Yugoslav Journal of Operations Research
34 (2024), Number 3, 407-421
DOI: https://doi.org/10.2298/YJOR220915040L

VNS ALGORITHM FOR THE PERIODIC PICK-UP AND DELIVERY HELICOPTER ROUTING PROBLEM IN OIL AND GAS OFFSHORE

Elena LUBNINA
JV Vietsovpetro Company, Vung Tau, Vietnam
elubnina@yandex.ru
Yury KOCHETOV
Sobolev Institute of Mathematics of the Siberian Branch
of the Russian Academy of Sciences, Novosibirsk, Russia
jkochet@math.nsc.ru

Received: September 2022 / Accepted: March 2023

Abstract: In offshore field development projects, the operating and transport expenses are crucial part of the total budget. In this paper, we introduce a new helicopter routing problem with splitting demands and a time horizon. A fleet of identical helicopters with known capacity should server predefined demands to deliver employees at the offshore platforms and return other employees to depot for every day of time horizon. All routes start and finish at the depot, the length of each route cannot exceed a given threshold. Our goal is to find the routes to satisfy all demands with minimal total length. To tackle this pick-up and delivery problem, we design the MILP model and adopt the VNS-algorithm. Some hard constraints are relaxed and included into the objective function with penalties. Computational results for real-world test instances of the JV «Vietsovpetro» Company illustrate ability for reduction the transport expenses up to 5–10%.

Keywords: Periodic VRP, split delivery, simultaneous delivery and pick up, Variable Neighborhood Search.

MSC: 90B06, 90C11, 90C59.

1. INTRODUCTION

Joint Venture «Vietsovpetro» was established in 1981 to perform exploration and production of oil and gas on the Southern continental shelf of Vietnam. For over three decades, it is one of the most effective oil producing enterprises in the world. The instability of the world oil prices has been encouraging company to reduce operating cost.

For an offshore field development project, the high operating cost can be a crucial part of total expenses. One of the potential ways to increase the profit of offshore projects lies in logistic. Helicopters are commonly used to transport staff to and from offshore platforms. Helicopter transportation is a fast but expensive way to transport employees. The cost of a flight is approximately 10–15 thousand dollars. On average, every year the company does up to 2000 flights, and transports almost 40 000 employees to platforms and back. Sometimes, up to 18 flights per day can be done. Annually, transportation costs can exceed 20 million dollars. Reducing flight distance can imply decreasing time of the flights, and therefore, the total cost. Each percent of this sum saves for the company at least 200 thousand dollars per year.

In this paper, we consider a new problem of employee transportation at a time horizon. We need to deliver employees at the offshore platforms every day and return other employees to depot, due to crew changes, repair work or well tests, management visits or other. We have a homogeneous fleet of helicopters with known capacity. We can split the demand for each platform and visit it many times. Each route starts and finishes at the depot. By the technical reasons, the length of each route cannot exceed a threshold. Our goal is to find a set of routes to satisfy all demands with minimal total travel length for the whole time horizon. An important feature of the problem is an ability to serve some part of demand later. We know the minimal demand for each day and must serve the total demand for each platform for picking up and delivering employees, respectively. This flexibility opens a new opportunity for expense reduction. To tackle this pickup and delivery problem, we design the MILP model and adopt the well-known Variable Neighborhood Search approach (VNS). Some hard constraints are relaxed and included in the objective function with penalties. Computational results for the real-world test instances of the JV Vietsovpetro Company illustrate the ability for reduction of the total route length up to 5–10% for a week horizon.

We organized the paper as follows. In Section 2, we present the detail description of the problem. In Section 3, we discuss a literature review of recent works to provide an overall view on the investigation of such problems. A proposed MILP model of the helicopter problem is described in Section 4. Adaptation of the VNS-algorithm is proposed in Section 5. Section 6 shows the computational results for real data of «Vietsovpetro» Company. Finally, the concluding remarks and some perspectives for future research are discussed in Section 7.

2. PROBLEM DESCRIPTION

Developing oil and gas offshore fields requires building a special construction on the sea surface to drill and service wells on the seabed (Fig.1). The depth of the sea within the field is not large, it is about 50 m. In the reservoir, wells are far from each other, but they are grouped at seabed. Platforms to drill wells can change locations due to schedule. Platforms to service wells are permanently installed. JV «Vietsovpetro» Company has many platforms, which are 100-200 km away from Vung Tau depot (Fig.2). The distance between neighboring platforms is approximately 5 km. Up to 100 employees can live and work on a platform, depending on its type and the number of wells connected to the platform.

Figure 1: Platforms

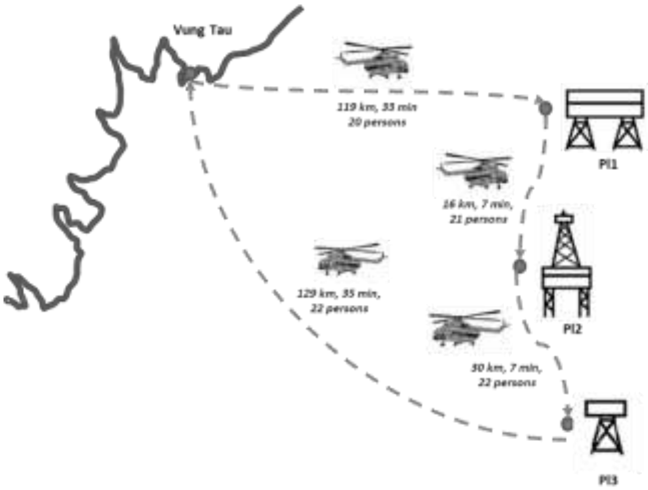

Figure 2: Example of a helicopter route

The helicopter fleet is based in Vung Tau. Each helicopter starts from an onshore depot, visits some offshore platforms to deliver and pickup employees and returns to the depot. The number of employees on a board of helicopter is 22 persons. The number of helicopters is limited, but they can perform several flights per day. Therefore, we assume that the fleet of helicopters is unlimited. The number of employees must be picked up from a platform or delivered to it can exceed the helicopter's capacity, sometimes twice or more. The demand of each platform must be fully satisfied. Therefore, we allow multiple visiting platforms by helicopters and splitting demand.

We have to consider the following aspects of the current needs to create a feasible schedule for helicopters:

1. Regular crew change with exact date of rotation.
2. Various operational and work-over activities, such as scheduled repairs, well surveying.
3. Force majeure circumstances, such as emergencies requiring fast repair.

4. Planned or unexpected management visits and others.

Some of these items can be planned for one or two weeks previously with or without exact dates (crew changes or work-over operations), some are appeared unexpectedly and should be done during one-two days. In other words, we do not know the exact demand for each day and each platform for picking up and delivering employees. We have a certain flexibility to move some demand during the time horizon. We can find a similar idea in [1,2]. Thus, we assume we can calculate the minimal demand for each day and each platform and must serve the total demand for the whole time horizon. This flexible model can open a new way for expense reduction. According to these aspects, solving of the problem is a challenge and crucial task for the Company.

3. LITERATURE REVIEW

The described problem is a variant of the well-known Capacitated Vehicle Routing Problem (CVRP). Its various generalizations have a over 60-year history [3]. The common idea of the classical version of this problem is to find a set of routes with minimum total length to service all clients. The CVRP belongs to the class of NP-hard problems. Many of models and optimization algorithms were proposed for them [4]. Its practical relevance and computational difficulty motivate the interest in CVRP. Large-scale instances may be solved to optimality in particular cases only. Heuristics and metaheuristics are the most useful approach for the practical purposes.

We can classify our problem of transportation employees from depot to platforms and back for a day as CVRP with Simultaneous Split pickup and delivery (CVRPSSPD). The capacity of helicopters and many personal needed to deliver or pickup implies splitting delivery and pickup demands to different helicopters. The length of each route cannot exceed a threshold. Heuristic approach for solving such kind of problem is very popular. Jing Fan [5] used a Tabu Search approach to solve the VRP with simultaneous Delivery and Pickup problem with Time windows. Customer satisfaction is inversely proportional to the waiting time for the vehicle. The main goals are to minimize the total length of routes and maximize all customer satisfactions. Also, an effective Tabu Search based procedure is developed in Yong Shi, Toufik Boudouh, Olivier Grunder [6] to minimize the number of vehicles and the total travelling costs without splitting demand. They consider two types of tabu search strategies and used two-dimensional and three-dimensional tabu lists. Authors Ran Liu, Xiaolan Xie, Vincent Augusto, Carlos Rodriguez [7] propose heuristic algorithms for a vehicle routing problem with simultaneous delivery and pickup and time windows in home health care. But in their case, they separated clients for delivery and clients for pickup. Heuristic approach for solving such kind of problem is very popular. Can B. Kalayci, Can Kaya [8] develop a hybrid metaheuristic algorithm based on the Ant Colony System and the Variable Neighborhood Search to solve the CVRPPD problem without splitting demand. Fermin Alfredo Tang Montane, Roberto Dieguez Galvao [9] studied the CVRPSSPD. Authors propose two variants of the mathematical formulation of the problem, with and without maximum distance constraint for each route. They were the first who solved this problem by metaheuristics. Tabu Search algorithm was proposed with four types of neighborhoods and two searching strategies. Also, Yong Wang, Xiaolei Ma, Yunteng Lao, Yinhai Wang, Hajjun Mao [10] formulated the VRP with simultaneous delivery and pickup with splitting demand as a mixed integer linear program. They developed a hybrid heuristic algorithm based on the local search method. The following operators are applied: relocate, 2-exchange, 2-opt, or-opt, swam move, relocate split in some specified order. In this paper, we address a Period CVRPSSPD problem where solution should be found for a time horizon. The idea of solving the CVRP problem for a time horizon is not new. It was studied in different variants in [11] [12] [13]. Vera C. Hemmelmayr, Karl F. Doerner, Richard F. Hartl [14] were the first who applied VNS to the periodic CVRP problem.

The problem of people transportation between oil and gas platforms, other maritime units and depot is known as Helicopter Routing Problem. Velasco N., Castagliola P. Dejaz P, Gueret C, Prins C [15] considered a problem of people transportation to offshore platforms by a helicopter and proposed a memetic algorithm to minimize the total route length. Thera a lot of studies where more complex objective functions were considered. Fubin Qian, Irina Gribkovskaia, Gilbert Laporte, Oyvind Halskau [16] [17] proposed a mathematical model and designed a Tabu Search heuristic to improve transport safety with objective function, which includes a risk for passengers and pilots, expressed as the expected number of fatalities during take-off and landing and cruise phases of a flight. Rodrigo de Alvarenga Rosa, André Manhães Machado, Glaydston Mattos Ribeiro, Geraldo Regis Mauri [18] proposed a mathematical model and solved the Capacitated Helicopter Routing Problem using Clustering Search metaheuristic to minimize the objective function, which includes a cost associated to the use of the helicopters and each mile travelled by the helicopters. Menezis F, Porto O, Reis M.L., Moreno L, Arago M.P.D., Uchoa E., Abeledo H, Nascimento N.C.D. [19] formulated the problem helicopter scheduling as a mixed integer program and solved it by developed column generation heuristic. In this work, a weighted objective function includes three main objectives: to serve all demands, reduce the total number of offshore landings, and minimize the helicopter operating costs by decreasing the total travel time. In this work, they rearrange flight doe to different requirements but didn't change routes. In the last years, different groups extensively studied the helicopter routing problems. One direction of research is an evacuation of employees from the platforms in case of unexpected circumstances because of environment or human incidents. Santiago-Omar Caballero-Morales, Jose-Luis Martinez-Flores [20] developed a mathematical model which integrates non-deterministic failure rate to determine the most reliable routes of minimum distance for multiple locations. An evolutionary meta-heuristic was proposed to provide suitable solutions for large-scale instances. Another research area is solving this problem as a scheduling problem and moving a set of routes during a day. Each route is considered as a job. Authors Thiago Vieira, Jonathan De La Vega, Roberto Traves, Pedro Munary, Reinaldo Morabito, Yan Bastos, Paulo Cesar Ribas [21] build a schedule, including pending flights transferred from the previous day with different recovering priorities to minimize flight delays and costs related to helicopter usage and reassignments. They consider only short routes to visit one maritime unit each time only. They proposed two mixed integer programming models and developed an effective heuristic approach based on constructive and improvement heuristics. Yan Bastos, Julia Fleck, Rafael Martinelli [22] suggested a stochastic programming approach to minimize the delays in departure time. Gaute Messel Nafstad, Amund Haugseth, Veborn Hoyland, Magnus Stalhane [23] presented the extended and compact mathematical formulations and developed an exact approach for the problem of operating a heterogeneous fleet of helicopters in different depots to transport personnel between offshore installations and/or helicopters onshore and minimize costs associated with operating a helicopter and the distance travelled.

4. MATHEMATICAL MODEL

Let us consider a complete undirected graph $G = (V, \mathrm{E})$ with the set of nodes $V = \{0\} \cup V'$ and a set of edges $E = \{(i,j): i, j \epsilon V,\ i \neq j\}$. We assume the node $\{0\}$ represents the depot, and the set $V' = \{1, \dots, n\}$ represents platforms. Let $c_{ij} \geq 0$ is a distance between platforms i and j from the set V'. We also assume that the matrix $\{c_{ij}\}$ satisfies the triangular inequality. The time horizon includes $W > 0$ days to transport of employees from depot to the platforms and back. Denote (D_i, P_i) the total demands to deliver D_i employees to platform i and pickup P_i employees from it during whole time horizon. The minimal delivery and pickup demands for each day *t* we denote $(d'_{it},\ p'_{it})$, respectively.

At the depot, we have a large homogeneous fleet of m helicopters with known capacity Q. The length of each helicopter's route cannot exceed *C* kilometers. Each route starts and ends at the depot. Values D_i, P_i can be significantly greater than the capacity of a helicopter. Thus, multiple visits of platforms by different helicopters are allowed any time. We need to find a set of routes with minimal total length to satisfy all the pickup and delivery demands for all platforms during the whole time horizon.

Introduce the decision variables:

$$x_{ijkt} = \begin{cases} 1, & \text{if helicopter } k \text{ moves from platform } i \text{ immediately to platform } j \text{ on day } t \\ 0 & \text{otherwise} \end{cases}$$

$d_{ikt} \geq 0$ is the number of employees for delivering to platform i by helicopter k on day t,

$p_{ikt} \geq 0$ is the number of employees for picking up from platform i by helicopter k on day t,

$u_{ikt} \geq 0$ are auxiliary integer variables for sub-routes elimination.

Now the periodic pickup and delivery helicopter routing problem can be presented:

$$\min \sum_{t=1}^{W} \sum_{k=1}^{m} \sum_{j=0}^{n} \sum_{i=0}^{n} c_{ij}\, x_{ijkt} \tag{1}$$

$$\sum_{k=1}^{m} \sum_{i=0}^{n} x_{ijkt} \geq 1,\ \forall\, j, t \tag{2}$$

$$\sum_{i=0}^{n} x_{ijkt} = \sum_{i=0}^{n} x_{jikt}\,,\ \forall\, j\,, t, k \tag{3}$$

$$n x_{ijkt} + u_{ikt} - u_{jkt} \leq n - 1,\ \forall\, i, j, k, t;\ \ i, j \neq \{0\} \tag{4}$$

$$\sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij} x_{ijkt} \leq \mathrm{C},\ \forall\, k, t \tag{5}$$

$$\sum_{t=1}^{W} \sum_{k=1}^{m} d_{ikt} = D_i,\ \sum_{t=1}^{W} \sum_{k=1}^{m} p_{ikt} = P_i,\ \forall\, i;\ i \neq \{0\} \tag{6}$$

$$d'_{it} \leq \sum_{k=1}^{m} d_{ikt}\,,\ p'_{it} \leq \sum_{k=1}^{m} p_{ikt} \quad \forall\, i, t \tag{7}$$

$$d_{ikt} \leq D_i \sum_{j=0}^{n} x_{jikt} \ , \ p_{ikt} \leq P_i \sum_{j=0}^{n} x_{jikt}, \quad \forall\, i,k,t \tag{8}$$

$$L_{0kt} = \sum_{i=1}^{n} d_{ikt} \ , \qquad \forall\, k,t \tag{9}$$

$$L_{jkt} \geq L_{ikt} - d_{jkt} + p_{jkt} - Q\big(1 - x_{ijkt}\big), \ \forall\, i,j\ k; \ \ j \neq \{0\} \tag{10}$$

$$0 \leq L_{ikt} \leq Q, \ \forall\, i,k,t \tag{11}$$

$$x_{ijkt} \epsilon \{0,1\}, \quad u_{ikt}, d_{ikt}, p_{ikt} \geq 0, \text{integer}, \quad \forall\, i,j,k,t. \tag{12}$$

The objective function (1) minimizes the total length of all routes. Constraints (2) ensure that at least one helicopter each day visits each platform. Constraints (3) guarantee that the helicopter must leave platform if it comes. Constraints (4) eliminate all routes without a depot. Because of constraints (5), the maximum distance traveled by each helicopter cannot exceed the known flight range. Constraints (6) guarantee that the total demands will be delivered and picked up for each platform. In constraints (7), we have lower bounds for picking up and delivering for each platform and day. We establish the relationship between decision variables (x_{ijkt}) and (d_{ikt}), (p_{ikt}) by constraint (8). In constraints (9), we define the number of employees for each helicopter and day at the depot before traveling. Constraints (10) control the load of each helicopter at each point of route. Constraints (11) guarantee that the load of helicopter at each platform of the route does not exceed its capacity. Constraints (11, 12) define the range of the decision variables. We can drop the integrality constraints for variables (u_{ikt}), (d_{ikt}), (p_{ikt}). This relaxation can improve the efficiency of the commercial solvers.

In this problem formulation, we have some capacity constraints (11), the route length constraints (5), and the lower bounds for a load of helicopters (7) which are difficult to satisfy. Thus, we relax these constraints and include some penalties into the objective function (1) with positive weight coefficients α, β, Υ for their violations.

For the load constraints (11), we define new non-negative slack variables Δ_{ikt} for each platform, helicopter, and day:

$$\Delta_{ikt} = \max\{0, L_{ikt} - Q\}$$

The total violation of the constraints $P_1 = \sum_{t=1}^{W} \sum_{i=0}^{n} \sum_{k=1}^{m} \Delta_{ikt}$ we include in the objective function with factor α.

For the route length constraint (5), we define new non-negative slack variables Δ_{kt} for each helicopter and day:

$$\Delta_{kt} = \max\left\{0, \sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij} x_{ijkt} - \mathrm{C}\right\}$$

and include the total violation $P_2 = \sum_{t=1}^{W} \sum_{k=1}^{m} \Delta_{kt}$ in the objective function with factor β.

For the lower bounds constraints (7), we introduce new non-negative slack variables Δ'_{it} for each platform, helicopter, and day:

$$\Delta'_{it} = \max\{0, d'_{it} - \sum_{k=1}^{m} d_{ikt}\} + \max\{0, p'_{it} - \sum_{k=1}^{m} p_{ikt}\}$$

and include the total violation $P_3 = \sum_{t=1}^{W}\sum_{i=0}^{n}\Delta'_{it}$ in the objective function with factor Υ. Note that the variables L_{ikt} are easily defined by variables d_{ikt}, p_{ikt} from constraints (9), (10). Thus, we have got a new objective function:

$$F(x_{ijkt}, d_{ikt}, p_{ikt}) = \sum_{t=1}^{W}\sum_{k=1}^{m}\sum_{j=0}^{n}\sum_{i=0}^{n} c_{ij}x_{ijkt} + \alpha P_1 + \beta P_2 + \Upsilon P_3.$$

We will use this penalized function in the VNS local search method and manipulate the weights α, β, Υ to get near optimal feasible solutions.

5. VNS APPROACH

To solve the periodic pickup and delivery helicopter routing problem, we use the well-known VNS metaheuristic approach based on local search ideas. Nenad Mladenovic and Pierre Hansen proposed it in 1997 [24]. This method shows its effectiveness for different classes of combinatorial problems, including routing problems [2] [25] [26], bi-level optimization [27], packing problems [28], and many other NP-hard problems [29]. The main idea of this approach is to change of neighborhood in the search. Using systematically this idea and apply randomized local improvement procedure, we have got a very simple and widely applicable metaheuristic. Contrary to other classical local search metaheuristics, Tabu Search and Simulated Annealing, the VNS does not follow a trajectory in the solution space but explores increasingly distant neighborhoods of the current incumbent solution and jumps from this solution to a new one if and only if an improvement has been made. In fact, we concentrate our attention on local optima and move from one local optimum to a better one. The performance of this approach strongly depends on the neighborhood structures we use. As a local optimum within some neighborhood is not necessarily one within another neighborhood, we need substantially different neighborhood structures for high performance (as layers in plywood). How to select the best collection of neighborhoods and which local optima to explore is still an open question. One can find the current reviews in this area in [30] [31].

5.1. Neighborhood structures

Let us define a helicopter's route as an ordered sequence of nodes (depot and platforms). A solution to the problem is a set of routes (x_{ijkt}) for each day and each helicopter and corresponding plan for picking up and delivering (p_{ikt}), (d_{ikt}) of employee. Sure, we can calculate the best plan (p_{ikt}), (d_{ikt}) as a feasible solution to the problem (1)-(12) for a given set of routes (x_{ijkt}). It is a linear integer program. We guess that it can be solved in polynomial time. Nevertheless, we include this plan into the solution coding scheme to reduce the running time of the VNS algorithm.

Neighborhood Move

For the current solution, we can define a neighborhood Move as a set of solutions which are differ from the current solution by moving a node to a new position in this route or to another route of this day or any other selected day. It is very large set with size *O(Wmn)*.

Therefore, we apply a randomized variant of the neighborhood. First, randomly select a node to move. Then, select a day randomly with uniform distribution and randomly select a route. Finally, to find the best position in the route, we check all variants with the same order of other nodes in the route. For each position, we try to change the picking up and delivering plan in an appropriative manner for new routes only. Figure 3 illustrates this idea.

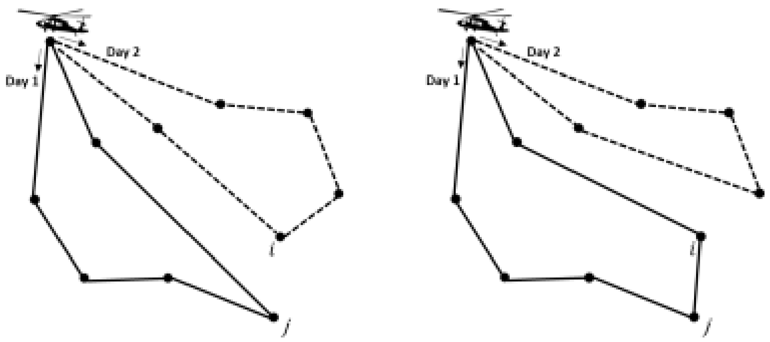

Figure 3: Neighborhood Move

Neighborhood Two Exchanges

In the neighborhood Two exchanges, two nodes can change their positions. Consider node i from route r_1 in day t_1 and node j from route r_2 in day t_2. We assume that $r_1 \neq r_2$. We try to swap the nodes if it produces a feasible solution for an appropriated picking up and delivering plan for new routes and decreases its total length. Otherwise, we split the node with maximal demand for picking up or delivering (say node j) by two nodes j' and j'' with the following pairs for delivery and pickup $(d_{jk_2t_2} - d_{ik_1t_1}, p_{jk_2t_2} - p_{ik_1t_1})$ and $(d_{ik_1t_1}, p_{ik_1t_1})$, respectively. Now we can swap the nodes j'' and i and find the best positions for them in the routes with the same positions for other nodes. The picking up and delivering plan can be modified for these two routes as well to reduce the penalties if a new solution is infeasible. Similar to the Move neighborhood, we apply the randomized procedure to reduce the time complexity. Figure 4 illustrates this idea.

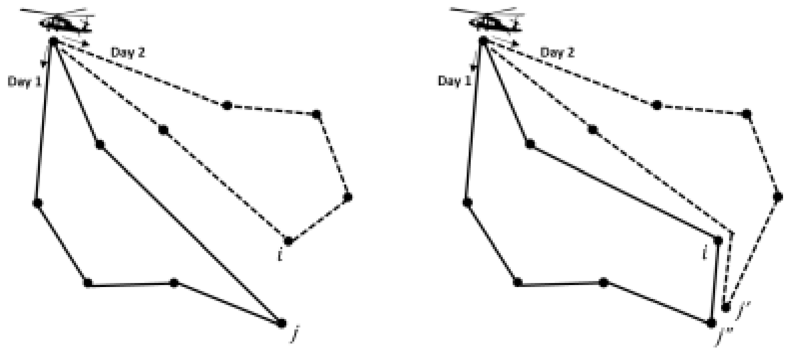

Figure 4: Neighborhood Two exchange

Neighborhood Cross

In this neighborhood, we select a few routes, divide each route into two parts, and create the same number of new routes from these parts. We have a lot of variants to create a neighboring solution here. The most part of them are infeasible but allow us to diversify the search drastically. We will not try to find the best neighboring solution. We will use this neighborhood at the Shake step of the VNS algorithm only. Figure 5 illustrates idea of this diversification rule.

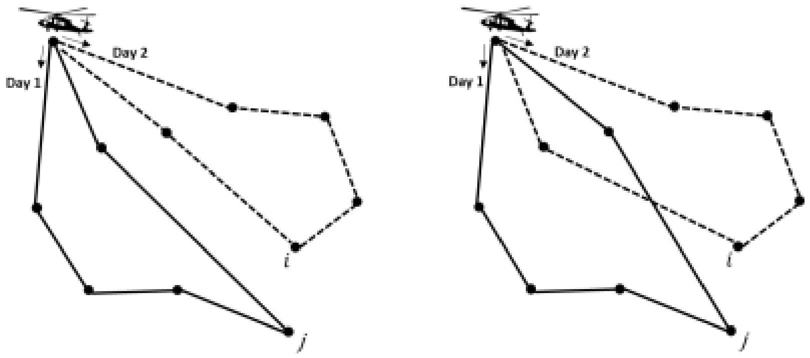

Figure 5: Neighborhood Cross

5.2. The VNS algorithm

In our VNS algorithm, we apply alternately a local improvement procedure, a shaking procedure, and a neighborhood change step, until reaching a stopping condition. The improvement procedure used within the heuristic is a randomized local search that explores one neighborhood structure, Move or Two Exchanges neighborhood. In the shaking procedure, we use a random element from the Cross neighborhood. The pseudocode of algorithm is presented below.

Algorithm 1. VNS for the periodic pick-up and delivery helicopter routing problem

1. **Initialize** set of neighborhoods N_s for $k = 1, \dots, k_{max}$;
2. Generate an initial solution $S = (x_{ijkt}, d_{ikt}, p_{ikt})$;
3. **while** the stopping condition is met **do**
4. Set $k \coloneqq 1$;
5. **while** $k \le k_{max}$ **do**
6. Apply **Shaking** to solution S by the neighborhood $N_k(S)$;
7. Let S' be the new solution obtained**;**
8. Apply local search with S' as initial solution;
9. Let $S^{"}$ be the improved solution;
10. **If** $F(S^{"}) \le F(S)$ **then** $S = S^{"}$ and k:= 1 **otherwise** k:=k+1;
11. **end while**;
12. **end while;**

At Step 2, we use a feasible solution of Company experts with reach experience. Alternatively, we generate initial solutions by the nearest neighbor algorithm and a two-stage approach: first, we distribute the employees to fulfill some helicopters as many as possible and later on, we create the routes. These greedy solutions are usually weaker than the expert's solutions. The computational results illustrate that the VNS algorithm can get the similar results but spent more iterations. Moreover, infeasible initial solutions can be created in such a way.

As the stopping condition, we use a number of iterations without improvement of the best found solution. In our computational experiments, we terminate the search after 100 iterations without improvement. The local search at Step 8 is the most time consuming. To reduce the neighborhoods, we ignore the pairs of nodes which are quite far from each other, the distance is at least a threshold D. Moreover, we try to decrease the penalties for the small routes by full enumeration search for their nodes. The penalty factors α, β, Υ are tuning in such a way to investigate the boundary of the feasible domain. We need the values when about half of the visited solutions are feasible one.

6. COMPUTATIONAL RESULTS

We conduct the computational experiments for 30 test instances based on Company real data. We consider historical flight schedules for 3, 5, or 7 sequential days and at most 45 platforms to form input data and try to improve them by modifying routes and moving some employees to other days (lower bounds d'_{it}, p'_{it}). We consider four variants for the values d'_{it} and p'_{it} in each node and define them as 0%, 25%, 50% and 75% of the historical data d_{ikt} and p_{ikt}, correspondently. The helicopter's capacity Q is 22. The length of each route cannot exceed ***C*** =500 km. We adjust penalty factors α, β, Υ manually and put $\alpha = 20$, $\beta = 1$, $\Upsilon = 40$. To reduce the running time of the algorithm and diversify the search, we consider a random part of Move and Two exchanges neighborhoods at Step 8 (local search) and ignore 70% of the neighboring solutions including the pairs of nodes with mutual distance greater than $D = 20$ km. We used the FORTRAN language to code the algorithm. We carry out all experiments on a PC with 11th Gen Intel(R) Core(TM) i7-11850H 2.5 GHz, 32 GB RAM running on Windows 10 Pro operating system.

Table 1 presents our computational results. For each instance, we run the algorithm 20 times. Columns Worst, Average, Best, and Diff. show the worst, average, best results, and the improvement according to the initial Company solution, column IS, respectively. As we see, the average improvement is about 7-8%. In some cases, it is 12–14%. As a rule, the length route constraints (5) are not active. Only one platform is quite far from the other ones. The capacity constraints (10,11) are the most hard for the instances. In initial solutions, all helicopters are almost filled or completely filled with employees. We cannot reduce the total number of flights. We can only decrease the total length of the routes. In other words, the initial solution is quite strong.

Table 1: Computational results

N	Period	Platforms	Requests		Initial solution (IS)	GUROBI (4h)	VNS (20 times)								
							Percentage of request for a day								
							0%						25%	50%	75%
			Delivery	Pickup			Worst	Average	Best	Diff.	Time (min)	% Improvement (respect. IS)			
												%	%	%	%
1	3	15	242	243	2475	2345	2398	2365	2352	123	3	5%	3,0%	2,6%	1,9%
2	3	16	150	170	1621	1564	1580	1555	1550	71	1	4%	1,9%	2,7%	2,6%
3	3	16	164	176	1669	1594,7	1618	1604	1595,3	73	2	4%	3,2%	2,4%	2,3%
4	3	17	240	230	2376	2170	2223	2165	2145	231	2	10%	7,2%	6,9%	5,8%
5	3	17	238	230	2164	2141	2154	2139	2122	42	1	2%	0,7%	0,6%	0,5%
6	3	19	230	236	2357	2179	2245	2193	2175	182	2	8%	5,2%	5,1%	4,5%
7	3	22	358	373	3814	-	3736	3432	3296	518	3	14%	8,6%	7,8%	7,4%
8	3	26	345	354	3577	-	3380	3329	3302	276	3	8%	4,8%	4,2%	4,6%
9	3	28	470	478	4897	-	4897	4687	4633	264	4	5%	4,3%	3,4%	2,7%
10	3	30	460	609	6061	-	5812	5779	5732	329	7	5%	3,6%	3,7%	3,5%
11	5	23	254	216	2611	-	2475	2361	2323	288	2	11%	6,5%	2,8%	2,4%
12	5	24	366	339	3828	-	3551	3499	3462	365	5	10%	6,2%	5,0%	4,3%
13	5	25	424	419	4216	-	3973	3909	3886	330	2	8%	5,4%	5,0%	3,4%
14	5	28	468	498	4797	-	4671	4414	4358	439	5	9%	6,4%	5,5%	4,7%
15	5	32	565	566	5302	-	5035	5001	4976	325	4	6%	3,3%	2,8%	2,5%
16	5	37	598	645	6915	-	6514	6425	6338	577	7	8%	5,1%	3,5%	3,5%
17	5	38	803	837	8412	-	8184	8106	8041	371	9	4%	2,5%	2,6%	2,3%
18	5	39	865	644	8702	-	8367	8288	8233	468	7	5%	3,9%	3,4%	3,4%
19	5	39	759	803	7956	-	7575	7397	7335	620	9	8%	5,7%	5,3%	4,5%
20	5	42	1001	1041	9762	-	9354	9314	9237	525	9	5%	2,8%	2,5%	2,2%
21	7	22	365	323	3445	-	3322	3289	3268	178	3	5%	2,1%	2,5%	1,9%
22	7	26	453	431	4365	-	4185	4085	4042	323	3	7%	3,6%	2,9%	2,7%
23	7	27	690	612	6348	-	6086	6024	5982	366	6	6%	3,4%	2,2%	1,3%
24	7	29	497	490	5157	-	4748	4696	4658	499	4	10%	6,2%	5,5%	4,4%
25	7	30	700	724	6675	-	6175	6125	6066	610	6	9%	3,8%	2,9%	2,5%
26	7	31	525	490	5702	-	5448	5171	4991	711	5	12%	4,8%	4,0%	1,7%
27	7	35	945	891	9588	-	9303	8994	8915	673	11	7%	4,2%	3,3%	2,5%
28	7	38	911	900	9018	-	8735	8558	8495	523	8	6%	3,0%	1,9%	1,3%
29	7	43	1347	1385	13376	-	12729	12556	12461	916	13	7%	3,9%	3,0%	2,8%
30	7	45	1822	1867	18321	-	17505	17121	16904	1417	20	8%	4,8%	3,1%	2,0%

Columns %Improvement indicate the average percentage for the total length reduction for different variants of the lower bounds (d'_{it}, p'_{it}). We may conclude from Table 1 that full freedom here (0%) can lead to high reduction, up to 12–14%. Nevertheless, small freedom (75%) can decrease as well, about 3–4%. It is important result for the Company.

To compare these heuristic solutions with the global optima, we apply the Gurobi commercial solver [32] to the mathematical model (1)–(12). Column GUROBI presents the best found solutions by the solver in 4 hours. For 6 test instances with 15–19 platforms, we have got the results which are very close to results of the VNS algorithm. In two cases, GUROBI solutions are slightly better but we do not know are they optimal solutions or not. For large scale instances, the solver cannot find even feasible solution.

Figure 6 shows the behavior of the objective function when the VNS algorithm runs. The dotted line corresponds to the objective function with penalties, and the solid line corresponds to the objective function without penalties. Dots represent feasible solutions. As we can see, the Shaking step (high picks) destroys the current solution drastically, but the algorithm can systematically improve the total length of the routes by the local improvement.

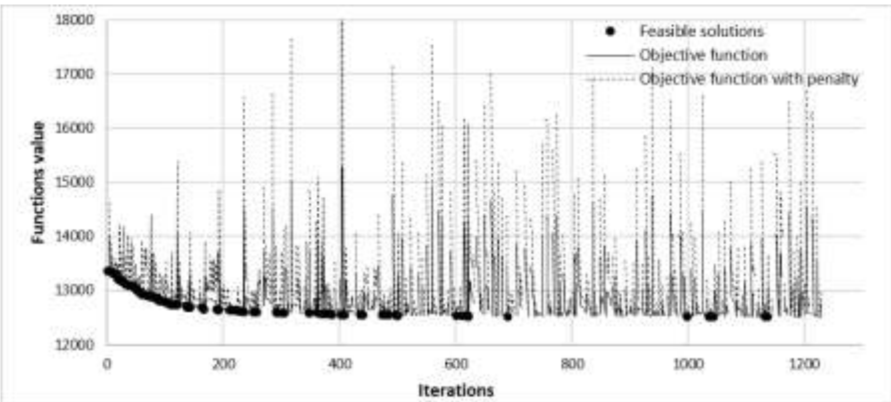

Figure 6: Typical behavior of the VNS with and without penalties

6. CONCLUSIONS

We addressed a real-life periodic helicopter routing problem for employee transportation between onshore depot and offshore platforms in the oil industry. We design the MILP model and apply a commercial solver for it. In this way, we can find near optimal solutions for small instances only. For the real dimension, we adopt the VNS-algorithm. Some constraints are relaxed and included in the objective function with penalties. Computational results show a reduction of the transportation expenses on average up to 5–10%. For further research, it is interesting to study a general case where we have helicopters and transport vessels at the same or different depots. In fact, we need to deliver employee and goods to platforms and back. Such a new model can lead to further reduction of total expenses.

Acknowledgement. The study was carried out within the framework of the state contract of the Sobolev Institute of Mathematics (project FWNF-2022-0019)

Funding. This research received no external funding.

REFERENCES

[1] I. Kulachenko and P. Kononova, "A hybrid local search algorithm for the consistent periodic vehicle routing problem," *Journal of Applied and Industrial Mathematics,* vol. 14, no. 2, pp. 340-352, 2020.

[2] I. Kulachenko, P. Kononova, Y. Kochetov and A.Kurochkin, "The variable neighborhood search for a consistent vehicle routing problem under the shift length constraints," IFAC-PapersOnLine, vol. 52, no. 13, pp. 2314-2319, 2019.

[3] G. Dantzig and J. Ramser, "The truck dispatching problem," *Management Science,* vol. 6, no. 1, pp. 80-91, 1959.

[4] P. Toth and D. Vigo, "The Vehicle Routing Problem," *Society of Industrial and Applied Mathematics*, 2002.

[5] J. Fan, "The vehicle routing problem with simultaneous pickup and delivery based on customer satisfaction," *Procedia Engineering,* vol. 15, pp. 5284-5289, 2011.

[6] Y. Shi, T. Boudouh and O. Grunder, "An efficient Tabu search based procedure for Simultaneous Delivery and Pick-up problem with time window," IFAC-PapersOnLine, vol. 51, no. 11, pp. 241-246, 2018.

[7] R. Liu, X. Xie, V. Augusto and C. Rodriguez, "Heuristic algorithms for a vehicle routing problem with simultaneous delivery and pickup and time windows in home health care," *European Journal of Operational Research*, Elsevier, vol. 230, no. 3, pp. 475-486, 2014.

[8] C. Kalayci and C. Kaya, "An ant colony system empowered variable neighborhood search algorithm for the vehicle routing problem with simultaneous pickup and delivery," *Expert Systems With Applications Journal*, vol. 66, pp. 163-175, 2016.

[9] F. Montane and R. Galvao, "A tabu search algorithm for the vehicle routing problem with simultaneous pick-up and delivery service,"Computer and Operation research, vol. 33, pp. 595-619, 2006.

[10] Y. Wang, X. Ma, Y. Lao, Y. Wang and H. Mao, "Vehicle routing problem: simultaneous delivery and pickups with split loads and time windows," *Transportation Research Records Journal of the Transportation Research Board,* vol. 2378, pp. 120-128, 2013.

[11] A. Rusdiansyah and D. Tsao, "An integrated model of the periodic delivery problems for vending-machine supply chains," *Journal of food engineering*, vol. 70, pp. 421-434, 2005.

[12] B. Vieira, .G. Ribeiro, L. Bahiense, R. Cruz, A. Mendes and G. Laporte, "Exact and heuristic algorithms for the fleet composition and periodic routing problem of offshore supply vessels with berth allocation decisions," *European journal of Operational research*, vol. 295, pp. 908-923, 2021.

[13] M. Mahjoob, S. Fazely, L. Tavassoli, M. Mirmozaffari and S. Milanlouei, "A greed multi-period inventory routing problem with pickup and split delivery: A case study in flour industry," *Sustainable Operations and Computers*, vol. 2, pp. 61-70, 2021.

[14] V. Hemmelmayr, K. Doerner, and R. Hartl, "A variable neighbourhood search heuristic for periodic routing problem," *European Journal of Operational Research*, vol. 195, no. 3, pp. 791-802, 2006.

[15] N. Velasco, P. Castagliola, P. Dejax, C. Gueret and C. Prins, "A memetic algorithm for a pick-up and delivery problem by helicopter," *Bio-inspired Algorithms for the Vehicle Routing Problem*, vol. 161, pp. 173-190, 2009.

[16] F. Qian, I. Gribkovskaia, G. Laporte and O. Halskau, "Passanger and pilot risk minimization in offshore helicopter transportation," *Omega*, vol. 40, no. 5, pp. 584-593, 2012.

[17] F. Qian, V. Strusevich, I. Gribkovskaia and O. Halskau, "Minimizations of passenger takeoff and landing risks in offshore helicopter transportation: Models, approaches and analysis," *Omega*, vol. 51, pp. 93-106, 2015.

[18] R. Rosa, A. Machado, G. Ribeiro and G.R. Mauri, "A mathematical model and a clustering search metaheuristic for planning the helicopter transportation of employees to the production platforms of oil and gas", *Computers and Industrial Engineering*, vol. 101, pp. 303-312, 2016.

[19] F. Menezis, O. Porto, M. Reis, L. Moreno, M. Arago, E. Uchoa and N. Nascimento, "Optimizing helicopter transport of oil rig crews at Petrobas," *INFORMS Journal of Applied Analytics*, vol. 40, no. 5, pp. 408-416, 2010.

[20] O. Caballero-Moralez and J. Martinez-Flores, "Helicopter routing model with non-deterministic failure rate for evacuation of multiple oil platforms," *Computers and Industrial Engineering*, vol. 139, 2020.

[21] T. Vieira, J. De La Vega, R. Tavares, P. Munari, R. Morabito, Y. Bastos and P. César Ribas, " Exact and heuristic approaches to reschedule helicopter flights for personnel transportation in the oil industry," *Transportation Research Part E*, vol. 151, 2021.

[22] Y. Barboza Bastos, J. Fleck and R. Martinnelli, "A stochastic programming approach for offshore flight scheduling," IFAC-PapersOnLine, vol. 53, no. 4, pp. 478-484, 2020.

[23] G. Nafstad, A. Haugseth, V. Høyland and M Stålhane, "An exact solution method for a rich helicopter flight scheduling problem arising in offshore oil and gas logistics," *Computer and Operation research*, vol. 128, 2021.

[24] N. Mladenović and P. Hansen, "Variable neighborhood search," *Computer and Operation research*, vol. 24, no. 11, pp. 1097-1100, 1997.

[25] S. Salhi, A. Imran and N. Wassan, "The multi-depot vehicle routing problem with heterogeneous vehicle fleet: Formulation and a variable neighborhood search implementation," *Computer and Operation research*, vol. 52, pp. 315-325, 2014.

[26] Y. Kochetov and A. Khmelev, "A hybrid algorithm of local search for the heterogeneous fixed fleet vehicle routing problem," *Journal of Applied and Industrial Mathematics*, vol. 9, no. 4, pp. 503-518, 2015.

[27] I. Davydov, Y. Kochetov, N. Mladenovic and D. Uroševic, "Fast metaheuristics for the discrete (r|p)-centroid problem," *Automation and Remote Control*, vol. 75, no. 4, pp. 677-687, 2014.

[28] Y. Kochetov, "A hybrid VNS matheuristic for a bin packing problem with a color constraint," *Yugoslav Journal of and Operations research*, [S.l.]. vol. 31, no. 3, pp. 285-298, 2021.

[29] N. Mladenovic, R. Todosijevic and D. Uroševic, "Less is more: Basic variable neighborhood search for minimum differential dispersion problem," *Information Sciences*, vol. 326, pp. 160-171, 2016.

[30] E. Talbi, "Metaheuristics: from design to implementation," Berlin, Wiley, 2009.

[31] S. Salhi, "Heuristic Search: The Emerging Science of Problem Solving," Germany, Springer, 2017

[32] Gurobi Optimizer Reference Manual, Available:
www.gurobi.com/documentation/9.5/refman/index.html