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Multi-Objective Forest Vehicle Routing Using Savings-Insertion and Reactive Tabu with a Variable Threshold

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ABSTRACT
This paper focuses on how the competitiveness of forestry companies in Canada is impacted by forest products distribution and transportation costs, especially in the context of exports. We propose a new two-steps approach, consisting of building a good initial solution and then improving it to solve multi-objective forest vehicle routing problem. The main objective of this paper is to solve a multi-objective forest vehicle routing problem using the Savings-insertion, followed by the Reactive tabu, with a variable threshold. To that end, first, a mathematical model is established; secondly, our new Savings-insertion builds a good initial solution, and thirdly, our new Reactive tabu with a variable threshold improves the initial solution. The three main objectives are the minimization of a number of routes, the minimization of total distance and the minimization of total time by respecting the specified time window and the demand of all customers, which are sometimes important in this field. Finally, the experimental results obtained with our methodology for the named vehicle routing problem are provided and discussed.
Keywords**:** Forest transportation, multi-objective, reactive tabu, time windows, vehicle routing

I. INTRODUCTION

Forest product distribution is a process by which forest products are moved from sources to customers. The increase of the distance between forest areas and mills causes a considerable in-crease in forest companies' transportation costs. According to [1], transportation costs typically represent 10-20% of the final price of goods on the market; ref. [2] point out that in Quebec, transportation accounts for over 30% of provisioning costs for wood transformation mills, i.e., approximately $15 per cubic meter of round wood. According to [2], the average distance between forest areas where wood is collected and mills to which the wood is transported is around 150 km, and about 50% of the fuel required per cubic meter of the wood collection is consumed by forest trucks traveling, half of the time empty, between forest areas and mills.

According to [3], in countries like Chile, Canada, Sweden, Finland and New Zealand, the forest industry is mainly dependent on exports. According to [4], Canada is the largest exporter of forest products in the world, with $31 billion in sales in 2014. The sector thus ranks second in exports after the oil and gas sector, accounting for almost 6% of all Canadian exports in 2014. Secondly, according to [5] and [6], transportation costs account for a great portion of the total cost of forest operation. Thirdly, according to [3], to be competitive, the forest industry must maintain or improve the effectiveness of all its operations.

Over the past 20 years, the Vehicle Routing Problem (VRP) was mainly solved through the use of meta-heuristics (see [7] and [8]). Ref. [9] carried out a taxonomic review of VRP characterizing this research field, and conducted a detailed classification of variants with many examples. Following the review of previous classifications and taxonomies, major journals having published articles on the subject issue are listed, and a taxonomy is proposed. It conducted a classification by type of study, scenario characteristics, physical characteristics of the problem, and by characteristics of information and data used. Ref. [10] in turn conducted a review of biologically-inspired algorithms used to handle the VRP. It highlighted the different variants of the problem and the different methodologies used to solve them. These include evolutionary algorithms, ant colonies, particle swarm optimization, neural networks, artificial immune systems and hybrid algorithms. Ref. [11] for its part conducted a review of the state of the art of large scale VRP, indicating the difficulty of solving the problems of more than 100 customers with exact methods. It criticized the major works on large scale VRP by highlighting the techniques used. The review compared the performance of different algorithms and conducted an analysis based on key attributes such as effectiveness, efficiency, simplicity, and flexibility.

Ref. [12] proposed a model of long-haul VRP and scheduling integrating working hour's rules. The resolution method used was a bi-objective tabu search algorithm. The first objective is to minimize the number of vehicles used, and the second, to minimize the total cost, which is the weighted sum of the total distance traveled and the corresponding total time. Ref. [13], based on the work of [12], established a multi-criteria optimization model of long-haul VRP and scheduling integrating working hours rules. The solution method used was a bi-objective tabu search algorithm determining a set of heuristic non-dominated solutions. The mechanism consists of a single thread in which the weights assigned to the two objectives, namely, operating costs and driver inconvenience, are dynamically modified, and in which dominated solutions are eliminated throughout the search. Ref. [14] proposed a multi-depot VRP with a simultaneous delivery and pick-up model. The resolution method used was the iterated local search embedded adaptive neighborhood selection approach. Ref. [15] tested local search move operators on the VRP with split deliveries and time windows. To that end, it used eight local search operators, in combinations of up to three of them, paired with a max-min ant system.

Ref. [16] developed a dynamic model for solving the mixed integer programming of forest plant location and design, as well as production levels and flows between origins and destinations. Ref. [17] proposed a multi-depot forest transportation model solving the tactical problem of the flow between origins and destinations without solving the operational problem of VRP. The solution method used was column generation. Ref. [6] proposed a model for forest transportation, solving the problem of flow between origins and destinations, and involving a sedimentation constraint. It did not address the VRP, and ignored the time windows constraint for customers. The resolution method used was the ant colony algorithm. Ref. [18] established a bi-level model using a genetic algorithm to solve the problems of locating and sizing mills and of transporting forest products. In this model, individual members of the initial population are found by solving the location and size of plants, at which point the VRP is solved for each individual. It does not integrate the time windows constraint for customers. Ref. [19] proposed a multi-depot forest transportation model. The resolution method it used involved the generation of transport nodes by solving the linear programming problem of flow distribution and routing of these nodes using a tabu search. Ref. [20] developed two linear programming models of planning for collaborative forest transportation for eight companies in the south of Sweden. The first model was based on the direct flow between supply and demand points, while the second one included backhauling. According to [20], in the Swedish forest industry, transportation costs represent approximately one-third of total raw material costs. According to [21], the Vehicle Routing Problem is assimilated to an extension of the traveling salesman problem. According to [22], this problem is known as an NP-complete problem. Therefore, the Vehicle Routing Problem is NP-complete.

Unlike other authors making an arbitrary hierarchy of optimality criteria, we evaluate them all simultaneously. This simultaneous evaluation provides good solutions least questionable. It is done by minimizing the total cost which is an aggregation of costs due to different optimality criteria: the number of vehicles, the total distance and total travel time. The goal of this paper is to present a new two-steps resolution approach for the Multi-Objective Forest Vehicle Routing Problem (MOFVRP). Our main contribution is the establishment of Savings-insertion heuristic for generating an initial solution and the establishment of Reactive tabu with a variable threshold improving the solution. Applying our methodology to a practical case shows its effectiveness in solving concrete problems. This methodology clearly provides a good compromise solution for the forest transportation optimization problem.

In the next section, we explain our methodology: first, we describe the problem and propose our mathematical model; secondly, we show our global methodology; thirdly, we establish our Savings-insertion heuristic, and fourthly, we establish our Reactive tabu with a variable threshold meta-heuristic. In the third section, we present our results, followed by a discussion, and finally, we end with a conclusion in the fourth section.

II. METHODOLOGY

2.1. Problem description and mathematical model

To perform an MOFVRP optimization, we propose an optimization based on Savings-insertion, followed by the Reactive tabu with a variable threshold. This allows the minimization of the total transport cost, including hard capacity and hard time windows. Below, we present our improved and completed mathematical model (see [23], [24] and [25]).

Let us assume that m vehicles, with a load capacity of Q, are needed. There are L customers and one depot, which takes the index 1 at the start of the route and the index $L+2$ at the route end. The fleet is homogeneous, and every customer demand must be satisfied within his time window. We split every customer having a demand upper than the vehicles' load capacity to get each customer demand lower than or equal to the vehicles' load capacity. The following assumptions are made in modeling the problem:

Assumptions

a. Each customer location (x_j, y_j), demand q_j, and time window (t^s_j = start time, t^e_j = end time) are known;
b. Each customer is served only by one vehicle at a time;
c. Each vehicle leaves the depot (index *1*) and returns to the depot (index $L+2$);
d. All vehicles needed are immediately available;
e. The average vehicle moving speed *VS* is known;
f. Each customer demand q_j is lower than or equal to vehicles' load capacity *Q*.

Notation

x_j, y_j	customer *j* location
t^s_j	customer *j* start time
t^e_j	customer *j* end time
q_j	customer *j* demand
C_t	total transport cost
m	number of vehicles used
VS	average moving speed of vehicles
Q	vehicles' load capacity
L	number of customers
c_f	unit vehicle fixed cost, covering loading and unloading
c_{ijk}	unit transport cost per kilometer of vehicle *k* from *i* to *j*
d_{ij}	distance between two locations *i* and j
x_{ijk}	indicates if vehicle *k* goes from *i* to *j*
c_{vt}	unit route time cost of vehicle
c_{dt}	unit work time cost of driver
t_{jk}	arrival time of vehicle *k* to customer *j*
w_{jk}	waiting time for vehicle *k* at customer *j*
s_j	customer *j* service time
t_{ij}	time spent from *i* to *j*
y_{jk}	indicates if customer *j* is served by vehicle *k*
T_k	end of vehicle *k* time

The studied problem is modeled and the mathematical model objective is given in (1):

$$\min C_t = mc_f + \sum_{i=1}^{L+1}\sum_{j=2}^{L+2}\sum_{k=1}^{m} c_{ijk} d_{ij} x_{ijk} + (c_{vt} + c_{dt})\sum_{i=1}^{L+1}\sum_{j=2}^{L+2}\sum_{k=1}^{m} x_{ijk}(t_{ij} + w_{jk} + s_j) \quad (1)$$

This objective function is the total transport cost, where the first element is the total fixed vehicle cost, the second is the total distance cost summation, and the third is the total vehicle route time cost and total driver work time cost summations. This aggregation permits to find a trade-off between three objectives: the minimization of a number of vehicles, the minimization of total distance traveled and the minimization of total time spends to travel. The time spent going from *i* to *j* is:

$$t_{ij} = d_{ij} / VS \quad i \in [1, L+1],\ j \in [2, L+2] \quad (2)$$

The waiting time for vehicle *k* at customer *j* is:

$$w_{jk} = \max(t^s_j - t_{jk}, 0) \quad j \in [2, L+2], k \in [1, m] \quad (3)$$

There are eleven constraints restrictions:

The (4) is the first constraint, and imposes the condition that the variable y_{jk} be binary. The (5) is the second constraint, and imposes the condition that the variable x_{ijk} be binary.

$$y_{jk} = \begin{cases} 1, \text{ the customer } j \text{ is served by the vehicle } k \\ 0, \text{ otherwise} \end{cases} \quad (4)$$

$$x_{ijk} = \begin{cases} 1, \text{ the vehicle } k \text{ goes from } i \text{ to } j \\ 0, \text{ otherwise} \end{cases} \quad (5)$$

The (6) is the third constraint, and imposes the condition that every vehicle leaves the depot (index *1*). The (7) is the fourth constraint, and imposes the condition that every vehicle returns to the depot (index $L+2$).

$$\sum_{k=1}^{m} y_{1k} = m \quad (6)$$

$$\sum_{k=1}^{m} y_{\{L+2\}k} = m \quad (7)$$

The (8) is the fifth constraint, and imposes the condition that every customer is served only by one vehicle. The (9) is the sixth constraint, and for each customer j, it means that the customer is served only by one vehicle passing through only one other customer. The (10) is the seventh constraint, and indicates that the total load for vehicle *k* cannot exceed the vehicles' load capacity *Q*.

$$\sum_{k=1}^{m} y_{jk} = 1 \quad j \in [2, L+1] \quad (8)$$

$$\sum_{i=1}^{L+1} x_{ijk} = y_{jk} \quad j \in [2, L+1],\ k \in [1, m] \quad (9)$$

$$\sum_{j=2}^{L+1} q_j y_{jk} \le Q \quad k \in [1, m] \quad (10)$$

The (11) is the eighth constraint, and gives the relation between vehicle *k* arrival time to the customer *i* and its arrival time to customer *j*. The (12) is the ninth constraint, and indicates that the service at customer *j* must begin before T_k, the end of the vehicle *k* time.

$$t_{jk} = x_{ijk}(t_{ik} + w_{ik} + s_i + t_{ij}) \ i \in [1, L+1], j \in [2, L+2], k \in [1, m] \quad (11)$$

$$t_{jk} + w_{jk} \le T_k \quad j \in [2, L+2], k \in [1, m] \quad (12)$$

The (13) is the tenth constraint, and indicates that no customer can be served before his start time. The (14) is the eleventh constraint, and indicates that no customer can be served after his end time.

$$t_{jk} + w_{jk} \ge t^s_j \quad j \in [2, L+2], k \in [1, m] \quad (13)$$

$$t_{jk} + w_{jk} \le t^e_j \quad j \in [2, L+2], k \in [1, m] \quad (14)$$

These eleven constraints restrictions allow the realization of the objective of minimizing the total transport cost by obtaining a feasible solution directly. In the next subsection, we explain the new global methodology proposed to solve this mixed-integer linear programming problem.

2.2. Global methodology

The proposed approach to solve the MOFVRP consists of two-steps. The initial solution technique for the MOFVRP based on the Savings-insertion technique for generating the initial solution is developed (Fig. 2) in order to serve as the starting point of our improvement technique. The improvement technique for MOFVRP developed is based on a Reactive tabu with a variable threshold, and is used to improve the initial solution (Fig. 3). This allows us to find a good solution of the problem. The different steps of the global methodology are presented in Fig. 1. In the next subsection, we propose and present our initial Savings-insertion solution technique.

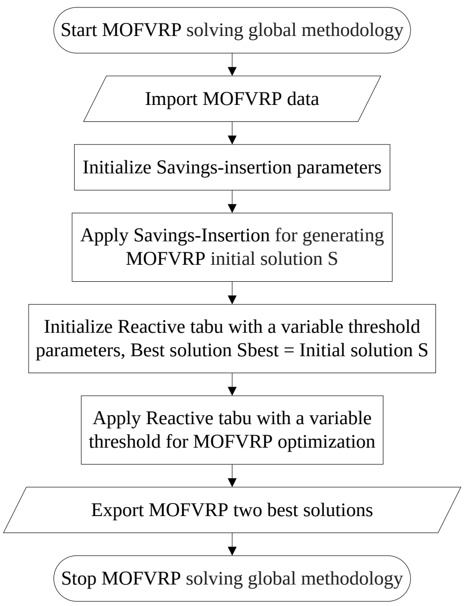

Figure 1: global methodology

2.3. Initial solution by Savings-insertion heuristic

The VRP is one of the most studied combinatorial problems in operations research. The well-known [26] saving algorithm, which formed the basis for many other solving algorithms for the capacitated VRP, is a very fast and simple algorithm for solving the VRP. Ref. [27] provided the historical background for the development of the savings method, and subsequently proposed variations to the basic savings formula and other improvements. Ref. [28] proposed a new way of merging routes and a corresponding formula for calculating savings. They applied the method and developed a new heuristic that dynamically recalculates savings during iterations. Based on [26] saving algorithm, a Savings-insertion technique is proposed for generating the initial solution. Our first main algorithm is presented in Fig. 2.

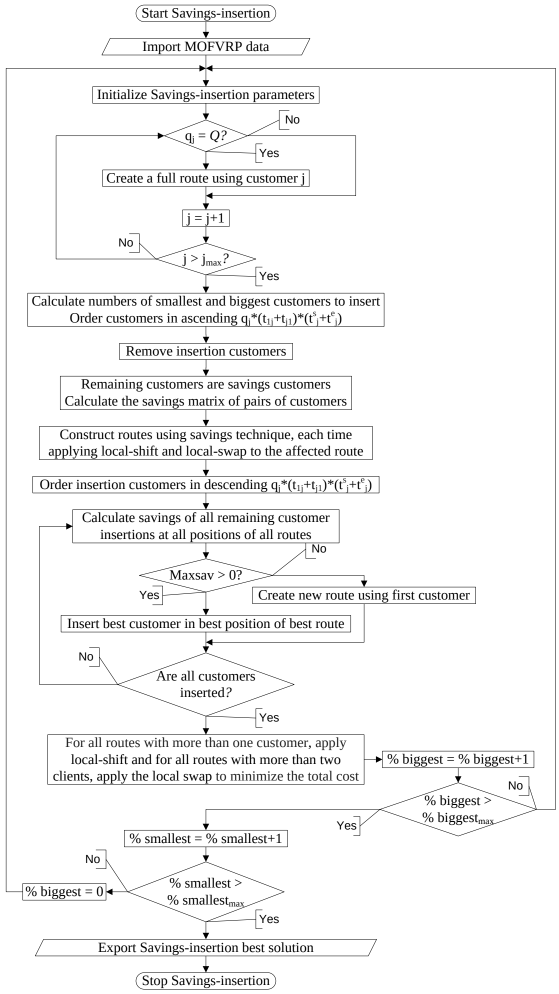

Figure 2: savings-insertion for generating the initial solution

This Savings-insertion technique extends the [26] savings heuristic by adding the insertion of smallest customers (using a percentage of smallest customers) and biggest customers (using a percentage of biggest customers) according to the value of $q_j(t_{1j}+t_{j1})(t^s_j+t^e_j)$. In the next subsection, we propose and explain our new Reactive tabu with a variable threshold.

2.4. Improvement by Reactive tabu with a variable threshold meta-heuristic

The tabu search is a meta-heuristic aims to avoid the weakness of neighborhood search algorithms which is its possible trap into local optima, by allowing non-improving moves. Our second main algorithm is presented in Fig. 3. This Reactive tabu with a variable threshold algorithm is an extension of the Reactive tabu search developed by [29]. This extension is done by adding a parameter for setting a minimum value of the tabu list size *tls* called Threshold. The variation of this parameter improves the exploration of the search space by varying the compromise between intensification and diversification. It allows us to get a dynamic compromise between intensification and diversification. In summary, the more the same solutions found are repeated, the more the tabu list size increases, and vice versa; conversely, the more the solutions are different, the more the tabu list size decreases. This mechanism whereby the number of tabu solutions is increased when reaching local optima allows us to avoid the local optima trap by exploring other solutions in this case because all neighbors have become tabu. The optimization technique for the Reactive tabu with a variable threshold aimed at improving the initial solution (improvement) is developed (Fig. 3) in order to find the best compromise (optimal) solution of the problem. It can quickly check the feasibility of the movement suggested, and then react to the repetition to guide the search. This algorithm is performed via a tabu list size (tls) update mechanism elaborated in five steps, as shown in Fig. 3. The counters and parameters used in Reactive tabu with a variable threshold are defined in accordance with [30] as follows, and initialized to the following values.

- Minimum of tabu list size (*tls*) value: *Threshold = 1 to 10*
- Counter for often-repeated sets of solutions: *Chaotic = 0*
- Moving average for the detected repetitions: *MovAvg = 0*
- Gap between two consecutive repetitions: *GapRept = 0*
- Number of iterations since the last change in *tls* value: *LastChange = 0*
- Iteration number when an identical solution was last noticed: *LasTimeRept = 0*
- Iteration number of the most recent repetition: *CurTimeRept = 0*
- Maximum limit for often-repeated solutions: *REP = 5*
- Maximum limit for sets of often-repeated solutions: *Chaos = 5*
- Increase factor for the tabu tenure value: *Increase = 2*
- Decrease factor for the tabu tenure value: *Decrease = 0.5*
- The constant used for comparison with GapRept to get the moving average: *GapMax = 100.*

According to [31], "The *λ-interchange* method is based on the interchange of customers between sets of routes. This technique generation mechanism can be described as follows. Given a solution to the problem represented by the set of routes $S = \{R_1,\dots,R_p,\dots,R_q,\dots,R_k\}$, where each route is the set of customers serviced on this route, a *λ -interchange* between R_p and R_q is the replacement of a subset of customers $S_1 \subseteq Rp$ of size $|S_1| \leq \lambda$ by another subset $S_2 \subseteq Rq$ of size $|S_2| \leq \lambda$, and vice-versa, to get two new routes $R'_p = (R_p - S_1) + S_2$ and $R'_q = (R_q - S_2) + S_1$ and a new neighboring solution $S' = \{R_1,\dots,R'_p,\dots,R'_q,\dots,R_k\}$". In this work, we limited ourselves to sequences of consecutive customers. The neighborhood $N_\lambda(S)$ of a given solution S is the set of all neighbors S' generated in this manner for a given value of λ. We established our *1-interchange+* by adding the operators (2, 1) and (1, 2) to *1-interchange*. Thus, we can more explore the search space than the *1-interchange* in less time than the *2-interchange.*

According to [30], "Neighborhood search algorithms can fall into the local optima trap. This can be avoided by using a metaheuristic that allows non-improving moves. The tabu search is a well-known metaheuristic, and is considered by some to be the best approach for solving VRP problems (see [32] for further information). The Reactive tabu search was introduced by [29], and focuses on a tabu search component called the tabu list size (tls), often referred to as Tabu tenure, which determines how long a move can be locked up before it is allowed to reappear. The Reactive tabu search scheme uses an analogy with the theory of dynamical systems, where the tabu list size depends on the repetition of solutions, and consequently, tls is determined dynamically, as opposed to the standard version of the tabu search, where tls is fixed. Reactive tabu search employs two mechanisms, and both react to repetitions. The first mechanism is used to produce a balanced tabu list size, and consists of two reactions. A fast reaction increases the list size when solutions are repeated, while a slow reaction reduces the list size for those regions of the search space that do not need large list lengths. The second mechanism provides a systematic way to diversify the search when it is only confined to one portion of the solution space. The experiments of [29] and [33] showed the superiority of Reactive tabu search compared to other tabu search schemes".

Below, we present details of our Reactive tabu with a variable threshold, which updates the value of the Tabu list size (*tls*) during the search, according to repetitions. First, our Reactive tabu with a variable threshold extends the Reactive tabu by adding a parameter for setting a minimum value of the tabu list size (*tls*) called the threshold. Secondly, in accordance with [30], we use local-shift, which is an intra-route move that relocates a customer to a different position within the route, if doing so improves the solution quality. Thirdly, we similarly use local-swap, which is an intra-route move that exchanges the positions of two customers within the route, if doing so improves the solution quality. In the next section, the experimental data and results of our initial Savings-insertion solution and Reactive tabu with a variable threshold improved solution results are presented.

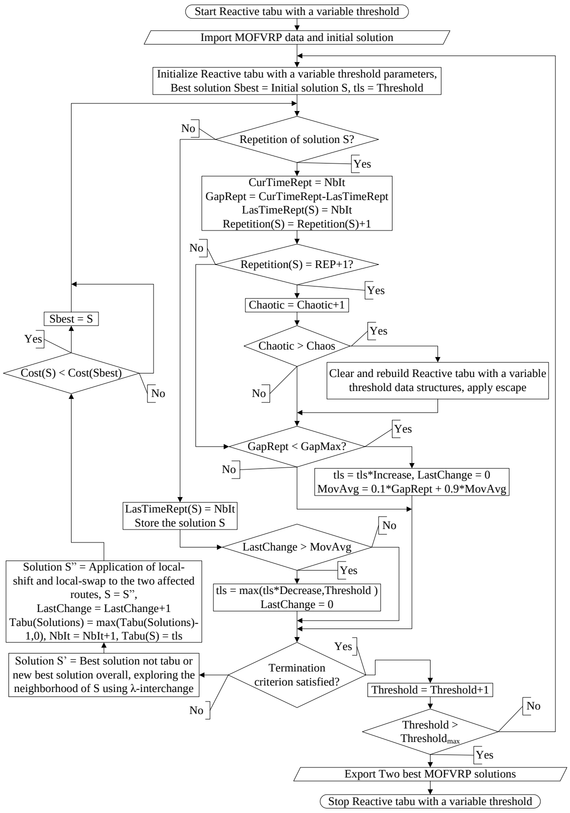

Figure 3: reactive tabu with a variable threshold for improving the solution

III. RESULTS AND DISCUSSION

Below on TABLE II, we present our completed data (see [23], [24] and [25]). In our previous works, these data were adapted from [18]. The central depot, which takes the index *1* at the start of the route and the index *L+2* at the route end, and from which all customers are served, is located at (0, 0), and is open from minutes 0 to 2400. TABLE II shows the data of each customer. The location coordinates are in kilometers; the weekly demand quantity is in cubic meters; the start and end times are in minutes. The fleet is homogeneous, and the vehicles used have a load capacity Q of 40 cubic meters, and an average speed VS of 60 kilometers per hour. For cost calculations, we assume that the unit vehicle fixed cost c_f = *$400*, the unit transport cost per kilometer c_{ijk} = *$2.8*, the unit vehicle route time cost per minute c_{vt} = *$1.85*, the unit driver work time cost per minute c_{dt} = *$0.45*. We used 50 as a maximum percentage of smallest customers and 49 as a maximum percentage of biggest customers. Thus, at one end, we fall on savings and the other on insertion. The distance between two locations i and j is calculated using a symmetric problem formula:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad i \in [1, L+1], j \in [2, L+2] \tag{15}$$

Each route duration is calculated according to [34], as follows: departure at the depot start time (t^s_1) and forward scan to determine earliest finish time; reverse scan from earliest finish time to determine the latest start time for this earliest finish time (t_{1k}); departure at the determined latest start time and second forward scan to delay waits as much as possible to the end of the route.

Table I: Initial Savings-insertion solution results

Savings-insertion route	*Cost ($)*
[1, 38, 54]	1493.2
[1, 46, 54]	2865.1
[1, 5, 6, 7, 8, 9, 10, 11, 14, 54]	5109.4
[1, 16, 3, 19, 17, 18, 50, 49, 41, 40, 39, 32, 54]	6143.4
[1, 15, 2, 52, 51, 42, 54]	5991.3
[1, 13, 20, 4, 12, 54]	3404.1
[1, 24, 22, 23, 28, 27, 29, 26, 25, 44, 43, 47, 54]	7048.8
[1, 31, 37, 36, 48, 53, 35, 34, 33, 54]	3265.1
[1, 21, 45, 54]	4807.6
[1, 30, 54]	466.3
Total cost	40,594.3

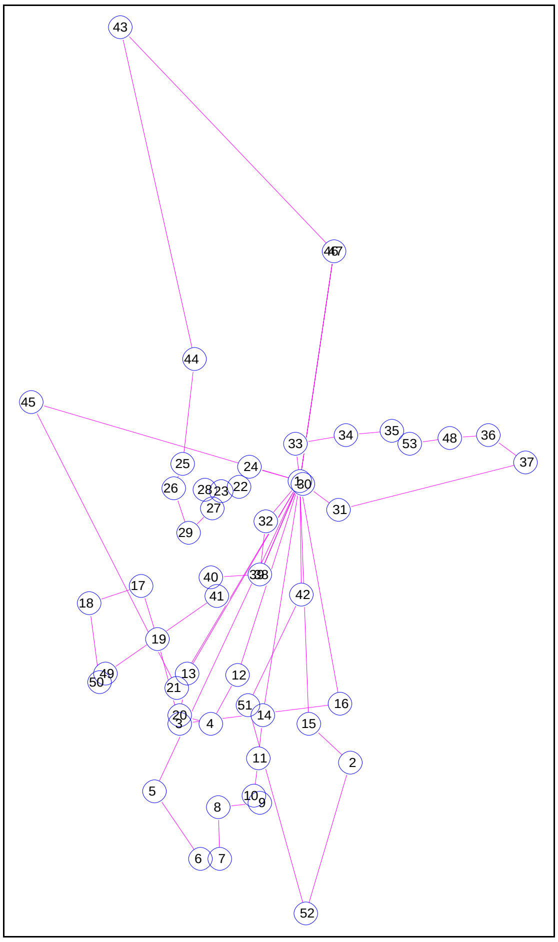

Figure 4: initial savings-insertion solution graphic

Table II: Experimental data

Customer	*Location*		*Demand*	*Start time*	*Finish time*	*Service time*
1	0	0	0	0	2400	0
2	50	-290	29.379	0	960	10
3	-120	-250	3.711	0	960	10
4	-90	-250	23.664	0	960	10
5	-145	-320	4.79	0	960	10
6	-100	-390	4.517	0	960	10
7	-80	-390	2.018	0	960	10
8	-82	-337	1.57	0	960	10
9	-40	-332	5.317	0	960	10
10	-46	-324.5	13.403	0	960	10
11	-42	-286	3.725	0	960	10
12	-63	-200.5	6.676	0	960	10
13	-112.5	-199	6.78	0	960	10
14	-38	-242	4.3	0	960	10
15	9	-251	2.065	480	1440	10
16	40	-230	5.335	480	1440	10
17	-159	-108	3.797	480	1440	10
18	-211	-126	0.856	480	1440	10
19	-142	-163	5.631	480	1440	10
20	-121	-242	1.496	480	1440	10
21	-124	-213	24.741	480	1440	10
22	-61	-6	3.464	480	1440	10
23	-79	-11	3.691	480	1440	10
24	-51	14	1.293	480	1440	10
25	-117	18	7.899	480	1440	10
26	-126	-8	2.255	480	1440	10
27	-88	-28	2.664	480	1440	10
28	-95	-9	1.504	960	1920	10
29	-112	-54	0.859	960	1920	10
30	3	-3	8.319	960	1920	10
31	38	-29	1.299	960	1920	10
32	-35	-41	1.715	960	1920	10
33	-5	39	1.535	960	1920	10
34	46	48	6.198	960	1920	10
35	91	52	18.079	960	1920	10
36	187	47	2.008	960	1920	10
37	225	19	1.692	960	1920	10
38	-40	-97	40	960	1920	10
39	-40.001	-96.999	4.018	960	1920	10
40	-90	-100	6.067	960	1920	10
41	-83	-118	0.539	1440	2400	10
42	0.5	-117	2.432	1440	2400	10
43	-180	468	1.978	1440	2400	10
44	-106	126	7.446	1440	2400	10
45	-269	81	11.174	1440	2400	10
46	34	237	40	1440	2400	10
47	34. 001	236.999	3.413	1440	2400	10
48	149.5	45	0.744	1440	2400	10
49	-195	-198	2.103	1440	2400	10
50	-200	-207	1.829	1440	2400	10
51	-52	-231	0.676	1440	2400	10
52	5	-446	3.978	1440	2400	10
53	109.5	38	3.116	1440	2400	10
54	0	0	0	0	2400	0

Table III: Final reactive tabu with a variable threshold solution results

Reactive tabu with a variable threshold route	*Cost ($)*
[1, 38, 54]	1493.2
[1, 46, 54]	2865.1
[1, 11, 10, 9, 8, 6, 7, 52, 51, 42, 54]	6668.0
[1, 13, 20, 3, 5, 19, 17, 18, 45, 28, 54]	6373.8
[1, 16, 2, 15, 32, 54]	3650.6
[1, 14, 4, 12, 39, 54]	3373.0
[1, 30, 24, 22, 23, 26, 25, 44, 43, 47, 54]	6672.4
[1, 33, 34, 35, 53, 48, 36, 37, 31, 54]	3265.1
[1, 27, 29, 40, 21, 50, 49, 41, 54]	3953.3
Total cost	38,314.5

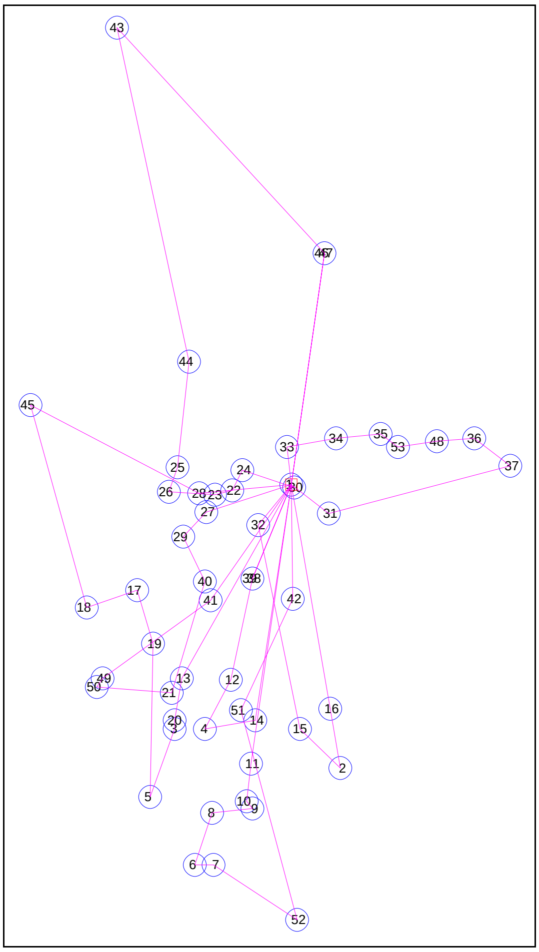

Figure 5: final reactive tabu with a variable threshold solution graphic

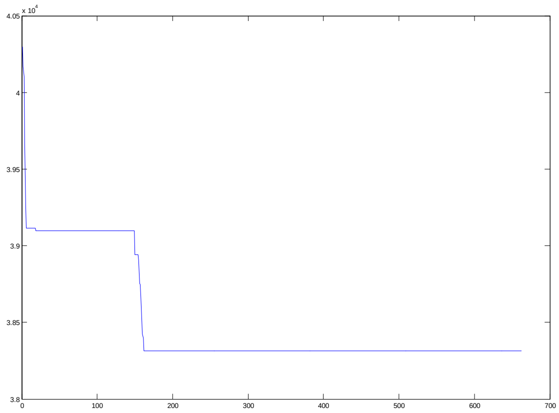

Figure 6: final reactive tabu with a variable threshold convergence graphic

TABLE I shows initial MOFVRP solution results generated by Savings-insertion. Each route's customers and cost are given, and the total cost is calculated. It is a ten-route solution having a total cost of $40,594.3. The corresponding total distance and total route duration are respectively 6731.8 kilometers and 7715.4 minutes. Fig. 4 shows the initial MOFVRP solution location sequences graphic. For example, the route [1, 31, 37, 36, 48, 53, 35, 34, 33, 54] to the right in this figure means that the vehicle leaves the depot (index *1*), goes successively to customers 31, 37, 36, 48, 53, 35, 34, 33 and returns to the depot (index 54). TABLE III shows the final MOFVRP solution results generated by the Reactive tabu with a variable threshold. Each route's customers and cost are given, and the total cost is calculated. It is a nine route-solution having a total cost of $38,314.5. The corresponding total distance and total route duration are respectively 6406.2 kilometers and 7294.4 minutes. Fig. 5 shows the final MOFVRP solution location sequences graphic. Fig. 6 shows the Reactive tabu with a variable threshold MOFVRP convergence graphic; it shows the number of iterations at which the best solution is reached. This methodology clearly provides a good compromise solution for the MOFVRP optimization.

IV. CONCLUSION

In our paper, we resolved a practical MOFVRP using our approach based on Savings-insertion, followed by the Reactive tabu with a variable threshold. To that end, we used our mathematical model to minimize the total transport cost, including hard capacity and hard time windows constraints. Our results show that minimizing the total cost, our methodology clearly provides a good compromise solution. We then conclude that Savings-insertion, followed by the Reactive tabu with a variable threshold is a promising approach, which will be used in our future research to further explore the MOFVRP.

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