GENETIC ALGORITHM FOR SOLVING A MULTI-OBJECTIVE HELICOPTER ROUTING PROBLEM

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Abstract: The petroleum industry uses helicopters to transport employees to and from the offshore installations. The helicopter transportation represents a major risk for the employees. The helicopter routing problem is an application of vehicle routing problem with combined pickup and delivery demands, which usually minimizes the total cost of the routes and the fleet size (the number of routes) in a classical form. It is also of interest to minimize the transportation risk. In this paper, a multi-objective genetic algorithm is presented for the helicopter routing problem. The algorithm uses a variation of the cluster-first route-second method for routing helicopters. We apply the proposed algorithm to instances derived from real data and evaluate its effectiveness by comparing with ε-constraint approach with a state-of-the-art single-objective tabu search metaheuristic.

1 INTRODUCTION

In the offshore petroleum industry, helicopter has been the main way of transporting personnel to and from offshore installations for decades. It is very costly to purchase and operate a helicopter. Take helicopter model Sikorsky S–92 as an example, which is widely used in the petroleum industry, the unit purchase cost is from US$ 13 million to US$ 14 million and the direct operating cost is US$ 2,381 per hour, comprising 1,194 fixed and 1,175 variable costs (2002)[1]. Helicopter transportation is perceived by many offshore employees to be a risky part of their work. Vinnem et al. (2006) claim that the hazards associated with helicopter transportation of personnel are among the main risks experienced by offshore employees.

Helicopter routing can be viewed as a vehicle routing problem with combined pickups and deliveries (VRPPD), in which each installation receives a delivery originating at a common heliport and sends a pickup quantity to the heliport. In literature, several papers on helicopter routing for passenger transportation have been published, and all of them focus on minimizing transportation cost in terms of travel distance or time (Galvão and Guimaraes, 1990, Fiala Timlin and Pulleyblank, 1992, Sierksma and Tijssen, 1998, Rosero and Torres, 2006, and Tang and Galvão, 2006). Moreno et al. (2006) and Menezes et al. (2010) seek to minimize the flight costs, the number of flights, and the total number of offshore landings in order to improve flight safety. The objective function in the optimization model uses weights to balance these multiple goals.

The purpose of this paper is to conduct a study of helicopter routing problem as a multi-objective VRPPD, in which the risk, the cost and the number of flights objectives are considered. We solve the multi-objective helicopter routing problem using a genetic algorithm (GA) by adapting the general purpose multi-objective evolutionary algorithm NSGA-II (Deb et al., 2002) to this particular application. An instance from literature was studied and the results are evaluated by comparing with ε-constraint approach with a state-of-the-art single-objective tabu search metaheuristic.

The remainder of this paper is organized as follows. In Section 2, a multi-objective model of the helicopter routing problem is presented. The GA components are provided in Section 3. A case study based on a real-life setting are presented in Section 4, followed by conclusions in Section 5.

[1] http://aviastar.org/helicopters_eng/sik_s-92.php. Last accessed 30 November 2011.

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2 THE MULTI-OBJECTIVE HELICOPTER ROUTING PROBLEM

The risk for passenger transportation is defined as the expected number of fatalities for passengers. Risk is decomposed into take-off and landing risk (TL_{risk}) and cruise risk (C_{risk}):

$$\begin{aligned} Risk &= TL_{risk} + C_{risk} \\ &= PTL \cdot f_{TL} \cdot p_{TL} + PFH \cdot f_C \cdot p_C, \end{aligned} \tag{1}$$

where PTL is the total number of person take-offs and landings, f_{TL} is the probability of an accident during a combined take-off and landing operation, defined as the mean number of take-off and landing accidents per million pairs of take-offs and landings, p_{TL} is the probability of a fatal outcome for an individual person involved in a take-off and landing accident; PFH is the total person flight hours, f_C is the probability of an accident during one cruise hour, defined from statistics as the mean number of cruise accidents per million flight hours, p_C is the probability of a fatal outcome for an individual involved in a cruise accident.

In this paper, we deal with the helicopter routing problem as a multi-objective vehicle routing problem under a general routing policy, in which the risk, the cost and the number of flights objectives are considered. In a general solution, each installation is allowed to be visited twice if necessary, once for delivery and once for pickup, and these visits to an installation may take place in two different flights. The cost objective is measured in terms of travel time of the routes. The risk objective contains the passenger risk.

3 A GENETIC ALGORITHM

3.1 GA Components for Helicopter Routing Problem

Non-dominated sorting genetic algorithm II (NSGA-II) was proposed by Deb et al. (2002) for multi-objective optimization. In the past years this algorithm has become very popular in solving multi-objective vehicle routing problems. It is adapted to solve vehicle routing problem with route balancing (Jozefowiez, Semet and Talbi, 2007a), covering tour problem (Jozefowiez, Semet and Talbi, 2007b) and traveling salesman problem with profits (Jozefowiez, Glover and Laguna, 2008). Maruta and Itai (2005) employ this algorithm to a vehicle routing problem where both the number of vehicles and the maximum routing time among them are minimized. It is also applied to a capacitated arc routing problem which seeks to minimize the total cost of the routes and minimize the cost of the longest trip (Lacomme, Prins and Sevaux, 2006).

3.1.1 Chromosome and Route Construction Heuristics

One way of encoding a VRP solution is using giant tour chromosome, in which a chromosome is a sequence of *n* client nodes, without trip delimiters (Prins 2004). An optimal splitting procedure *Split* is also proposed to retrieve the best VRP solution respecting the sequence. It is regarded as a route-first, cluster-second heuristic for the VRP.

In our implementation, a solution chromosome *S* is a permutation of *n* installations, which is interpreted as the order in which the installations are routed by some constructive heuristics. The installations are inserted into a route sequentially along the *S* until no more installation can be inserted without violating capacity constraint. The rest installations are inserted into a new route in the same manner, and so on. This process finishes when the last installation in the chromosome is inserted.

To construct each route, we adapted a Generalized Insertion Procedure (GENI) initially developed for Traveling Salesman Problem in Gendreau, Hertz and Laporte (1992). We implement two versions of GENI heuristics by modifying the original GENI heuristic. In the first version GENIc, we implement *the least cost insertion* which does not incur any capacity violations to obtain cost efficient solutions. In the second version GENIr, we evaluate the increment in risk instead of cost for each possible insertion, and implement *the least risk insertion* to yield solutions with small risk values.

The installations appeared in the routes may not follow the installation sequence in the chromosome due to the insertion procedure. In this regard, our scheme is different from the chromosome representation and *Split* procedure in Prins (2004), in which the installations appeared in the route respect the sequence in the chromosome. Our scheme can be viewed as a cluster-first, route-second heuristic, since only the consecutive installations in chromosome be inserted in the same route.

3.1.2 Initial Chromosomes

We apply a modern version of Fisher-Yates shuffle algorithm (Durstenfeld, 1964) for generating *N* random chromosomes. The Fisher-Yates shuffle is an algorithm for generating a random permutation of a finite set. This algorithm is unbiased, so every permutation is equally likely.

3.1.3 Crossover

A classical Order Crossover (OX) is used to construct child chromosomes (Prins, 2004).

3.1.4 Mutation

Three mutation operators are implemented: *Swap*, *Inversion* and *Relocation*.

3.1.5 Stopping Criterion

The genetic algorithm is terminated after running a predefined number of generations *MaxGen*.

4 COMPUTATIONAL STUDY

The genetic algorithm is tuned experimentally. The computational results are generated based on the following setting of parameters: Size of the population: $N = 256$; Probability of *Swap* mutation 0.5; Probability of *Inversion* mutation 0.1; Probability of *Relocation* mutation 0.1; Probability of *the least risk insertion* 0.85; Maximum number of generations $MaxGen = 10,000$.

4.1 ε-constraint Approach

As far as we know, there is no other approach in the literature that addresses the helicopter routing problem as a multi-objective problem. To assess the efficiency of the proposed genetic algorithm, an ε-constraint approach is used to transform the multi-objective problem to a single-objective one. In our case, the risk objective is optimized and the other objectives are considered as constraints. The single-objective problem is then solved with an adapted version of tabu search heuristic, with which high quality solutions are reported in literature.

4.2 Case Study

The algorithms were coded in C using Pelles for Windows, version 5.00.8. All experiments were performed on a personal computer with an inter(R) Core(TM)2 Duo CPU E8400 @ 3.00GHz, 2.99GHz, and 3.25 GB of RAM, with the operating system Microsoft Windows XP Professional Version 2002, Service Pack 3.

An test instance from literature is presented here to demonstrate the solutions from the GA approach. The GA approach identified 143 solutions for this instance. The risk value and the travel time varies in $[718.24, 837.73]$ and $[34.04, 53.09]$, respectively. The number of routes varies in $[14, 24]$. These solutions are illustrated in Figure 1, in which the y axis represents the risk value and the x axis represents the travel time. The GA solutions are well dispersed (symbol $\times$). There are 26 solutions found by the ε-constraint approach (symbol $+$). For this instance, the ε-constraint outperforms the GA approach approach in terms of solution quality. For each solution found by the ε-constraint approach, we can find one or several dominated GA solutions. On the other hand, the GA approach uses less time to find more solutions as compared to the ε-constraint approach. The GA approach found these solutions in 2688 CPU seconds, while the ε-constraint approach use 5067 CPU seconds to identify the relatively small amount of solutions.

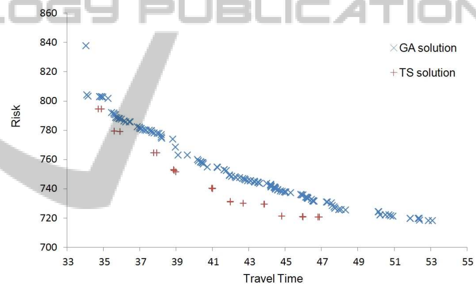

Figure 1: Risk and travel time objectives of the case instance.

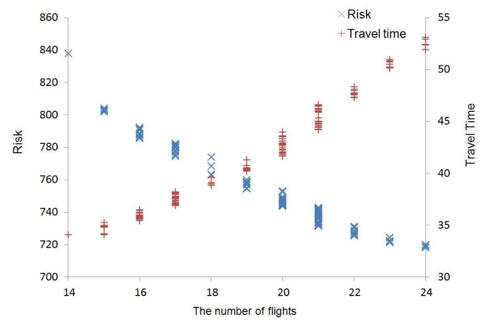

Figure 2: Inter-relationship among the three objectives of the case instance.

The inter-relationship among the three objectives including the number of flights of the GA solutions are illustrated in Figure 2. We use symbol $+$ for the travel time and symbol $\times$ for the risk at each given number of flights (x axis) in the figure. At a given number of flights, both the risk and cost objectives may vary to some extent. The general trend is that as the number of flights increases, the risk decreases but the travel time increases.

In the GA solutions with low risk, each flight first performs deliveries, and then it starts with pickups after finishing all the deliveries. All installations are visited twice, expect those at which the helicopters perform their last delivery and their first pickup.

In the GA solutions with low travel time, Hamiltonian routes are often identified. The installations in Hamiltonian routes are visited only once to simultaneously perform pickup and delivery.

5 CONCLUSIONS

We have addressed a helicopter routing problem arising in the transportation of offshore employees as a multi-objective problem, in which the risk, the cost and the number of flights objectives are considered. A genetic algorithm is applied to the problem and it is evaluated by comparing with ε-constraint approach with a single-objective tabu search metaheuristic. Preliminary case study shows that the genetic algorithm can generate high quality solution, in terms of the spread and convergence of solutions.

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