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A HYBRID METHOD INTEGRATING A RANK-BASED ANT SYSTEM ALGORITHM WITH INSERT AND SWAP ALGORITHM FOR THE CAPACITATED VEHICLE ROUTING PROBLEM SOLUTION

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ABSTRACT

This study focused on solving the Capacitated Vehicle Routing Problem (CVRP). Here, the Traveling Salesman Problem (TSP) is generalized. The two problems are highly related, and solving them is the key to solving many optimization Problems and applications in real life, particularly in the field of transport and distribution. The hybrid Rank-Based Ant System (HAS_{rank}) Algorithm that is presented in this research, relies on the principle of combining insert and swap algorithms, with the aim of improving tours and reducing transmission and distribution costs. To test the effectiveness of the proposed hybrid algorithm, the results of the study have been evaluated with the results of the standardized CVRP, in addition to comparing the results with those obtained in other studies. The results of the comparisons proved that the performance of the proposed algorithm in terms of finding optimal solutions, is better than those of other algorithms to find optimal solutions.

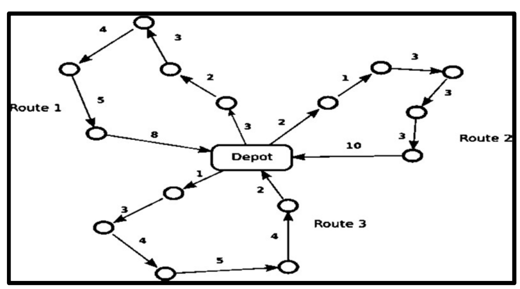
Keywords: *Capacitated Vehicle Routing Problem, Elite Ants, Savings Algorithm, 3-Opt Local Search Algorithm.*

1. INTRODUCTION

For the first time in 1959, the Capacitated Vehicle Routing Problem (CVRP) which is a well-known problem, was proposed by J.H.Ramser. This problem is a kind of problem that needs an optimal solution in several applications in the areas of distributions, transportation, and logistics [2]. As an NP-hard problem, the CVRP is a generalization of the travelling salesman, and for this reason, polynomial-time algorithms may be non-existent (Yu et al., 2009) and [4]. For over 50 years of the existence of the problem, researchers have proposed a wide range of heuristic, exact and metaheuristic methods and algorithms. In this work, the solutions that have been offered by researchers based on the Ant Colony Optimization (ACO) theory, are presented. In this work, an ACO algorithm which is inspired by nature has been proposed, where ants search their environment with the aim of finding food. The algorithm which is proposed in this work, is a probabilistic method that is categorized as a swarm intelligence method.

Figure 1: Routes routing for CVRP with a single central depot of the vehicle fleet [5]

A. Exact algorithms



Is the first approach through which the capacitated vehicle routing problem has been solved. With this method, a comprehensive research of all possible solutions is carried so that the best solution can be found. However, finding the potential solutions is very challenging as the search space is too large (Hameed, et al., 2018), and (Hameed et al., 2019), and this in turn increases the time required for the calculation. For this reason, many solutions provided by researchers cannot be applied on large cases involving over 50 customers. In other words, a large case involving over 50 customers cannot be solved within a reasonable time frame [8], [9], (Hameed et al., 2018) and [11].

B. Approximate algorithms

If optimal solutions cannot be found for problems within a reasonable time frame, then approximate solution can be searched for. This approach is the most efficient approach that has been used in solving the problems of combinatorial optimization successfully [12]. So the approximate algorithms should be preferred when available because they are effective for large standard problems, and these algorithms try as much as possible to obtain the approximate solution within a reasonable time, with no guarantee of optimization [13]. Over the past few decades, more efforts have been directed towards the development of metaheuristic more than heuristic algorithms. The metaheuristic algorithms are a kind of approximate algorithms that have their roots in artificial intelligence and operation research. In addition, they are inspirational and simulate natural processes such as evolution, as well as biological and physical phenomena, and they can be used in solving a wide range of combinatorial optimization problems. Asides that, it is specifically developed to solve a particular problem by combining heuristic techniques in a higher level framework, so as enable the efficient exploration of the search space [14], and [15].

The goal of this work is developing an Elitist Ant System (EAS) algorithm based on the principle of consolidation with insertion and switching algorithms to solve the CVRP. The HAS hybrid algorithm that is developed uses many effective modifications so that the search can be further diversified and activated. The rest of the paper is organized as follows: in section 2, the Formulation of Capacitated Vehicle Routing Problem (CVRP) has been presented, then, Materials and Methods are contained in section 3. Section 4 presents the Proposed hybrid Rank-Based Ant System (HAS_{rank}) Algorithm. Section 5 presents the experimental results and discussion, and finally, the conclusion and future work are contained in section 6.

2. FORMULATION OF CAPACITATED VEHICLE ROUTING PROBLEM (CVRP)

For the first time in 1959, J.H. Ramser introduced the VRP's mathematical model, and since then, researchers have studied the model and found the best solution to the model [16], (Mutar et al. , 2017), and [18]. The model contains the decision variable x and for each rib (i, j) [19], [20] and [21]. For each vehicle, the decision variable: $x_{ij}^k \in \{0,1\}$ is known as follows:

i. All tours must begin and end at the distribution center v_0.
ii. Each customer is served once by one vehicle.
iii. The total number of customers' requests in each tour shall not exceed the capacity of the vehicle Q.
iv. The length of each road does not exceed the pre-determined L length and expresses the objective function in relation (1) [19], and (DING, 2018):

$$min\, z = \sum_{i=0}^{n} \sum_{\substack{j=0 \\ j\neq i}}^{n} \sum_{k=1}^{m} c_{ij} x_{ij}^k \tag{1}$$

$$x_{ij}^k = \begin{cases} 1 & if\ vehile\ k\ goes\ from\ i\ to\ j \\ 0 & otherwise \end{cases} \tag{2}$$

Subject to the following restrictions:

$$\sum_{k=1}^{m} \sum_{j=1}^{n} x_{ij}^k \leq m \quad ; i = 0 \tag{3}$$

$$\sum_{i=0}^{n} x_{ij}^k - \sum_{j=0}^{n} x_{ji}^k = 0 \quad ; \ k \in \mathbf{K} \tag{4}$$

$$\sum_{k=1}^{m} \sum_{\substack{i=0 \\ j\neq i}}^{n} x_{ij}^k = 1 \quad ; \ j \in \{1, \dots, n\} \tag{5}$$

$$\sum_{k=1}^{m} \sum_{\substack{j=0 \\ i\neq j}}^{n} x_{ij}^k = 1 \quad ; \ i \in \{1, \dots, n\} \tag{6}$$

$$\sum_{j=1}^{n} x_{0j}^k \leq 1\ \forall\, k \in \mathbf{K} \tag{7}$$

$$\sum_{i=1}^{n} x_{i0}^k \leq 1\ \forall\, k \in \mathbf{K} \tag{8}$$

$$\sum_{j=1}^{n} \sum_{\substack{i=0 \\ i\neq j}}^{n} q_j x_{ij}^k \leq Q \quad \forall k \in \mathbf{K} \tag{9}$$

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Where:
Equation (1) represents the objective function which is related to the reduction of the overall distance traveled under the constraint of an available vehicle as seen in (3). The use of Constraint (4) is employed in controlling all the vehicles that leave the depot and are required to come back to the depot upon completion of customer service. With the aid of constraints (5) and (6), all the customers that are entitled to receiving one service just once. Meanwhile, the constraints (7) and (8) are used to ensure that all vehicles can leave and return to the depot just once throughout the entire service time. Equation (9) is the major equation that can be used to solve CVRP, and this is because it can allocate the capacity of vehicle, ensuring that the load-bearing capacity of each vehicle is not exceeded.

3. MATERIALS AND METHODS

Before presenting the various steps of the proposed algorithm, the algorithms used in our approach are discussed as follows:

3.1 Nearest Neighbor (NN) Algorithm

The nearest neighbor algorithm is a constructive method of generating an initial practical solution to the CVRP through the introduction of the nearest neighbor to the newly entered customer on the road. Here, the first customer to be served is randomly selected, or based on certain criteria like the customer standard, the distance between the distribution point and the different customers, as well as the capacity of the vehicle; the aim of this is to obtain a solution within reasonable time [23], [24], and [25].

3.2 Local Search Algorithm 3-OPT

Is a simple local search algorithm that has been used in solving the Traveling Salesman Problem (TSP). In each tour, it works to delete three ribs, replace them with two new ones, and then continue to search for other optimal tours for all possible ribs. Afterwards, the process is repeated using a different set of ribs and so on, and it is important to note that there are many works that have been done on this technique, taking into account the limitations of the problem [14]. The swap procedure takes two different nodes v_i, v_j of $\{v_1, v_2, \dots, v_n\}$, and the exchange of these nodes is shown in figure 2. This process is easier and is used in many problems that are solved using the local search of the CVRP, which allows the intersection between the roads to be gotten rid of as shown in figure 2 [26], and [27].

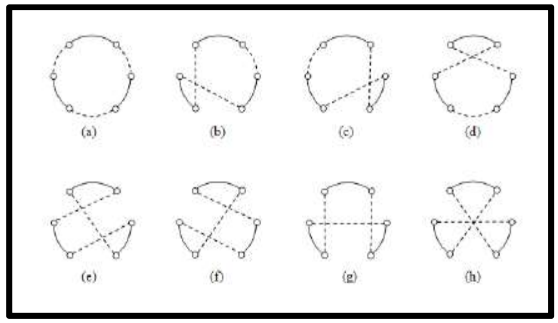

Figure 2: All possible 3-opt recombination cases [28]

3.3 Saving Algorithm SA

The Savings Algorithm (SA) is a heuristic algorithm [29], [30], and [31] that does not guarantee finding the optimal solution, but produces a relatively good solution, and it expresses the cost savings obtained as shown in Figure 3.

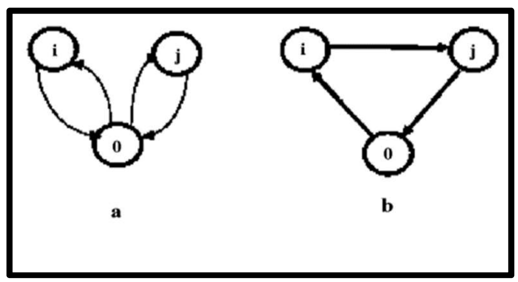

Figure 3: Illustrates the concept of savings, where 0 represents the main depot

In order to estimate the initial solution so as to build other solutions, the demand that is provided between all nodes is calculated, and sorted in descending order. The algorithm in the previous solutions are saved, and the solution obtained as the lowest cost so far is kept. Customers i and j were visited through different routes in Figure (3-a), and the best alternative is to visit customers on the same route. For example in i-j as shown in Figure (3-b), because transportation costs are given, the savings can be calculated resulting from transmission on the road in Figure (3-b) instead of the two roads in Figure (3-a), and denotes the transport cost between the two nodes i,j and the total transport cost as in Figure (3-a).

$$D_a = c_{0i} + c_{i0} + c_{0j} + c_{j0} \quad (10)$$

Equally, D_a the transport cost as in Figure (3-a) is:

$$D_b = c_{0i} + c_{ij} + c_{j0} \quad (11)$$

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And by combining the two roads in one road savings S_{ij} is derived as follows:

$$S_{ij} = D_a - D_b = c_{i0} + c_{0j} - c_{ij} \quad (12)$$

The resulting values of the combination are relatively large and attractive, because we moved directly from node i to node j [32], and [14].

3.4 Rank-Based Ant System Algorithm (AS $_{rank}$)

The AS $_{rank}$ algorithm is one of the improvements of the first ant system algorithm (AS) where the strategy of the elitist ant system depended on ranking (AS), and the idea of the algorithm is the enhancement of the pheromone by all the elitist ants in each repetition on the ribs that belongs to the best tour found. This is because the beginning of the algorithm can be applied and extended to the ant system [33], [34], and [35].

(i) Transition Rule

The *K* ant in node *i* chooses to move to node *j* according to the following rule:

$$p_{ij}^{k}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{l\in N_k(i)}[\tau_{il}(t)]^{\alpha}[\eta_{il}]^{\beta}} & if\ j \in N_k(i) \\ 0 & otherwise \end{cases} \quad (13)$$

Where $\eta_{ij} = 1/d_{ij}$ is the heuristic value of the rib (i, j), and d_{ij} is the distance between nodes i and j and is given by the relationship $d_{ij}=\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$ and $N_k(i)$ is the set of nodes that were not visited by the ant k in node. $\tau_{ij}(t)$ the amount of pheromone deposited on the road between nodes i and j in time t by ant k, and α, β is an adjustable positive parameter that controls the relative weights of the effect of the pheromone and heuristic information, respectively. It represents the density of the pheromone that guides the ant in choosing its way as well as the relationship of choosing the road in its length, where α‹β > 0.

Subsequent to the generation of a tour by all *m* ants, the sorting of the ants is done based on tour length ($L_1 \le L_2 \le \ldots \le L_m$), and an ant's contribution to the trail level update is measured based on the rank μ of the ant. More so, priority is given to only the *w* best ants. Therefore, it is possible to avoid the danger associated with over-stressed pheromone trails that are caused by numerous ants using sub-optimal routes. Since σ denotes the weight of the trail level contribution of the best tour found so far, it should not be exceeded by any other weight. Meanwhile, using "one" as the minimum weight appeared to be a reasonable decision. Thus, the decision to use the weight $\sigma - \mu$) for the $\mu - th$ best ant and to set $w = \sigma - 1$ was taken, meaning that the number of elitist ants exceeded the number of plants by one. Given the combined setting, with ranking and elitism, the novel updating trail levels is done based on Formula (14).

(ii) Pheromone update

The updating rule of pheromone is described as follow:

$$\tau_{ij}(t+1) = \rho\, \tau_{ij}(t) + \Delta\tau_{ij} + \Delta\tau_{ij}^{*} \quad (14)$$

$$\Delta\tau_{ij} = \sum_{\mu=1}^{\sigma-1} \Delta\tau_{ij}^{\mu} \quad (15)$$

Where

$$\Delta\tau_{ij}^{\mu} = \begin{cases} (\sigma-\mu)\frac{Q}{L_\mu} \\ if\ the\ \mu - th\ \ best\ ant\ travels\ on\ edge\ (i,j) \\ 0 \quad otherwise \end{cases} \quad (16)$$

And

$$\Delta\tau_{ij}^{*} = \begin{cases} \sigma\frac{Q}{L^{*}} \\ if\ edge(i,j)\ is\ par\ to\ f\ the\ best\ solution\ found \\ 0 \quad otherwise \end{cases} \quad (17)$$

Where μ represents ranking index, $\Delta\tau_{ij}^{\mu}$ is increase of trail level on edge (i, j) caused by the $\mu - th$ best ant, L_μ denote tour length of the $\mu - th$ best ant, increase of trail level on edge (i, j) caused by the elitist ants, number of elitist ants, L^* tour length of best solution found, t iteration counter, ρ ∈ (0, 1] parameter to regulate the reduction of τ_{ij} . The main function of the global update section is to sum the experience of the previous iteration. This is achieved by updating the pheromone of the best solution by means of a coefficient which is different from the one used for distinct solutions. Although the efficiency of these solutions is lesser, they are regarded as solutions elitist.

4. PROPOSED HYBRID RANK-BASED ANT SYSTEM (HAS $_{RANK}$) ALGORITHM

The pheromone deposit should be abandoned in the elite ant algorithm AS $_{rank}$, because it is not a good guide to finding the best path in each replication. So, it must be abandoned so that the ant can use of a global pheromone deposit to find new solutions. This attracts the ants' attention to the ribs that belong to the best tour found, knowing that the

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accuracy of the solutions in the AS $_{\text{rank}}$ algorithm is low at first. However, the accuracy increases with the increase in the frequency of the algorithm and the deposit of the pheromone. In this work, the AS $_{\text{rank}}$ algorithm is modified as follows:

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}[\mu_{ij}]^{\lambda}}{\sum_{j\in N_i}[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}[\mu_{ij}]^{\lambda}} & if\ j \in N_i \\ 0 & Otherwise \end{cases} \quad (18)$$

Where λ, α, β are positive control barometers through which the relative significance of the effect of the pheromone versus the distance is determined.

(a) Local Search

The aims of the section local search in the AS $_{\text{rank}}$ algorithm is to change the nodes, enhance the road of every vehicle, and to enhance the solutions that have been built by all the ants through the improvement of the quality of every ant's solution. On the other hand, when applying the local search, the best local improved solutions may have a major chance to be found. At this stage, the built solution applies local search in order to address these solutions. This achieved through the application of 3-opt to the sub-tour so that the maximum can be obtained from the improvement, enabling the identification of the best result.

(b) Pheromone Update

Here, an update of pheromone is done for all the ribs that belong to the roads obtained by the ants in the AS $_{\text{rank}}$ algorithm. In the hybrid algorithm provided by HAS $_{\text{rank}}$, the density of the pheromone is not only increased on the ribs of the best solution at each iteration, but also the reduction of the concentration of the pheromone is used in order to disperse the ants from the ribs of the worst solution. The HAS $_{\text{rank}}$, which is the proposed hybrid will give further focus on the best and worst roads found after each iteration. It is clear that this strategy increases the potential for diversity of research and helps in the exploration of unused roads to produce different solutions, and thus avoid falling into local optimization.

5. Experimental Results and Discussion

The results of the experiment for the suggested hybrid algorithm HAS $_{\text{rank}}$ were obtained using C ++, a corei7 processor and 8 GB of random-access memory, and the optional parameters obtained through several tests were set as follows:

α =2, β =2, λ = 2, ρ =0.98

In this section, two scenarios are covered: the first involves the implementation of the proposed algorithm on the instances from the dataset of CVRP, whereas, the second one comparison with other studies.

5.1 Implementations of the proposed algorithm HAS_{rank}

This section has presented the implementation of the proposed algorithm HAS $_{\text{rank}}$ on 50 instances ("Set A" and "Set B") from the dataset of CVRP. The accuracy (gap) has been used in evaluating the efficiency of the hybrid algorithm proposed according to the following relationship:

$$\text{Gap} = (C_{\text{Best}} - C^*) / C^* \times 100 \quad (19)$$

Where C_{Best} is denotes the best objective value found over 10 runs, while C* is the best-known value taken from CVRP instances. The results obtained by the proposed algorithm has been compared with the best-known standard solutions, as shown in Table 1.

The results in the below table reveals that the proposed algorithm was able to find optimal solutions for fourteen instances (A-n33-k6, A-n36-k5, A-n37-k5, A-n38-k5, A-n39-k5, A-n44-k6, A-n45-k7, A-n46-k7, A-n48-k7, A-n54-k7 , A-n60-k9 , A-n63-k9 , A-n64-k9 , and A-n69-k9) out of 27 instances, meaning that the gap of these instances is up to 0 %, and their results represent a competitive approach compared to the known standard results. Also, the algorithm was able to find solutions with a gap of less than 1% for (A-n37-k6, A-n39-k6, A-n55-k9, A-n61-k9, A-n62-k8, A-n63-k10, and A-n65-k9). On another hand, for the instances (A-n32-k5, A-n33-k5, A-n34-k5, A-n45-k6, A-n53-k7, and A-n80-k10) the gap was up to 1 % and less than 4 %. The algorithm was able to escape the local optimum points, and it improved the solutions and succeeded in achieving the optimal solutions.

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Table 1: Experimental results of proposed algorithm HAS $_{rank}$ on a benchmark set A

Problems	***n*** **Number of nodes**	***m*** **Number of Vehicles**	**Best-Known Standard Results**	**Best-Known by proposed algorithm**	**Gap %**
A-n32-k5	32	5	784	797	1.700
A-n33-k5	33	5	661	683	3.300
A-n33-k6	33	6	742	**742**	**0.000**
A-n34-k5	34	5	778	786	1.000
A-n36-k5	36	5	799	**799**	**0.000**
A-n37-k5	37	5	669	**669**	**0.000**
A-n37-k6	37	6	949	950	0.100
A-n38-k5	38	5	730	**730**	**0.000**
A-n39-k5	39	5	822	**822**	**0.000**
A-n39-k6	39	6	831	838	0.800
A-n44-k6	44	6	937	**937**	**0.000**
A-n45-k6	45	6	944	957	1.400
A-n45-k7	45	7	1146	1146	**0.000**
A-n46-k7	46	7	914	**914**	**0.000**
A-n48-k7	48	7	1073	**1073**	**0.000**
A-n53-k7	53	7	1010	1020	1.000
A-n54-k7	54	7	1167	**1167**	**0.000**
A-n55-k9	55	9	1073	1081	0.700
A-n60-k9	60	9	1354	**1354**	**0.000**
A-n61-k9	61	9	1034	1038	0.400
A-n62-k8	62	8	1288	1292	0.300
A-n63-k9	63	9	1616	**1616**	**0.000**
A-n63-k10	63	10	1314	1321	0.500
A-n64-k9	64	9	1401	**1401**	**0.000**
A-n65-k9	65	9	1174	1181	0.600
A-n69-k9	69	9	1159	**1159**	**0.000**
A-n80-k10	80	10	1763	1787	1.400

Another implementation of the proposed algorithm has been presented in table 2 as follows:

Table 2: Experimental results by proposed algorithm HAS $_{rank}$ on a benchmark set B

Problems	***n*** **Number of nodes**	***m*** **Number of Vehicles**	**Best-Known Standard Results**	**Best-Known by proposed algorithm**	**Gap %**
B-n31-k5	31	5	672	**672**	**0.000**
B-n34-k5	34	5	788	**788**	**0.000**
B-n35-k5	35	5	955	968	1.400
B-n38-k6	38	6	805	812	1.600
B-n39-k5	39	5	549	**549**	**0.000**
B-n41-k6	41	6	829	834	1.400
B-n43-k6	43	6	742	**742**	**0.000**
B-n44-k7	44	7	909	**909**	**0.000**
B-n45-k5	45	5	751	767	2.100
B-n45-k6	45	6	678	696	2.700
B-n50-k7	50	7	741	**741**	**0.000**

B-n50-k8	50	8	1312	1340	2.100
B-n51-k7	51	7	1032	1032	**0.000**
B-n52-k7	52	7	747	**747**	**0.000**
B-n56-k7	56	7	707	**707**	**0.000**
B-n57-k7	57	7	1153	1168	1.300
B-n57-k9	57	9	1598	1598	**0.000**
B-n63-k10	63	10	1496	**1496**	**0.000**
B-n64-k9	64	9	861	**861**	**0.000**
B-n66-k9	66	9	1316	**1316**	**0.000**
B-n67-k10	67	10	1032	1041	1.600
B-n68-k9	68	9	1272	1295	1.800
B-n78-k10	78	10	1221	1245	2.000

The results of this implementation show the capability of the algorithm to find the optimal solutions for 13 instances (B-n31-k5, B-n34-k5, B-n39-k5, B-n43-k6, B-n44-k7, B-n50-k7, B-n51-k7, B-n52-k7, B-n56-k7, B-n57-k9, B-n63-k10, B-n64-k9 and B-n66-k9) out of 23 instances, meaning that the gap obtained for these instances was up to 0 %, and solutions with a gap between 1% to 2% was found for the 6 instances (B-n35-k5, B-n38-k6, B-n41-k6, B-n57-k9, B-n67-k10, and B-n68-k9). In the same context, the proposed algorithm obtained the value of the gap between 2% to 3 % for the instances (B-n45-k5, B-n45-k6, B-n50-k8, and B-n78-k10).

5.2 Comparisons with other studies

This section involves the comparison of the performance of the proposed algorithm HAS $_{rank}$ with those of other studies highlighted in the literature review including:

- The study done by [36] who presented a hybrid heuristic approach based on the Sweep algorithm and the Nearest Neighbor algorithm (SA & NN) for Solving the Capacitated Vehicle Routing Problem.
- The study carried out by [37], who suggested an improved hybrid firefly algorithm (CVRP-FA) for the capacitated vehicle routing problem.

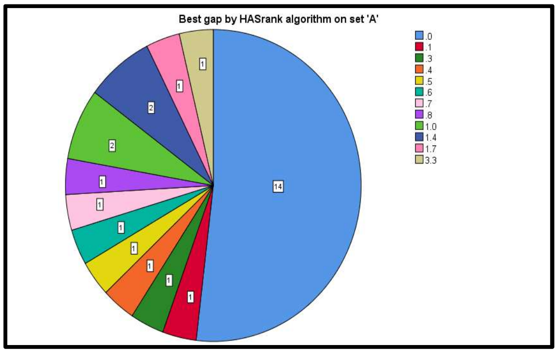
The results of these comparisons are recorded in the tables 3 and 4 below. Table 3 shows the results of the comparisons in instances of the set A from the dataset of the CVRP. It can be seen from the table that the algorithm SA & NN did not reach an optimal solution for all instances of that set, whereas, the algorithm CVRP-FA was able to achieve 12 optimal solutions out of 27. Meanwhile, the proposed algorithm HAS $_{rank}$ obtained 14 optimal solutions among 27.

Table 3: The results of the comparisons for set A

Problems	Best-Known Standard Results	Gap %		
		SA & NN	CVRP-FA	HAS $_{rank}$
A-n32-k5	784	29.100	1.500	1.700
A-n33-k5	661	28.100	0.000	3.300
A-n33-k6	742	23.900	0.000	0.000
A-n34-k5	778	19.900	0.000	1.000
A-n36-k5	799	40.900	0.000	0.000
A-n37-k5	669	30.000	0.000	0.000
A-n37-k6	949	24.300	0.000	0.100
A-n38-k5	730	26.000	0.000	0.000
A-n39-k5	822	39.500	0.000	0.000
A-n39-k6	831	28.200	0.000	0.800
A-n44-k6	937	44.700	0.000	0.000
A-n45-k6	944	28.200	1.000	1.400
A-n45-k7	1146	18.800	0.100	0.000
A-n46-k7	914	17.200	0.000	0.000
A-n48-k7	1073	20.400	0.000	0.000
A-n53-k7	1010	24.900	0.100	1.000
A-n54-k7	1167	21.200	0.400	0.000
A-n55-k9	1073	22.700	0.100	0.700
A-n60-k9	1354	28.000	0.100	0.000
A-n61-k9	1034	24.300	0.500	0.400
A-n62-k8	1288	24.500	0.800	0.300
A-n63-k9	1616	23.800	0.900	0.000
A-n63-k10	1314	17.400	0.000	0.500
A-n64-k9	1401	30.000	1.400	0.000
A-n65-k9	1174	21.700	0.300	0.600
A-n69-k9	1159	15.000	0.300	0.000
A-n80-k10	1763	31.500	0.600	1.400

Figures 4, 5, and 6 are graphic representations of Table 3 as follows:

Figure 4: best gap by SANN algorithm on set A



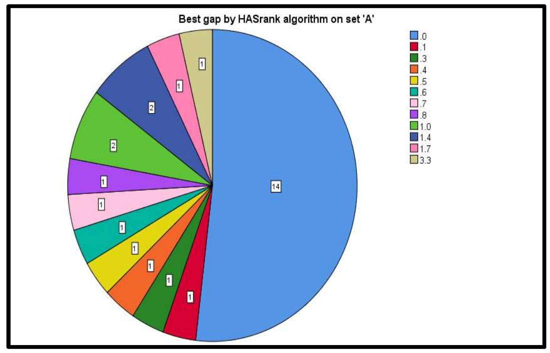


Figure 5: Best gap by CVRP-FA algorithm on set A

The second comparison is done using the instances of set B from the dataset of the CVRP, and the results of that comparison are presented in Table 4. The algorithm SA & NN did not reach an optimal solution for all instances of that set, whereas, the algorithm CVRP-FA was able to achieve 12 optimal solutions out of 23 instances. As for the algorithm proposed in this work, 13 optimal solutions were achieved out of 23.

Table 4: The results of the comparisons for set B

Problems	Best-Known Standard Results	Gap %		
		SA & NN	CVRP-FA	HAS_{rank}
B-n31-k5	784	6.100	0.000	0.000
B-n34-k5	661	26.300	0.000	0.000
B-n35-k5	742	5.300	0.000	1.400
B-n38-k6	778	10.300	0.100	1.600
B-n39-k5	799	24.400	0.200	0.000
B-n41-k6	669	11.800	0.000	1.400
B-n43-k6	949	6.300	0.000	0.000
B-n44-k7	730	33.300	0.000	0.000
B-n45-k5	822	25.600	0.000	2.100
B-n45-k6	831	24.500	1.200	2.700
B-n50-k7	937	27.900	0.000	0.000
B-n50-k8	944	18.900	0.500	2.100
B-n51-k7	1146	14.100	0.000	0.000
B-n52-k7	914	19.300	0.000	0.000
B-n56-k7	1073	18.200	0.300	0.000
B-n57-k7	1010	28.100	0.000	1.300
B-n57-k9	1167	9.100	0.800	0.000
B-n63-k10	1073	12.800	0.500	0.000
B-n64-k9	1354	19.300	0.100	0.000
B-n66-k9	1034	19.900	0.200	0.000
B-n67-k10	1288	24.700	1.000	1.600
B-n68-k9	1616	10.000	0.500	1.800
B-n78-k10	1314	11.600	0.200	2.000

Figures 7, 8 and 9 are graphic representations of the results in Table 4:

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Figure 6: Best gap by HAS_{rank} algorithm on set A

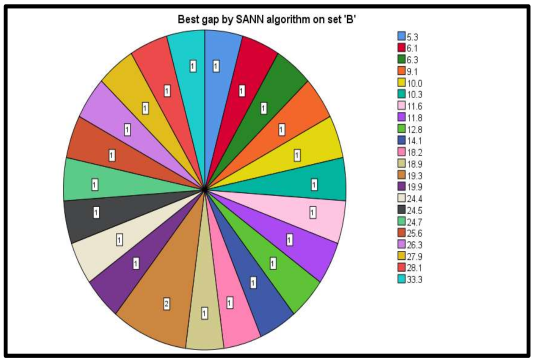

Figure 7: Best gap by SANN algorithm on set B

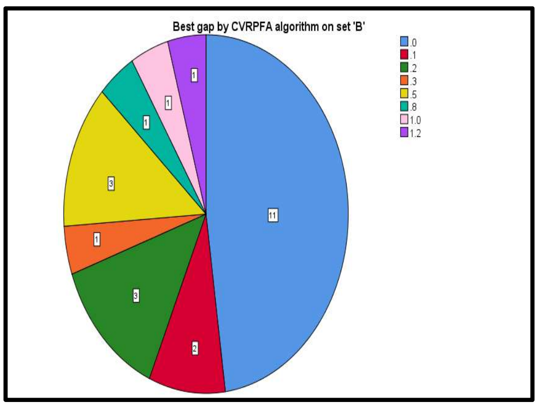

Figure 8: Best gap by CVRP-FA algorithm on set B

The hybridization approach takes a long time and for some instances, results are not so good. Although for some instances initially, the solution accuracy was low, as the iterations increased the accuracy also increased. There is a tradeoff between the quality of solutions and their computational times.

6. CONCLUSION AND FUTURE WORK

In this paper, the hybrid algorithm HAS_{rank} has been suggested based on the combination of the Rank-Based Ant System with insert and swap algorithms as a means of solving the Capacitated Vehicle Routing Problem (CVRP). The AS_{rank} belongs to the category of metaheuristic algorithms that have been successfully applied to NP-Hard problems. It conducts search and explores intelligence in promising areas (which combines different concepts to explore the search space using different strategies).

In view of the computational results, the empirical results obtained have shown the quality of solutions achieved through the proposed approach, and the impact of the approach on the quality of solutions. The results showed that the proposed algorithm performs better in terms of convergence speed and the ability to find better solutions compared with the other algorithms it was compared with. As shown in this study, efforts are continuously geared towards the development of hybrid algorithms. For future works, the following recommendations are given:

- **i)** Apply the proposed hybrid algorithm to other types of vehicle routing problems.
- **ii)** Other hybrid algorithms should be developed based on the local search algorithms, and they should be used in solving optimization problems.
- **iii)** Apply the proposed hybrid algorithm to solve real world applications such as Hospital Layout Problem.

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