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Implementation of the ACS-RVND algorithm on the VRP variant and its application to distribution optimization

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Abstract. Distribution optimization has an important role to distribute products to consumers. The selection of the right route will have an impact on the distribution process resulting in minimal costs. The application of graph theory that can be used to determine the optimum route in the distribution process is the study of the Vehicle Routing Problem (VRP) variant. The VRP variants discussed in this article are MDVRP and VRPTW. The method used to solve the VRP variant of this article is the ACS-RVND algorithm. The ACS-RVND algorithm consists of several main stages, namely the initial solution formation stage using the ACS algorithm, the solution improvement stage using the RVND procedure and the acceptance criteria stage. The data needed for the application of the ACS-RVND algorithm in solving the distribution optimization problem of MDVRP cases are the number of depots, the number of customers, the capacity of the vehicle, the number of ants, the number of iterations, the number of customer requests and the distance between customers. While in the case of VRPTW data multiple depots are replaced by time windows depot and service time. The results of solving distribution optimization problems in the form of the route, the total distance traveled and the result of the route in the graph model. The performance of the ACS RVND algorithm can be compared with the performance of the ant colony optimization (ACO) algorithm and the Hybrid Ant Colony Optimization (HACO) algorithm. Analysis of the results using several dataset test cases showed that the ACS RVND algorithm on MDVRP obtained a better solution than the ACO algorithm and the ACS RVND algorithm on VRPTW was better than the Hybrid Ant Colony Optimization (HACO) algorithm when viewed from the total distance distribution route.

1. Introduction

The application of graph theory can be used to model and solve distribution optimization problems [1] and [2]. In order for the distribution process to run well, it is necessary to optimize the route. The optimal route can minimize time and cost in the distribution process. Route optimization problems can be solved using one of the applications of graph theory, namely the Vehicle Routing Problem (VRP). VRP problems can be seen in [3-9]. This graph model can be used to determine a distribution route with a minimum distance that starts at a depot, serves all customers who are visited once and returns to the original depot. In its development, there are many problems with additional constraints such as more than one depot, additional delivery time constraints and delivery order requirements. This causes the emergence of new variants of VRP. The VRP variants with the addition of more than one depot constraint are called MDVRP. Research on MDVRP can be seen in [10-15] Vehicle Routing Problem with Time Windows (VRPTW) is a variant of VRP with additional time constraints. Some previous



studies on VRPTW can be seen in [11] and [16-20]. Various methods can be used to solve MDVRP and VRPTW.

In the optimization problem, there is a possibility that the solution produced by a method is not optimal so that the improvement stage is carried out. The method that is often used is the local search method. Several previous studies on local search can be seen in [21-23]. One of the local search algorithms is the Randomized Variable Neighborhood Descent (RVND) algorithm. The RVND algorithm has been combined with many other methods to solve various problems. Several combinations of algorithms have been carried out, namely the IG-RVND algorithm which combines the Iterated Greedy algorithm and the RVND algorithm [24], the ILS-RVND algorithm, namely Iterated Local Search and combined with the RVND algorithm [25], and the LCRVND algorithm which combines the GRASP algorithm and the RVND algorithm. [26]. In general, the research shows that the RVND algorithm can produce a final solution that is more optimal than the initial solution.

The Ant Colony System (ACS) algorithm is one of the metaheuristic algorithms, namely an algorithm that does not depend on a problem (independent problem) and performs the concept of an iterative approach to the solution. The ACS algorithm adopts the behavior of ants in social interaction. Ants leave pheromones in their paths as they move from one position to another. The pheromone intensity is used by other ant colonies as the best trajectory information. The ACS algorithm on the VRP variant An ant colony system empowered variable neighborhood search algorithm for the vehicle routing problem with simultaneous pickup and delivery can be seen in [27].

The HACO algorithm is an algorithm that combines the ACO algorithm and the mutation process to produce a variety of solutions. The first stage of the HACO algorithm is to form an initial solution by constructing a number of ants that depart from the depot and visit the customer by paying attention to certain constraints. Then apply the mutation process to the solution produced by the ants in order to obtain a more diverse solution. Optimal conditions are achieved when the best fitness value is obtained after the specified iterations have been performed. Algorithm A hybrid ant colony optimization (HACO) on the VRP variant can be seen [28]. Improvements to the ACO algorithm can be used to solve VRP variants, can be seen in [29].

Based on the description above, this article will discuss the implementation of the ACS-RVND algorithm on MDVRP and VRPTW with performance analysis of the ACO and HACO algorithms and their application to distribution optimization.

2. Formulation model

2.1. MDVRP formulation

The mathematical notation and model of MDVRP is explained as follows:

Mathematical Models:

The objective function is to minimize the total distance traveled by the vehicle in the entire depot,

given by the following equation: $\min \sum_{p=1}^m \sum_{q=1}^{k_p} \sum_{i=1}^n \sum_{j=1}^n c_{ij} x_{ijqp}$

Decision Variables

$$x_{ijqp} = \begin{cases} 1, & \text{if vehicle } q \text{ at depot } p \text{ runs from point } i \text{ to } j \\ 0, & \text{other} \end{cases}$$

$$y_{iqp} = \begin{cases} 1, & \text{if vehicle } q \text{ visits customer } i \text{ served by the depot } p \\ 0, & \text{other} \end{cases}$$

With the following constraints:

Constraint 1. The total customer demand on each vehicle route must not exceed the vehicle capacity. $\sum_{i=1}^n d_i y_{iqp} \leq Q$

Constraint 2. The number of customers visited by each vehicle route must not exceed the number of customers that can be served at the depot.

$$0 \leq n_{pq} \leq n_p$$

Constraint 3. The total number of customers visited by all vehicle routes must be equal to the number of customers served by the depot.

$$\sum_{q=1}^{k_p} n_{pq} = n_p, \forall p = 1 \text{ to } m$$

Constraint 4. Each customer is served by one depot

$$\sum_{p=1}^m n_p = n$$

Constraint 5. Each customer is only visited exactly once by one vehicle.

$$\sum_{p=1}^m \sum_{q=1}^{k_p} y_{iqp} = 1$$

Constraint 6. Decision variable value

$$x_{ijqp} = 1 \text{ atau } 0$$

$$y_{iqp} = 1 \text{ atau } 0$$

Information:

c_{ij} : distance between point i and j , $i \neq j$

d_i : customer request i

n_p : number of customers at depot p

n_{pq} : number of customers served by vehicle (route) q at depot p

k_p : number of vehicles (route) at the depot p

m : number of depots

n : number of customers

2.2. VRPTW formulation

The mathematical notation and model of VRPPTW is explained as follows:

Mathematical Models:

The objective function is to minimize the total distance traveled by the vehicle in the entire depot, given by the following equationmin: $\sum_{k \in K} \sum_{(i,j) \in A} c_{ij} x_{ijk}$

$$x_{ijk} = \begin{cases} 1 & \text{if the vehicle passes from point } i \text{ to } j \\ 0 & \text{other} \end{cases}$$

With the following constraints:

Constraint 1: Every vehicle departing from the depot must return to the depot

$$\sum_{j \in V \setminus \{0\}} x_{0jk} = 1, \forall k \in K$$

$$\sum_{i \in V \setminus \{0\}} x_{i0k} = 1, \forall k \in K$$

Constraint 2: Each customer is visited exactly once by one vehicle on one route

$$\sum_k \sum_j x_{ijk} = 1, \forall i \in V \setminus \{0\}$$

Constraint 3: The demand capacity must not exceed the vehicle capacity

$$\sum_i d_i \sum_j x_{ijk} \leq Q, \quad \forall k \in K$$

Constraint 4: Vehicle service time must not exceed time windows

$$e_i \leq f_i \leq l_i, \quad \forall i \in V, k \in K$$

Constraint 5: Each vehicle returns to the depot before the end of the depot waktu

$$\sum_i \sum_j x_{ijk} (t_{ij} + w_i + f_i) \leq T, \quad \forall k \in K$$

Information:

Q = vehicle capacity

K = number of vehicles

c_{ij} = distance from customer i to customer j

x_{ij} = binary variable declaring vehicle status

d_i = capacity request from customer i

e_i = vehicle start time to serve customer i

b_{ik} = the time it takes for vehicle k to arrive at customer i

w_i = waiting time before serving customers i

l_i = vehicle end time to serve customer i

t_{ij} = travel time from customer i to customer j

f_i = the customer service time i

T = depot end time

3. Results and Discussion

Ant Colony System Algorithm with Randomized Variable Neighborhood Descent (ACS-RVND). The ACS-RVND algorithm is a metaheuristic Ant Colony System algorithm which is then combined with the RVND procedure to produce a better solution than the previously formed solution. The ACS-RVND algorithm is briefly as in Algorithm 1 below.

```

Algoritma 1. ACS-RVND
1: Procedure ACS-RVND
2: LoadData ();
3:  $Pbest := CreateHeuristicSolution()$ ;
4: While StopCondition() do
5:   for  $i=1$  to  $m$  do
6:      $S_i := ConstructSolution()$ ;
7:     if  $f(S_i) \leq f(Pbest)$  then
8:        $f(Pbest) := f(S_i)$ ;
9:        $Pbest := S_i$ ;
10:    end
11:   LocalUpdatePheromone();
12:    $Pbest' := RVND(Pbest)$ ;
13:   if  $f(Pbest') < f(Pbest)$  then
14:      $Pbest := Pbest'$ ;
15:      $f(Pbest) := f(Pbest')$ ;
16:   end
17: GlobalUpdatePheromone();
18: end

```

Figure 1. The ACS-RVND algorithm.

The ACS-RVND algorithm consists of a solution initialization stage using the ACS algorithm and a solution improvement stage using the RVND algorithm. The ACS algorithm is used as an initial

solution generator because it is able to produce a variety of alternative solutions so that it is expected to provide an optimal solution. While the RVND algorithm is used in the solution improvement stage because the neighborhood sequence is chosen randomly so that it does not require neighborhood order requirements. The Ant Colony System (ACS) algorithm is one of the metaheuristic algorithms, namely an algorithm that does not depend on a problem (independent problem) and performs the concept of an iterative approach to the solution. The ACS algorithm adopts the behavior of ants in social interaction. Ants leave pheromones in their paths as they move from one position to another. The pheromone intensity is used by other ant colonies as the best trajectory information. After obtaining the best trajectory, pheromone evaporation occurs so that the intensity of the selected trajectory is different from that of the unselected trajectory. The selected trajectory has a high pheromone intensity, allowing other ants to choose that trajectory.

Randomized Variable Neighborhood Descent (RVND) is a variant of the VND procedure by selecting a random neighborhood order [24]. Neighborhood in the current solution is defined as all possible solutions that can be obtained after moving or repairing with a predetermined operator [30]. RVND consists of two fixes namely inter-route and intra-route. Inter-route is an improvement made on two different routes. While intra-route is an improvement that occurs in one route so that it does not affect the sequence of paths on other routes.

Several inter-route neighborhood structures.

Swap(2,1) : exchanges made on the connected points a and b of route 1 with point k of route 2.

Swap(2,2) : exchanges made on connected points a and b of route 1 with connecting points k and l of route 2.

Swap(1,1) : exchange made at point a of route 1 with point k of route 2.

Shift(1,0) : Moves made at one point i from one route to another.

Shift(2,0) : Moves made on two points or one side (i,j) from one route to another.

Cross : Deletion performed on the (i,j) side of route 1 and the (k,l) side of route 2. Then replace them with the (i,l) and (k,j) sides.

Several intra-route neighborhood structures.

2-opt : Removal of two unconnected edges (a,b) and (i,j) . Then replace it with new sides (a,i) and (b,j) .

Or-opt : The removal of one, two, or three connected points to be re-inserted to a different position in one route.

Exchange: The exchange of two points on the same route.

Reinsertion : The removal of a single point to be reinserted into a different position in one route.

4. Hybrid Ant Colony Optimization (HACO) Algorithm

Referring to [31] the HACO algorithm is an algorithm that combines the ACO algorithm and the mutation process to produce various solutions. The HACO algorithm stage is initialization to form an initial solution by constructing a number of ants that depart from the depot and visit the customer, the mutation process in the solution produced by the ants in order to obtain a more diverse solution and optimal conditions are achieved when the best fitness value is obtained after the specified iterations are repeated.

4.1. ACS RVND Algorithm on MDVRP

The ACS RVND algorithm on MDVRP consists of 2 stages, namely grouping and routing by initializing it using the ACS algorithm and repairing it with the RVND algorithm using the inter-route and intra-route neighborhoods. The input to the program consists of many depots, many points and point positions. In the next section there are inputs for vehicle capacity, number of ants, many iterations, customer requests, and the distance between points. While the output of the program is in the form of route results, distances and route results in graph form.

Algoritma ACS RVND pada MDVRP

File Uji Dataset

Input Titik Input Data Perhitungan Hasil Graph

Kapasitas Kendaraan (box): 70
 Banyak Semut: 10
 Banyak Iterasi: 10

OK

Permintaan Customer (box)

Customer	Permintaan
2	15
3	20
4	10
5	25
6	15
7	25
8	20
9	30
10	25

Jarak Antar Titik (km)

	0	1	2	3	4	5	6	7	8	9	10
0		160	50	70	80	165	143	154	93	60	185
1	160		185	157	87	100	60	75	90	195	120
2	50	185		38	110	160	150	193	137	10	180
3	70	157	38		75	125	115	176	130	48	145
4	80	87	110	75		51	36	119	97	120	71
5	165	100	160	125	51		36	140	140	170	20
6	143	60	150	115	36	36		100	100	160	56
7	154	75	193	176	119	140	100		58	203	160
8	93	90	137	130	97	140	100	58		147	160
9	60	195	10	48	120	170	160	203	147		55
10	185	120	180	145	71	20	56	160	160	55	

Figure 2. Example of MDVRP implementation view (input display).

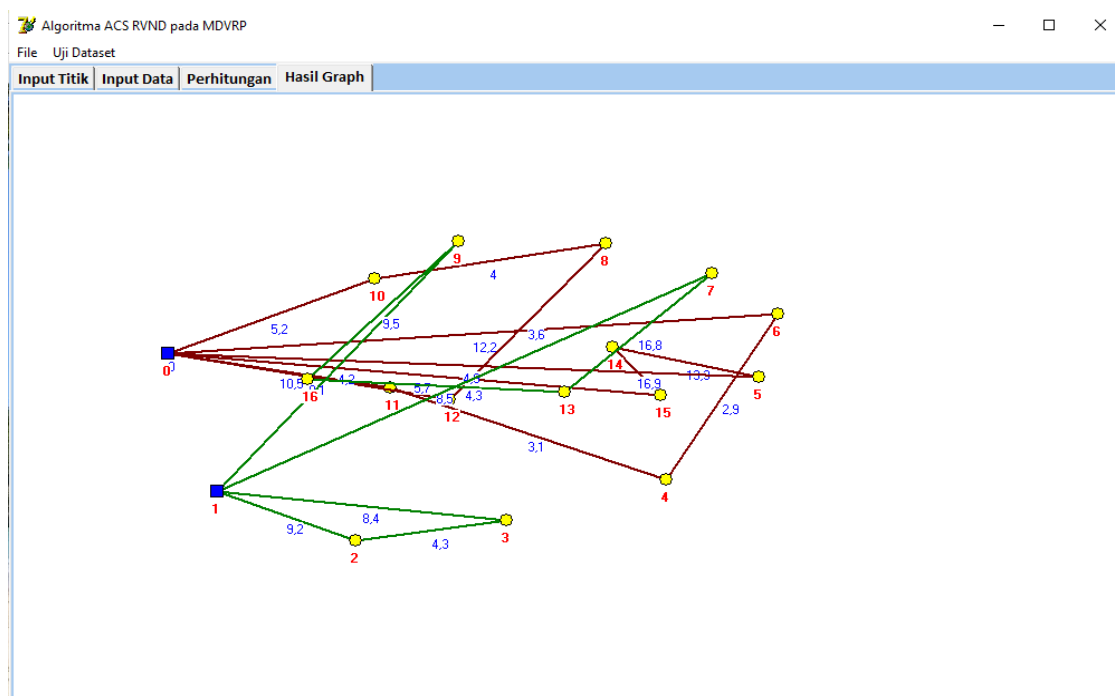


Figure 3. Example of MDVRP implementation view (result display).

4.2. ACS-RVND Algorithm on VRPTW

There are 3 stages in applying the ACS-RVND algorithm to solve VRPTW problems. These stages consist of the initial solution initialization stage, the solution improvement stage, and the optimal conditions or acceptance criteria. The initialization phase of the initial solution is carried out using the ACS algorithm. Then, the solution improvement stage is carried out using the RVND algorithm.

Acceptance of the criteria is done by choosing the best solution from the existing feasible solutions as the final solution. Input the data required for the average vehicle speed, time windows depot, vehicle capacity, distance between customers and the distance between the depot and each customer, the travel time required for the vehicle from the depot to each customer, request data from each customer and service time .

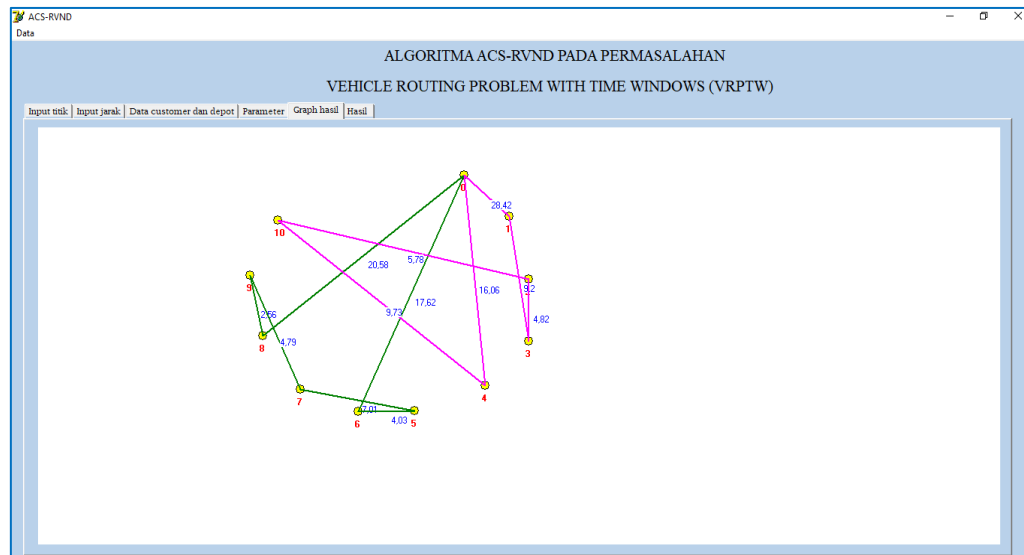


Figure 4. Example of VRPTW display results.

The comparison analysis of the ACS RVND best solution algorithm with the best solution ACO algorithm on the MDVRP problem refers to the article in [32]. Then calculated deviations that occur in the ACS RVND algorithm and the ACO algorithm, deviations are seen in Best Solution Known [33].

The ACS RVND algorithm has a gap of between 1.58% to 10.64% for Best Solution Known, while the ACO algorithm has a gap of 9.14% to 54.02% for Best Solution Known, respectively. The ACS RVND algorithm is closest to Best Solution Known by reaching a gap of 1.58%. While the lowest gap obtained by the ACO algorithm is 9.14%. Based on the analysis, the gap obtained by the ACS RVND algorithm is lower than the ACO algorithm so that the ACS RVND algorithm produces a better solution than the ACO algorithm.

The ACS-RVND algorithm on VRPTW was compared with the HACO algorithm using a fruit logistics problem in China with 16 customers in [31]. The analysis of the calculation results using the ACS-RVND algorithm produces a total mileage that is smaller than the calculation results of the HACO algorithm.

5. Conclusion

The ACS RVND algorithm on MDVRP consists of 2 stages, namely grouping and routing by initializing using the ACS algorithm and repairing with the RVND algorithm, while in VRPTW it has three stages, namely initial formation, repair stage using RVND, and acceptance of optimal criteria. The data needed for the implementation of ACS-RVND implementation in the case of solving the distribution optimization problems of MDVRP and VRPTW are many customers, vehicle capacity, many ants, many iterations, many customer requests and distance between customers. Meanwhile in the case of VRPTW data, the number of depots in the MDVRP case is supported by the time window for depots and services time in the VRPTW case. The results of solving distribution optimization problems are in the form of routes, total distance traveled and route results in the graph model. To determine the effectiveness of the performance of the ACS RVND algorithm, it is compared with the performance of the ant colony optimization (ACO) algorithm and the Hybrid Ant Colony Optimization (HACO) algorithm. Analysis of the results using several test case datasets shows that the ACS RVND

algorithm on MDVRP obtains a better solution than the ACO algorithm and the ACS RVND algorithm on VRPTW is better than the Hybrid Ant Colony Optimization (HACO) algorithm when viewed from the total distance distribution route. From the results of this study, the ACS RVND algorithm is recommended used to the solving the VRP variant distribution optimization problem. The development of other VND variant algorithms such as ILS-RVND and its variants needs to be studied to solve the VRP variant problem.

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References

- [1] Liu J, Kang J E, Zhou X, and Pendyala R 2017 Network-oriented Household Activity Pattern Problem for System Optimization *Transp. Res. Procedia* **23** 827–847
- [2] Wang X, Wang M, Ruan J, and Zhan H 2016 The Multi-objective Optimization for Perishable Food Distribution Route Considering Temporal-spatial Distance *Procedia Comput. Sci.* **96** 1211–1220
- [3] Chen D, Pan S, Chen Q, and Liu J 2020 Vehicle routing problem of contactless joint distribution service during COVID-19 pandemic *Transp. Res. Interdiscip. Perspect.* **8** 100233
- [4] Chaabane A 2021 Vehicle routing problem for reverse logistics of End-of-Life Vehicles (ELVs) *Waste Manag.* **12**
- [5] Doan T, Bostel N, and Hà M H 2021 The vehicle routing problem with relaxed priority rules,” *EURO J. Transp. Logist.* **10** 100039
- [6] Aerts B 2021 The joint order batching and picker routing problem: Modelled and solved as a clustered vehicle routing problem **19**
- [7] Haixiang G 2021 Period sewage recycling vehicle routing problem based on real-time data,” *J. Clean. Prod.*, p. 14,.
- [8] Sawik B, Faulin J, and Pérez-Bernabeu E 2017 A Multicriteria Analysis for the Green VRP: A Case Discussion for the Distribution Problem of a Spanish Retailer *Transp. Res. Procedia* **22** 305–313
- [9] Korablev V, Makeev I, Kharitonov E, Tshukin B, and Romanov I 2016 Approaches to Solve the Vehicle Routing Problem in the Valuables Delivery Domain *Procedia Comput. Sci.* **88** 487–492
- [10] Li J, Li Y, and Pardalos P M 2016 Multi-depot vehicle routing problem with time windows under shared depot resources,” *J. Comb. Optim.* **31** 10878-014-9767-4.
- [11] Afshar-Nadjafi B and Afshar-Nadjafi A 2017 A constructive heuristic for time-dependent multi-depot vehicle routing problem with time-windows and heterogeneous fleet *J. King Saud Univ. - Eng. Sci.* **29** 29–34
- [12] Sadati M E H and Çatay B 2021 A hybrid variable neighborhood search approach for the multi-depot green vehicle routing problem *Transp. Res. Part E Logist. Transp. Rev.* **149** 102293
- [13] Sadati M E H 2020 A trilevel r-interdiction selective multi-depot vehicle routing problem with depot protection **18**
- [14] Bernardes de Oliveira F, Enayatifar R, Sadaei H J, Guimarães F G, and Potvin J Y 2015 Erratum to ‘A cooperative coevolutionary algorithm for the Multi-Depot Vehicle Routing Problem *Expert Syst. Appl.* **54** 398–402
- [15] Fan H, Zhang Y, Tian P, Lv Y, and Fan H 2021 Time-dependent multi-depot green vehicle routing problem with time windows considering temporal-spatial distance *Comput. Oper. Res.* **129** 105211

- [16] Pan B 2021 Multi-trip time-dependent vehicle routing problem with time windows *Eur. J. Oper. Res.* **14**
- [17] Jalilvand M 2021 An effective Progressive Hedging algorithm for the two-layers time window assignment vehicle routing problem in a stochastic environment *Expert Syst. Appl.* **12**
- [18] Shi Y, Zhou Y, Boudouh T, and Grunder O 2020 A lexicographic-based two-stage algorithm for vehicle routing problem with simultaneous pickup–delivery and time window *Eng. Appl. Artif. Intell.* **21**
- [19] Chiang W C and Cheng C Y 2017 Considering the Performance Bonus Balance in the Vehicle Routing Problem with Soft Time Windows *Procedia Manuf.* **11** 2156–2163
- [20] Dhahri A, Mjirda A, Zidi K, and Ghedira K 2016 A VNS-based Heuristic for Solving the Vehicle Routing Problem with Time Windows and Vehicle Preventive Maintenance Constraints *Procedia Comput. Sci.* **80** 1212–1222
- [21] de Sousa M M, González P H, Ochi L S, and de S Martins L 2021 A hybrid iterated local search heuristic for the traveling salesperson problem with hotel selection *Comput. Oper. Res.* **129** 105229
- [22] Andelmin J and Bartolini E 2019 A multi-start local search heuristic for the Green Vehicle Routing Problem based on a multigraph reformulation *Comput. Oper. Res.* **109** 43–63
- [23] Bayliss C, do L Martins C and Juan A 2020 A two-phase local search with a discrete-event heuristic for the omnichannel vehicle routing problem *Comput. Ind. Eng.* **148** 106695
- [24] Santos V L A and Arroyo J E C 2017 Iterated Greedy with Random Variable Neighborhood Descent for Scheduling Jobs on Parallel Machines with Deterioration Effect *Electron. Notes Discrete Math.* **58** 55–62
- [25] Silva M M, Subramanian A, and Ochi L S 2015 An iterated local search heuristic for the split delivery vehicle routing problem *Comput. Oper. Res.* **53** 234–249
- [26] Araujo R P, Rios E, Coelho I M, Marzulo L A J, and Clícia Castro M 2018 A novel List-Constrained Randomized VND approach in GPU for the Traveling Thief Problem *Electron. Notes Discrete Math.* **66** 183–190
- [27] Kalayci C B and Kaya C 2016 An ant colony system empowered variable neighborhood search algorithm for the vehicle routing problem with simultaneous pickup and delivery *Expert Syst. Appl.* **66** 163–175
- [28] Kyriakakis N A 2021 A hybrid ant colony optimization-variable neighborhood descent approach for the cumulative capacitated vehicle routing problem **20**
- [29] Li Y, Soleimani H, and Zohal M 2019 An improved ant colony optimization algorithm for the multi-depot green vehicle routing problem with multiple objectives *J. Clean. Prod.* **227** 1161–1172
- [30] Zeng Z, Yu X, He K, Huang W, and Fu Z 2016 Iterated Tabu Search and Variable Neighborhood Descent for packing unequal circles into a circular container *Eur. J. Oper. Res.*, **250** 615–627
- [31] Zhang H, Zhang Q, Ma L, Zhang Z, and Liu 2019 hybrid ant colony optimization algorithm for a multi-objective vehicle routing problem with flexible time windows *Inf. Sci.* **490** 166–190
- [32] Demirel T and Yilmaz S 2012 A New Solution Approach To Multi Depot Vehicle Routing Problem With Ant Colony Optimization *J. Mult.-Valued Log. Soft Comput.* **18** 421–439
- [33] Stodola P 2020 Hybrid ant colony optimization algorithm applied to the multi-depot vehicle routing problem *Nat. Comput.* **19** 463–475