to solutions that use different team assignments compared with the initial solution. The trim heuristic is extremely simple: for each technician in the team it tests whether the team would still be able to serve its tasks after removing that technician. If more than one technician can be removed, then one of these is randomly selected for removal. This process continues as long as technicians can be removed.

After removing tasks we also *compress* the solution. This means that we try to serve tasks earlier whenever possible. Our compress procedure only explores a limited number of possibilities. It does not allow tasks to change teams or to be served on earlier days, and it only examines whether the task can be served earlier on the same team because a task removed from the team has “left a hole”. There are three reasons for this choice: 1) a compression mechanism that would investigate further options would be too time consuming, 2) it might not be a good idea to compress the solution too much as this would leave no room for the repair heuristic to insert the removed tasks (most of them would have to be served at the end of the schedule), and 3) it would be complicated to implement such a mechanism and simplicity is important in a heuristic.

Before invoking the removal heuristic the number of tasks u to remove is determined. This number is chosen randomly in the interval $[\max\{n^-, r^-n\}, \min\{n^+, r^+n\}]$, where n^- and n^+ are the absolute minimum and maximum number of tasks we ever remove, and r^- and r^+ indicate the minimum and maximum proportions of the total number of tasks. For a sensible parameter settings, n^- and n^+ are only useful for very small and very large instances. Successors of removed tasks are included when calculating how many tasks have been removed.

4.1.1 Random destroy

Random destroy is the simplest destroy method. It selects u tasks at random and removes these. It works well as a diversification method.

4.1.2 Related destroy

Related destroy is similar to the removal method of the same name proposed by Shaw [1998] for the vehicle routing problem. For every pair of tasks (i, i') the coefficient $\gamma_{ii'}$ defined in Section 1 measures the similarity of i and i' in terms of their skill requirements. The algorithm works as follows. Initially, a task i is selected at random and the set S of tasks to remove is initialized as $S = \{i\}$. The heuristic then adds tasks to S as long as $|S| < u$ in the following way: a random task i' from S is selected, the tasks in $N \setminus S$ are sorted in a list L according to their decreasing similarity with i' , a random number $r \in [0, 1]$ is drawn, and the element at position $r^v(|L| - 1)$ in L is added to S . We index the positions in L from 0 and $v \geq 1$ is a parameter that controls how deterministic the removal method is. The larger v is, the more likely it is that the heuristic selects tasks similar to those already in S .

The goal of this heuristic is to remove similar tasks from the current schedule, hoping that the repair method will be able to group them together in a few teams, and hopefully freeing some technicians in the process. The related destroy method also increases the likelihood of filling the holes left by removed tasks by a similar, but different task during the repair process.

4.1.3 Last-random and last-related destroy

As observed earlier, only the last tasks of each priority type contribute to the objective function. The two destroy heuristics described in this section attempt to take advantage of this feature by removing some of the last tasks of each priority type. If the repair method is capable of moving at least some of these tasks to earlier positions without delaying other tasks, then one can hope for a reduction of the objective function value.

The heuristics first removes τu tasks that are the latest of one of the priority types ($0 < \tau \leq 1$), and then $(1 - \tau)u$ tasks by selecting either random tasks (*last-random destroy*) or tasks that are related to the already removed tasks (*last-related destroy*) by using the principles described in Section 4.1.2. The idea behind not only removing the latest tasks but also some random or related tasks is to make room elsewhere in the plan for the latest tasks.

The removal of the latest tasks works as follows. First the number of planned tasks n_p of each priority type p is calculated. At each step the heuristic removes the latest task of priority p with probability $n_p/(n_1 + n_2 + n_3 + n_4)$, and n_p is updated. If several tasks tie to

be the latest task of a certain priority, then the task with lowest index is removed first. The heuristic keeps removing the latest tasks until the number of removed tasks reaches τu .

4.1.4 Whole team destroy

The *whole team destroy* heuristic attempts to remove complete teams from the solution. This is done to make it easier for the repair heuristic to regroup the technicians into new teams. The heuristic always attempts to remove two teams from the same day in order to create more opportunities for new teams. The heuristic repeats the following operation until u tasks have been removed. First a day is selected at random. If the day contains less than two teams, then the heuristic proceeds to the next day until a day with at least two teams is found. If no such day is found the heuristic terminates. When a day with two teams is identified the heuristic selects two of those teams at random and removes all tasks assigned to them.

4.2 Repair heuristics

The ALNS heuristic uses two variants of the construction heuristic described in Section 3 as repair heuristics: a version with fixed parameters, and a version that uses randomized parameters as described in Section 3.3.2

4.3 Selection of removal and repair heuristics

This section describes how removal and repair heuristics are selected. We use the approach suggested by Ropke and Pisinger [2006a] with a slight simplification. The vectors ρ^d and ρ^r , introduced in the overview of ALNS heuristic, control the probabilities of choosing destroy and repair heuristics. These vectors contain components corresponding to the weights of the heuristic: ρ^d contains five components and ρ^r contains four components. For example, ρ_j^d is the weight of the j^{th} destroy heuristic. We denote the number of destroy and repair heuristics by η^d and η^r , respectively. The vectors determine the probability of choosing a given heuristic in line 4 by using the weight of the heuristic in a *roulette wheel selection mechanism*. The probability ϕ_j^d of choosing the j^{th} destroy heuristic is

$$\phi_j^d = \frac{\rho_j^d}{\sum_{k=1}^{\eta^d} \rho_k^d},$$

and the probabilities for choosing the repair heuristics are determined in the same way.

The weights are adjusted automatically, based on the recorded performance of the heuristics. The idea is that the ALNS heuristic should *adapt* to the instance at hand since the

best heuristic is not the same for all instances. Also, we may expect that one set of weights works well at the beginning of the search when it can be easy to find improvements, while another set of weights are necessary towards the end of the search when improvements are hard to find.

When an iteration in the ALNS heuristic is completed a score ψ for the destroy and repair heuristic used in the iteration is computed as

$$\psi = \begin{cases} \omega_1 & \text{if the new solution is a new global best,} \\ \omega_2 & \text{if the new solution is better than the current one,} \\ \omega_3 & \text{if the new solution is accepted,} \\ \omega_4 & \text{if the new solution is rejected,} \end{cases} \quad (21)$$

where $\omega_1, \omega_2, \omega_3$ and ω_4 are parameters satisfying $\omega_1 \geq \omega_2 \geq \omega_3 \geq \omega_4$. In our tests we have used $\omega_1 = 100, \omega_2 = 40, \omega_3 = 10, \omega_4 = 1$. The first matching option in (21) is always preferred (for example if the new solution is better than the current one, it would always be accepted, but we would still set $\psi = \omega_2$). Let a and b be the indices of the selected destroy and repair heuristics respectively. The elements corresponding to the selected destroy and repair heuristics in the ρ^d and ρ^r vectors are updated using equations (22) in line 12 of Algorithm 2:

$$\rho_a^d = \lambda \rho_a^d + (1 - \lambda)\psi, \quad \rho_b^r = \lambda \rho_b^r + (1 - \lambda)\psi, \quad (22)$$

where $\lambda \in [0; 1]$ is the *decay* parameter that controls how sensitive the weights are to changes in the performance of the destroy and repair heuristics. A value of 1 means that the weights remain unchanged, while a value of 0 implies that historic performance has no impact: only the last attempt at using the heuristic counts. Obviously a value between the two extremes is preferable; in our tests we used $\lambda = 0.99$. Note that the weights that are not used at the current iteration remain unchanged. This dynamic weight adjustment mechanism was proposed by Ropke and Pisinger [2006a]. The approach implemented in that reference is slightly more complicated than ours since it maintains a vector of heuristic weights and a vector of temporary scores with an element per heuristic. Our procedure only needs the vector of weights. However, we have no reason to believe that either approach dominates the other when it comes to selecting good values for the weights.

4.4 Variants and improvements

This section describes further refinements of the ALNS heuristic. All refinements aim at improving the solution quality obtained by the heuristic. In Section 4.4.1 an artificial objective is defined. In Section 4.4.2 a strategy for resetting the temperature in the simulated annealing heuristic is described, and Section 4.4.3 shows how the ALNS heuristic is divided into several phases.

4.4.1 Artificial objective function

One major difficulty of the TTSP is the flatness of its objective function. Because only the last tasks of each priority type count in the objective, many solutions share the same objective value, even though they can be very different. In this sense the objective value is not very useful for guiding a local search because it does not reveal whether a solution is easy or difficult to improve. As a remedy we introduce an artificial objective function which considers the ξ last tasks of the priority types 1, 2 and 3 and the ξ last tasks overall, where ξ is a parameter. Let t_1^ξ, t_2^ξ and t_3^ξ be average end time of the ξ last tasks of priority type 1, 2 and 3 respectively, and let t_4^ξ be the average end time of the ξ last tasks overall. The artificial objective function is then defined as

$$\sum_{j=1}^4 w_j t_h + 0.1 \sum_{j=1}^4 w_j t_h^\xi.$$

The first term is the original objective, while the second term takes more tasks into account. It is scaled in such a way that it does not contribute too much to the artificial objective.

The artificial objective is used when deciding whether to accept or reject a solution in line 6 of Algorithm 2. If a new solution is better than the global best solution according to the original objective, then the new solution is accepted no matter what the artificial objective indicates.

4.4.2 Restarts

The rules of the ROADEF challenge enforced a strict time limit on the run time of the heuristic. Each instance, no matter its size, should be solved within 20 minutes on a particular PC. The simulated annealing metaheuristic is set to perform short runs of 25,000 iterations (we chose this number of iterations as it was shown to be sufficient in the experiments performed in Ropke and Pisinger [2006a] and in Pisinger and Ropke [2007]). For small and medium size instances performing 25,000 iterations takes only a fraction of the allocated time and, in order to utilize the entire allowed time, the heuristic is restarted from the best found solution. We found that it was beneficial to use a reduced initial temperature T_0^r in the first run and an increased initial temperature T_0 in the following runs. There are two reasons for this. First, for several of the large instances it is not possible to perform 25,000 iterations within the time limit. A lower initial temperature is beneficial for these instances since a more intensifying search is performed right from the start. Second, the initial solution constructed by the heuristic of Section 3 is sometimes of very high quality and a high initial temperature will tend to destroy this solution without being able to reconstruct it. In this case it is preferable to intensify the search instead of diversifying it.

4.4.3 Prioritized strategy

Priority 1 tasks are more costly (in the objective function) than priority 2 tasks which, in turn, are more costly than priority 3 tasks, and so on. It therefore seems natural to focus on the tasks in the order of their priority, creating solutions that first serve priority 1 tasks, then priority 2 tasks, and so on. However, such a strategy is not always the best option. Figure 1 shows the best known solution to a small TTSP instance in which priority 2 tasks are finished before priority 1 tasks. It often pays to finish priority 2 or 3 tasks early if there only are a few of them compared to priority 1 tasks. In this case, serving the priority 2 tasks as early as possible instead of waiting until most or all priority 1 tasks have been served does not significantly affect the latest ending time of priority 1 tasks, but it can significantly decrease the ending time of priority 2 tasks.

This observation leads to an algorithm that tries different permutations of the insertion priorities. The algorithm could in principle examine the 24 permutations of the numbers 1, 2, 3 and 4, but we always insert priority 4 tasks as the last set of tasks and we limit the search to the six permutations of the numbers 1, 2 and 3. Little is lost through this simplification since priority 4 tasks seldom contribute significantly to the objective function. For each permutation $(\varphi_1, \varphi_2, \varphi_3)$ of $\{1, 2, 3\}$ the algorithm first constructs a solution that only contains tasks of priority φ_1 and their predecessors. This is done by applying the algorithm described in Section 3. After a solution has been constructed a short LNS phase is applied. Only improving solutions are accepted and only 15 iterations are performed. The best solution from this LNS phase is used as starting point for the next phase in which all tasks from the previous phase are locked (they are not allowed to be moved from their current position), and tasks of priority φ_2 are inserted in the same way. The process continues until all tasks have been inserted and the next permutation is processed. The output of this algorithm is the permutation that yielded the best solution. This permutation is used as the input of the main part of the ALNS algorithm. Note that the permutation approach leads to a change in the outsourcing algorithm described in Section 3.3.1. The weights $\chi(p_i)$ are set according to the position of priority p_i in the permutation: for example, if the permutation is (3,1,2) then priority 3 tasks get a weight of 28^2 , priority 1 tasks get a weight of 14^2 and priority 2 tasks get a weight of 4^2 . This change was implemented to encourage outsourcing of the tasks that are to be served first.

We now describe how the priority permutation is used in the main part of the ALNS algorithm. Let $(\varphi_1, \varphi_2, \varphi_3)$ be the best permutation found. Define four sets of tasks: B_1 is the set of all priority φ_1 tasks and their predecessors, B_2 is the set of all priority φ_2 tasks and their predecessors that are not in B_1 , B_3 is the set of all priority φ_3 tasks and their predecessors that are not in $B_1 \cup B_2$, and $B_4 = N \setminus (B_1 \cup B_2 \cup B_3)$. The available run time for the heuristic is then split into seven stages. In stage 1 we only consider tasks from B_1 and optimize their placement using the ALNS heuristic. In stage 2 we start from the best solution identified in stage 1 and consider tasks from $B_1 \cup B_2$. Tasks from B_1 are locked:

they cannot be moved from their current position. The ALNS heuristic will try to find good positions for the tasks in B_2 while respecting the placement of the tasks in B_1 . In stage 3 we consider tasks from $B_1 \cup B_2$, and all tasks can be moved. These stages are summarized in Table 1. The time allocated for each stage is proportional to the number of new tasks considered (e.g. in stages 4 and 5 the ratio $|B_3|/|N|$ determines the allocated time). The temperature in the simulated annealing algorithm is reset to T_0^r every time a new stage begins.

Stage	Tasks considered
1	B_1
2	$B_1 \cup B_2$, tasks in B_1 are locked
3	$B_1 \cup B_2$
4	$B_1 \cup B_2 \cup B_3$, tasks in $B_1 \cup B_2$ are locked
5	$B_1 \cup B_2 \cup B_3$
6	N , tasks in $B_1 \cup B_2 \cup B_3$ are locked
7	N

Table 1: Stages in the prioritized ALNS strategy

At the start of stages 1, 2, 4 and 6 a new set of tasks have to be inserted. This is of course done with the construction heuristic from Section 3. We try the construction heuristic several times before applying the ALNS heuristic. The first time the construction heuristic is attempted the default parameters are selected, while in the subsequent attempts the randomized parameters are used to create new solutions. The best solution found during these attempts serves as a starting point for the ALNS heuristic. We execute the construction algorithm several times since we have noticed that the construction algorithm is occasionally able to find good solutions that are hard to obtain with the ALNS heuristic. This staged ALNS heuristic involves some extra bookkeeping in the removal heuristics as we have to ensure that locked tasks are not removed, but this appears to be worthwhile.

It should be noted that the idea of trying permutations of the priorities was not part of our original solution method developed for the ROADEF challenge. The strategy was implemented as several of the competing teams reported good results with such a strategy.

5 Computational results

The algorithm was implemented in C++ and run on an AMD Opteron 250 computer (2.4 GHz) running Linux. The computer used in the competition was an AMD Athlon 64 3000+ computer (1.8 GHz) running Linux. The allotted time per run on this computer was 20 minutes. Running the heuristic on both computers revealed that 20 minutes on the competition computer roughly corresponded to 12 minutes on our computer. Consequently we have used

a time limit of 12 minutes in the experiments performed in this paper.

5.1 Data sets

The organizers of the ROADEF 2007 challenge provided 30 test instances. These are grouped into three sets, A, B and X, of ten instances. The A instances were made available at the start of the competition and involve up to 100 tasks and 20 technicians. The B instances were revealed during the competition and contained larger instances with up to 800 tasks and 150 technicians. The X instances were kept secret until the evaluation phase and the heuristics were judged by their performance on these instances. Table 2 shows the characteristics of each instance. We report the number n of tasks, the number m of technicians, the number q of skill domains and the number s of skill levels.

	Dataset A				Dataset B				Dataset X			
Instance	n	m	q	p	n	m	q	p	n	m	q	p
1	5	5	3	2	200	20	4	4	600	60	15	4
2	5	5	3	2	300	30	5	3	800	100	6	6
3	20	7	3	2	400	40	4	4	300	50	20	3
4	20	7	4	3	400	30	40	3	800	70	15	7
5	50	10	3	2	500	50	7	4	600	60	15	4
6	50	10	5	4	500	30	8	3	200	20	6	6
7	100	20	5	4	500	100	10	5	300	50	20	3
8	100	20	5	4	800	150	10	4	100	30	15	7
9	100	20	5	4	120	60	5	5	500	50	15	4
10	100	15	5	4	120	40	5	5	500	40	15	4

Table 2: Characteristics of the instances in the three datasets.

5.2 Parameter setting

The ALNS heuristic and its various procedures are controlled by several parameters whose values were determined in a rather *ad hoc* manner. The parameters controlling the simulated annealing component are set as follows: $\zeta = 0.99965$, $T_0 = 500$ and $T_0^r = 50$. The parameters controlling the number of tasks to remove in each iteration have the following values: $r^+ = 0.4$, $r^- = 0.1$, $n^+ = 80$, $n^- = 15$. The removal heuristics define two parameters $v = 4$ (related destroy) and $\tau = 0.2$ (last-random and last-related destroy). The number of tasks to include in the artificial objective function is set to $\xi = 8$.

5.3 Experiments and results

Table 3 shows results from two variants of the greedy heuristic. The standard version described in Section 3 and the variant that attempts to insert tasks in different orders based on permutations of the three first priorities and performs a few LNS iterations (described in Section 4.4.3). The table reports the time spent by each heuristic (columns 3 and 6), the solution obtained (columns 4 and 7) and the gap between the solution obtained and the best known solution (columns 5 and 8). The best known solution is reported in column 3. It is the best among all the solutions found in our experiments and all solutions obtained in the competition by the challengers. It is clear that the permutation variant by far produces the best results, but it does so by consuming much more time than the standard version. The standard version of the construction algorithm is relatively quick although an even faster heuristic would be preferred as it is an important component of the ALNS heuristic.

In Table 4 the ALNS heuristic is compared with the best two entries in the competition. The first two columns indicate the data set and the instance number. The third column presents the best known solution value of all the heuristics presented in the competition, the next column shows the best solution value when new solutions found by the ALNS heuristic is taken into account. The last six columns show the results from the top three heuristics. For each heuristic we report the objective of the solution found and the gap relative to the (new) best known solution. The columns with heading *Hurkens* report the results from the heuristic by C. Hurkens (winner), the columns *EsGaNo* report the results from the heuristic by the team of B. Estellon, F. Gardi and K. Nouioua (tied second place), and the last columns report the results from our ALNS heuristic. The last row is the sums of the objective and averages the gap columns. The results for the two competing heuristics are those obtained during the competition when the heuristic was run for 20 minutes on the computer provided by the organizers. The results for the ALNS were obtained by running the heuristic for 12 minutes on our test computer.

It is clear that when all instances are considered, the ALNS heuristic is very close to the winning heuristic in terms of relative gap. Table 5 reports the average gap of the three heuristics on the three test sets A, B and X. Here three different results for the ALNS heuristic are reported: 1) results for one run (as in Table 4), 2) average results over ten runs 3) best results over ten runs. The fairest comparison is between the ALNS one-run results and the results from the two competing heuristics. The results obtained as the best of ten runs are also interesting as they indicate that an improved solution quality is within reach of the ALNS heuristic if the time limit is increased. However, a direct comparison between these results and the competing heuristics would be unfair. A final remark is that the performance of Hurkens’s heuristic on the X data set is very impressive.

Instance	Best	Greedy			Permutation Greedy			
		Time (s)	Objective	Gap (%)	Time (s)	Objective	Gap (%)	
A	1	2340	0.0	3690	57.7	0.0	2340	0.0
A	2	4755	0.0	4755	0.0	0.0	4755	0.0
A	3	11880	0.0	16950	42.7	0.0	13710	15.4
A	4	13452	0.0	17520	30.2	0.0	13620	1.2
A	5	28845	0.0	42495	47.3	0.0	31095	7.8
A	6	18795	0.0	26775	42.5	0.0	21495	14.4
A	7	30540	0.0	36630	19.9	0.1	32940	7.9
A	8	16920	0.0	23280	37.6	0.1	19140	13.1
A	9	27348	0.0	40290	47.3	0.1	30504	11.5
A	10	38296	0.0	50640	32.2	0.1	40440	5.6
B	1	34395	0.0	93120	170.7	0.1	41100	19.5
B	2	15870	0.0	37425	135.8	0.2	18195	14.7
B	3	16020	0.1	47250	194.9	0.2	18360	14.6
B	4	23775	0.2	63705	167.9	1.2	28410	19.5
B	5	89700	0.4	148620	65.7	4.9	122280	36.3
B	6	26955	0.1	47850	77.5	0.4	31875	18.3
B	7	33060	0.3	43680	32.1	1.6	34740	5.1
B	8	33030	0.7	62160	88.2	4.2	36120	9.4
B	9	28200	0.0	34620	22.8	0.3	32280	14.5
B	10	34680	0.0	50820	46.5	0.2	38040	9.7
X	1	151140	1.8	272055	80.0	36.7	172800	14.3
X	2	7260	1.0	11700	61.2	3.3	9960	37.2
X	3	50040	0.1	67920	35.7	1.0	54480	8.9
X	4	65400	0.8	95520	46.1	4.1	69430	6.2
X	5	147000	2.1	235080	59.9	42.6	170880	16.2
X	6	9480	0.0	19350	104.1	0.2	12120	27.8
X	7	33240	0.1	51120	53.8	1.0	48840	46.9
X	8	23640	0.0	35020	48.1	0.4	29700	25.6
X	9	134760	1.4	213120	58.1	24.5	159360	18.3
X	10	137040	0.7	213240	55.6	12.5	156480	14.2
		1287856	0.3	2106400	65.4	4.7	1495489	15.1

Table 3: Results for greedy heuristics.

Instance		Old best	New best	Hurkens		EsGaNo		ALNS	
				Obj.	Gap (%)	Obj.	Gap (%)	Obj.	Gap (%)
A	1	2340	2340	2340	0.0	2340	0.0	2340	0.0
A	2	4755	4755	5580	17.4	4755	0.0	4755	0.0
A	3	11880	11880	12600	6.1	11880	0.0	11880	0.0
A	4	13452	13452	13620	1.2	14040	4.4	13452	0.0
A	5	28845	28845	30150	4.5	29700	3.0	29355	1.8
A	6	18795	18795	20280	7.9	18795	0.0	18795	0.0
A	7	30540	30540	32520	6.5	30540	0.0	30540	0.0
A	8	16920	16920	18960	12.1	20100	18.8	17700	4.6
A	9	27692	27348	29328	7.2	28020	2.5	27692	1.3
A	10	38296	38296	40650	6.1	38296	0.0	38636	0.9
B	1	34395	34395	34710	0.9	34395	0.0	37200	8.2
B	2	15870	15870	17970	13.2	15870	0.0	17070	7.6
B	3	16020	16020	18060	12.7	16020	0.0	18015	12.5
B	4	25305	23775	26115	9.8	25305	6.4	23775	0.0
B	5	89700	89700	94200	5.0	89700	0.0	117540	31.0
B	6	27615	26955	30450	13.0	27615	2.4	27390	1.6
B	7	33300	33060	33300	0.7	38220	15.6	33900	2.5
B	8	33030	33030	35490	7.4	37440	13.4	33240	0.6
B	9	28200	28200	28200	0.0	32700	16.0	29760	5.5
B	10	34680	34680	34680	0.0	41280	19.0	35640	2.8
X	1	151140	151140	151140	0.0	188595	24.8	159300	5.4
X	2	7260	7260	9120	25.6	8370	15.3	8280	14.0
X	3	50040	50040	50400	0.7	50100	0.1	50400	0.7
X	4	65400	65400	65400	0.0	68120	4.2	66780	2.1
X	5	147000	147000	147000	0.0	183720	25.0	157800	7.3
X	6	9480	9480	10320	8.9	10440	10.1	9900	4.4
X	7	33240	33240	33240	0.0	37200	11.9	47760	43.7
X	8	23640	23640	23640	0.0	25480	7.8	24060	1.8
X	9	134760	134760	134760	0.0	159660	18.5	152400	13.1
X	10	137040	137040	137040	0.0	152040	10.9	140520	2.5
		1290630	1287856	1321263	5.6	1440736	7.7	1385875	5.9

Table 4: Comparison of ROADEF challenge top three heuristics.

	Hurkens (%)	EsGaNo (%)	ALNS one run (%)	ALNS avg. (%)	ALNS best (%)
A	6.9	2.9	0.9	1.1	0.5
B	6.3	7.3	7.2	7.4	5.0
X	3.5	12.9	9.5	10.0	8.0
	5.6	7.7	5.9	6.2	4.5

Table 5: Summary of ROADEF challenge top three heuristics.

6 Conclusion

We have developed a construction heuristic and an adaptive large scale neighborhood search heuristic for the technician and task scheduling problem. This difficult problem was the subject of the ROADEF 2007 challenge in which our team tied for second place. Further enhancements to our original algorithm enabled us to gain significant improvements and come closer to the best results achieved in the competition.

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