Ant Colony Optimization for the Crew Rescheduling Problem

José Ricardo Torres*†, António Pereira*, Fernando Vieira†,
*FEUP - Faculty of Engineering,
University of Porto
{ricardo.torres, amcp}@fe.up.pt
†OPT - Optimização e Planeamento de Transportes
{jrtorres, fvieira}@opt.pt

***Abstract*—Disruption management is one of the newest research paths in scheduling problems due to the growing service quality demanded in the transportation field. This paper presents an approach for the rescheduling of crews using an Ant Colony algorithm for costs optimization. The main goal is to find an optimized recovery solution after the occurrence of unexpected events that make the original assignment non-feasible. The algorithm is integrated with a Decision Support System and results obtained from a real dataset show that this approach can be successfully used to solve the crew rescheduling problem.**

***Index Terms*—crew rescheduling, disruption management, ant colony optimization, A-TSP**

I. Introduction

Public transportation is surely an important component of the life quality for a lot of people. In recent years the demand for service quality in association with the growing operating costs, e.g. fuel costs, requires higher levels of resource optimization in public transportation companies. One of the major sources of inefficiency is related with unexpected events that arise every day and require dynamic adjustments on the operational plan. The costs associated with crew wages are the most important, representing about 45% of the total operational costs [3]. Traditionally the rescheduling task is done by a supervisor that uses his experience and intuition to solve the unexpected events [5], e.g. sick crews, delays, and variations on the scheduled trips. Meta-heuristics such as ACO (Ant Colony Optimization) can obtain good results in high constrained problems and are suited for transportation rescheduling. The rest of the paper is organized as follows. In section 2 the crew rescheduling problem is analyzed. Sections 3 and 4 present the proposed approach with some results and discussion. Finally the last section is about future work and the conclusions.

II. Crew Rescheduling Problem

Rescheduling presents challenges that are different from those arising in traditional VSP and CSP (vehicle and crew scheduling problems) by requiring shorter solving times and new optimization criteria such as differences to the initial schedule. Beyond that, the rescheduling results are dependent of the robustness of the initial assignments.

In order to generate a recovery solution for a set of unexpected events, new assignments, i.e. swaps and allocations, can be made within the possible crews covering all the work blocks involved.

Our approach is based on a graph representation where work blocks are nodes and edges between them represent feasibility, a variation of the approach proposed by [6],[7]. This representation can embed several hard constraints, e.g. starting times and locations of the work blocks, relief points and crew travel times. Additionally there are crew nodes representing each one of the crews that are connected to the possible work blocks at time of the disruption. Figure 1 presents an example, if crew 1 cannot do work block D due to a disruption, crew 2 can cover it after work block G. A solution for this problem can be seen as modified A-TSP (Asymmetric Travelling Salesman Problem) tour, covering all the work block nodes using the available crew nodes.

In terms of crew specific constraints we consider crew duty amplitude, total work, driving times, meals and overtime. The objective function is defined as $\sum_{c\in C} Cost_c + Overtime_c + Penal_c + \sum_{w\in W} Uncover_w + Diff_w$, where C is the set of crews, $Cost_c$ and $Overtime_c$ represent fixed and variable costs for each crew and $Penal_c$ reflects the soft constraints penalties, W is the set of work blocks, $Uncover_w$ and $Diff_w$ are penalties for uncovered work and differences to the original schedule.

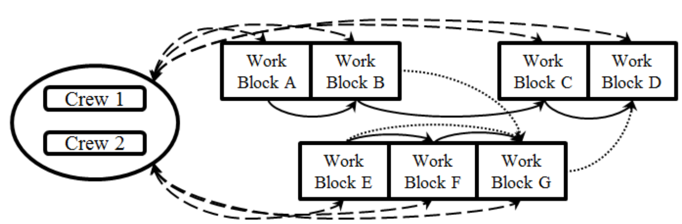

Fig. 1. Problem graph representation

III. Ant Colony Optimization

ACO was first introduced by Dorigo et al. [1] and is a nature inspired meta-heuristic that simulates ants foraging behaviour while searching for food. This approach can applied to optimization problems that can be represented by graphs, where ants can deposit pheromones. Pheromone trails evaporate with time and stronger concentrations represent shorter paths, this attracts ants that likely reinforce them.

Ants will incorporate crews and find paths within the work block schedule representation minimizing costs. When a crew duty is completed an ant will choose one of the remaining crews and repeat the process, non-visited work blocks will be assumed as cancelled. Initially each ant is assigned with a random crew node and then it chooses the next nodes to visit accordingly with a probability function.

With probability $q_0, 0 \leq q_0 \leq 1$, ant k chooses work block j for which the product between pheromone value τ_{ij} and heuristic information η_{ij} is maximum, that is, $j = \max_{w \in N_i^k} [\eta_{iw}]^\alpha [\tau_{iw}]^\beta$. With probability $1 - q_0$ ant k will choose next node with probability $p_{i\,j}^k = \frac{[\eta_{ij}]^\alpha [\tau_{ij}]^\beta}{\sum_{w \in N_i^k} [\eta_{iw}]^\alpha [\tau_{iw}]^\beta}, if j \in N_i^k$.

Parameters α, β are used to set the relative importance of pheromone and heuristic values, higher q_0 values will favour exploitation over exploration and N_i^k represents the set of work blocks that ant k can visit from work block node i while incorporating a specific crew. N_i^k changes dynamically accordingly to the constraints applied to ant's current crew using an edge visibility function.

A local update is done after an ant chooses an edge promoting the exploration on different paths, by reducing the pheromone concentration, $\tau_{ij} = (1 - \sigma) * \tau_{ij} + \sigma * \tau_0$, where τ_0 is the initial pheromone concentration and σ is the local evaporation factor. When all the ants find their path a global update is done, adding pheromone to the edges used by the best ant in the colony, $\tau_{ij} = (1 - \rho) * \tau_{ij} + \rho * \Delta\tau_{i\,j}^k$, $\Delta\tau_{i\,j}^k = \frac{Q}{cost_k}$, where Q is a constant for the reinforcement of the trail, ρ is the global evaporation factor and $cost_k$ is the multi-objective function value for ant k that includes the costs described before.

The heuristic function η_{ij} includes problem information about the closeness of the nodes and in this case is set as a weighted sum of the time distance between the two work blocks and penalty costs for taking work block j after i while incorporating a specific crew. The authors in [4] include swap penalizations in the aircraft recovery in a similar way. If a work block is no longer covered by the original schedule due to a unexpected event no penalty is applied making ants feel strong attraction.

IV. Results and Discussion

The presented approach was tested on a dataset of one day with 358 trips and 28 crews representing 230 work blocks assignment optimized with a genetic algorithm from Dias et al. [2]. This original assignment was perturbed by two "unexpected" situations, representing 6 hours of uncovered work.

The parametrization was set to achieve the best results with the minimum changes within the unaffected work blocks, i.e. high penalization factors for both uncovered work blocks and differences, the remaining parameters were: number of ants $= 50, \beta = 1, \alpha = 3, q_0 = 0.9, \rho = 0.1, \sigma = 0.4$. A high local evaporation factor reduced the premature convergence to local minimums.

The original schedule was optimized not to have extra hours. The manual approach from the supervisor would be the allocation of the uncovered work to one crew for each situation which would lead to a minimum of 4h06m of extra work.

Results on Figure 2 show that the overall colony results improve significantly in the first iterations due to the learning process and then variations are needed to avoid local minimum, as we can observe in the final iterations, and maintain diversity within the colony. Uncovered work and differences result in big steps in the best solution cost. This approach achieved 3h27m without making changes to the unaffected work.

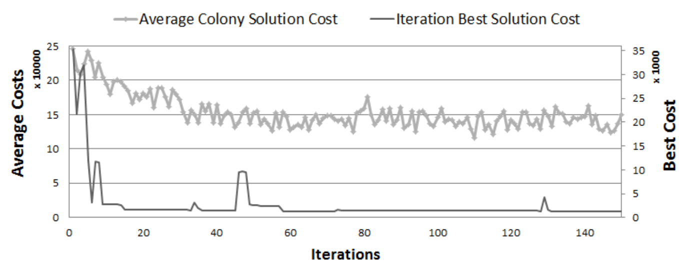

Fig. 2. Rescheduling costs optimization with ACO

V. Conclusion and Future Work

An approach to reschedule crews due to unexpected events is presented and although the algorithm is not completely finished, the results show the capability of ACO to handle this kind of problem providing a powerful decision tool for transportation companies.

The use of the penalty values within the attraction function makes ACO a flexible framework that can better reflect the user preferences. The problem representation opens the possibility to new constraints such as crew depot definition.

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