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MULTI-OBJECTIVES ANT COLONY SYSTEM FOR SOLVING MULTI-OBJECTIVES CAPACITATED VEHICLE ROUTING PROBLEM

[1,*] MODHI LAFTA MUTAR, [1]M.A. BURHANUDDIN, [1,2]ASAAD SHAKIR HAMEED, [1]NORZIHANI YUSOF, [3]MOHAMMED F. ALRIFAIE AND [1]ALI A. MOHAMMED

[1] Faculty of Information and Communication Technology Universiti Teknikal Malaysia Melaka Hang Tuah Jaya, Durian Tunggal, Melaka, Malaysia
[2] Al-Ayen University, Iraq
[3] Basra University College of Science and Technology, Basra, Iraq

*E-mail: modhiutem@yahoo.com

ABSTRACT

As a combinatorial optimization problem, the capacitated vehicle routing problem (CVRP) is a vital one in the domains of distribution, transportation and logistics. Despite the fact that many researchers have solved the problem using a single objective, only little attention has been given to multi-objective optimization. As compared to multi-objectives, the comparison of solutions is easier with single-objective optimization fitness function. In this paper, the following objectives were achieved: (i) in view of the domain of the multi-objective CVRP, the total distance traveled by the vehicles and the total number of vehicles used are reduced, and (ii) in the view of the technique, a multi-objective Ant Colony System is proposed to solve the multi-objective of CVRP based on the experience of sub-paths. The proposed algorithm was evaluated using some standard benchmark problems of CVRP. The results show that the algorithm which has been proposed in this study is highly competitive and quite effective for multi-objective optimization of CVRP.

Keywords: *Combinatorial Optimization Problem, Ant Colony System Algorithm, Capacitated Vehicle Routing Problem, Multi-Objectives Capacitated Vehicle Routing Problem)*

1. INTRODUCTION

Transportation of goods and passengers is an important task in real life, which requires an enormous amount of money that is spent on fuel and driver remuneration, etc [1]. One of the most critical tasks in the area of operations research is determining how transportation resources can be used effectively. The field of transportation is accompanied by some problems such as the vehicle routing problem (VRP) and the traveling salesman problem (TSP) [2]. The capacitated vehicle routing problem (CVRP) is a significant problem in the area of distribution, transportation, and logistics. As a combinatorial optimization problem, the CVRP seeks to serve a number of customers using a fleet of vehicles. The CVRP can be described as the problem of designing delivery routes for vehicles that depart from a single depot to supply given goods to a set of customers at known locations.

This research has presented the points of view that motivated the researchers to study CVRP as follows: From the theoretical point of view, the CVRP is an NP-hard problem and is impossible to be solved in polynomial time when the problem size increases. From the practical point of view, the CVRP has many applications in the real-life that can be modeled as CVRP such as Collection of waste, Street cleaning, Transmission and distribution of energy, Collection, and delivery of goods, and Routing the school bus. From the techniques point of view, the enhancement of optimization techniques for CVRP has still recommended as open and active research, where metaheuristics are the core of a huge number of successful heuristic algorithms for Combinatorial Optimization Problems (COPs), including the CVRP because of the fewer implementation efforts required as compared with the exact approaches. In VRP, there must be a single departure and return depot, each customer must not be visited more than once by a single vehicle, and the total demand of all the customers must not be more than the capacity of the vehicle [3]. The CVRP is a type of VRP that is often present in a wide range of real-life situations, and in theory, is fascinating but difficult to solve. Consequently, the attention of so many academic researchers has been drawn to this problem.

The role of the CVRP is critical and cannot be underestimated due to the importance of the

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optimal solution to this problem in numerous practical applications in the areas of distribution and transportation. For example, the role of using IoT applications to reduce the vehicle energy or fuel or in some modern software such as cloud computing services may be used in the system development process [4] and [5]. Also, the numerous studies carried out on CVRP is as a result of the growing interest in its applications in logistics and supply of many firms that are involved in transporting of humans or goods. On a regular basis, the distribution systems of such firms are faced with this problem, and the efficiency of their logistics may be directly influenced by the quality of the solution [6], [7]. Presently, there are no exact algorithms that can be used to solve large-size instance within a reasonable computational time frame because the CVRP is categorized as a complex and NP-hard problem [8].

Therefore, majority of the studies carried out with the aim of solving the CVRP have been directed towards the development of meta-heuristic and heuristic algorithms so as to obtain approximate solutions to the CVRP, including Simulated Annealing algorithm (SA), ant colony optimization (ACO) algorithm, tabu search algorithm (TS), and genetic algorithm (GA) [9], [10], [11] and [7].

In real life situations, especially logistics and distribution real cases, the problems are inherently multi-objective. Basically, CVRP seeks to minimized the total distance travelled, driver remuneration, number of vehicles, route balance, to increase profit and the satisfaction of customers [12] and [13]. Despite the fact that the use of single objective optimization has been employed by many researchers to solve the CVRP, the use of multi-objective optimization has rarely been employed due to the following reasons. Comparing the fitness function of solutions is easier in single-objective optimization than in multi-objective optimization. The aim of the designed approach is to reduce the number of vehicles that are required in order to meet all customers' demands and to reduce the total distance traveled by the vehicles [14], and (Juan et al., 2018).

The contributions of this study have summarized as follows: From the point of the domain of the CVRP, the number of vehicles has been optimized. From the point of technique, the contribution includes developing the ACS algorithm relying on the experience of the sub-paths and the Pareto concept for a multi-objective solution of CVRP. The paper is organized as follows: Section 2 contains Review on Multi-Objective Problem, in Section 3, the Materials and Methods, section 4 includes the Computational Results, Conclusion has been presented in section 5.

2. REVIEW ON MULTI-OBJECTIVE PROBLEM (MOP)

A good number of studies have been conducted on routing problems like vehicle routing problem and traveling salesman. These problems have been extensively studied as a result of their wide range of applications, and because they are academically appealing. Similarly, the field of multi-objective optimization is increasingly becoming an appealing area of research due to the new opportunities it offers in terms of defining problems [16], and [17]. In recent times, there has been an increase in the growth of logistics and transportation enterprise, especially delivery and pick up services, and the distribution of goods. Therefore, most real-world optimization problems [18], [19] include several objectives and factors that can be represented as multi-objective optimization problems (MOP).

The MOP is basically aimed at finding the best solutions with optimization of the objectives under constraints. Also, VRP can be represented as multi-objective problems [20], and [14]. Since MOP are naturally combinatorial problems, it can only solve using metaheuristic. Here, ACS is proposed for solving this multi-objective formulation of the CVRP [21], and [17].

Historically, the multi-objective problem has been studied and converted to a one-objective problem by multiplying each objective with a weight that expresses its importance and then collecting them. This way, the multi-objective problem is converted to single-objective problem, and this method has some disadvantages. For example, objectives are contradictory even in measurements and units, and so combining them can be difficult. Here, the population-based approaches were used, and finally, Pareto-based approaches were used. Multi-objective optimization depends on the existence of conflicting objectives between them, and an optimal solution that corresponds to the best values must be found for each objective separately. Thus, this refers to a set of optimal solutions for conflicting objectives, instead of just one solution, where they work jointly to form a single and optimal solution to the problem studied [22], [23], [24].

Multi-objective improvement is an important area of the vehicle routing problems, because of its relevance to the problems of daily life, and solving the problem of multi-objective is done in some stages including, the stage of finding the best possible solutions by the improved algorithm, followed by the selection stage that involves the selection of algorithms, and finally the differentiation stage that depends on certain metrics to find the best solution. Here, the selection of algorithms is reviewed alongside the metrics used for differentiation to apply multi-goal optimization (Sivaram et al., 2014), [14], and (Juan et al., 2018).

In this work, other methods used in solving CVRP multi-objective other than the one proposed in this study are reviewed. Table 1 below presents the review.

Table 1 (related to studies that focused on the solution of multi-objective of CVRP)

Reference	Problem	Method	The first objective	The second objective	Remarks
[12]	The capacitated vehicle routing problem (CVRP)	Genetic Algorithm (GA)	minimizing travelled distance	minimizing number of vehicles	Proposed Method was implemented and tested on few instances of standard benchmarks for the capacitated vehicle routing problem and fitness aggregated genetic algorithm (FAGA) was used as selection method
[14]	The capacitated vehicle routing problem (CVRP)	NSGAII	minimizing distance	minimizing time	The preference methods are suggested for expressing the decision maker's preferences and determine the most preferred solutions after obtaining the approximation of Pareto-optimal solutions through a multi-objective selection algorithm, NSGA-II.
[15]	The capacitated vehicle routing problem (CVRP)	Tabu Search Metaheuristic	minimizing total distance travelled	minimizing number of vehicles	The authors proposed an approach to address the problem of vehicle routing based on heuristic and metaheuristic methods. The method is competitive in terms of response quality and computational time by Tabu Search Metaheuristic

3. MATERIALS AND METHODS

This section presents the concepts and techniques that were used to enhance the proposed algorithm.

3.1 Pareto Optimization

The Optimality Pareto (OP) was presented by an Italian researcher (Vilfredo Pareto, 1848-1923), who first compared two solutions with the mathematical relations, which he used in the multi-objective optimization area when he assumed that there is no more important objective than the other [24]. Then he took two solutions X, Y from the set of accepted solutions S (Pareto Set) of the problem and compared them; this comparison has three possible outcomes (X is better than Y, Y is better than X, or there are none of the solutions that are better than the other), where in the first and second cases, it is referred to as the dominant solution over another solution. The latter case has two distinct states, which are $w(X) = w(Y)$ and $w(X) \neq w(Y)$. The pareto set (PS) is a set of optimal and effective solutions, and the solutions belonging to the pareto front (PF) are called non-dominated solutions; all these solutions are equally acceptable with regards to achieving all the objectives of the problem studied [21]. Figure 1 shows the representation of the Pareto front from the two-objective problem, where the dominant solution can be seen clearly, and since any

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of the solutions in the pareto set is the best solutions ever from the dominated solutions, all solutions are equally acceptable with regards to achieving all objectives [25], [26], [27], [28], and [17].

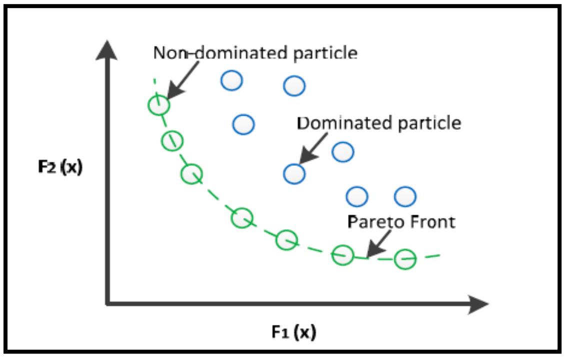

Figure 1: Dominated, non-dominated and Pareto-front solution set [29]

3.2 NSGA-II Algorithm

A non-dominated sorting genetic algorithm II (NSGA-II) was first suggested in the work done by [30]. It is popularly used in solving Multi-Objective problems. Since the algorithm was proposed, it has been widely researched on by researchers due to its high convergence speed, stronger robustness, and good draw near the Pareto-optimal front. More so, the algorithm benefits from the elitist technics, and it also uses the concept of Pareto-optimality in its selection mechanism; it is one of the most importance selection algorithms [31]. The NSGA-II algorithm has proven to be one of the effective algorithms used in solving the multi-objective problem. It helps in finding a diversified set of solutions set, and also in converging from the true Pareto-front. In recent times, the NSGA-II has been successfully applied in different problems, because it is of great importance to Pareto-front with good diversification [32], [33]. A main improvement of the NSGA was carried out, and a fast and elitist new version of NSGA (i.e., NSGA-II) was suggested; crowding-distance was employed in it [30]. In the NSGA-II algorithm, the main operation contains two sides. One side includes the three classical operation processes in the GA algorithm, like crossover, mutation, and selection, while the other side concerns the unique non-dominated sorting process in the multi-objective optimization algorithm. The selection process holds over some of the best individuals with the values of their fitness (that indicates the value of non-dominated sorted) and NSGA-II is briefly described as follows: NSGA-II uses non-dominated sorting for fitness assignments. All solutions that are not dominated by any other solutions are appointed front number 1. All solutions only dominated by solutions in front number 1 are appointed front number 2, and so on. Table 1: Center Table Captions Above the Tables.

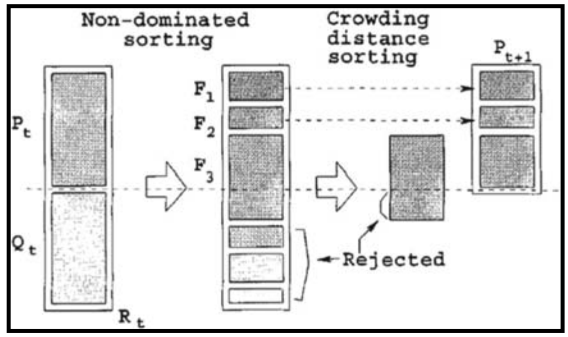

Figure 2: NSGA-II algorithm [30]

3.3 Mathematical Model of Multi-Objective Problem

We will proceed from the using of vehicles similar with known and specific capacities, and the demand of each customer i was specified and the total demand of any customer should be less than the capacity of the vehicle, the main depot v_0 is a lone depot for each road (maximum time, distance or cost). Transport costs are defined as the cost of driving a vehicle from one customer to another so that the cost of moving back and forth between customers is the same $c_{ij} = c_{ji}$ and all vehicles are empty in the main depot, and for each rib (i, j) the cost of c_{ij} and the travel distance d_{ij} on rib (i, j), where the model of the multi-objective problem is given as follows:

$$minimize\ f(x) = [f_1(x), f_2(x)] \quad (1)$$

Where:

$$f_1(x) = minimize\ D \quad (2)$$

$$f_2(x) = minimize\ K \quad (3)$$

Where *D* is total distance traveled by all vehicles and *K* is the total number of vehicles. Equation (2) is the objective function for minimization of total distance travelled by all vehicles, Equation (3) is the objective function for minimization of the total number of vehicles used.

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3.4 Proposed Multi-Objective of ACS algorithm Based on Experience of Sub-Paths (MACS-P)

In this work, the development of ACS algorithm (one of the Ant Colony Optimization family) is proposed based on the experience of sub-paths (MACS-P) to solve the multi-objective of CVRP (distance and number of vehicles). In previous works, the use of sub-paths was employed to improve the efficiency of local search to support the mechanism of exploitation [34], and there are other works in which the sub-paths were used in creating standards for updating the global pheromone based on the number of sub-paths which all solutions pass through [35], and since ACS suffers from a deficiency in the exploration mechanism that leads to the issues of premature convergence and stagnation, the use of experience of the sub-paths is suggested in this work as a way of improving the exploration mechanism in the transition equation that proved the ability of the algorithm to find the best solution in a reasonable time through applying ACS using the experience of the sub-paths (ACS-P). On the other hand, since ACS is suffering from low diversity, in the next section, it is proven that the use of ACS-P helps to discover the new solutions and solve the problem of low diversity by entering the sub-paths experience as a term in the transition equation among the nodes. The steps of the proposed algorithm are presented as follows:

Step I: Initialization

In the beginning, the pheromone primary matrix, the vision matrix, the distance matrix, the number of ants used and the parameters setting are initialized (τ, α, β, ρ, $Q \geq 0$), (τ_{ij}, η_{ij}, α, $\beta \geq 0$). The total quantity of goods that a vehicle carries should be less than its capacity Q. The initial level of pheromone which depends on distance experience for each edge (i, j) is based on the relationship: $\tau_0^d = \frac{1}{n l_{NN}}$ and $\tau_0^d > 0$ is a parameter of the initial value of the effects of the pheromone that depends on distance experience, The initial level of pheromone which depends on vehicles number experience for each edge (i, j) is based on the relationship:$\tau_0^v = \frac{1}{m}$ And $\tau_0^v > 0$ is a parameter of the initial value of the effects of the pheromone that depends on vehicles number experience, *n* the number of nodes, and l_{NN} is the cost produced by the nearest neighbor algorithm (NN).

Step II: Solution Construction

In the classic transitional equation, a tour is constructed node by node: every ant iteratively adds new nodes until all nodes have been visited. When ant *k* is located in node *i*, it takes the next node *j* in the set of feasible nodes U (i.e., the set of the nodes that still have to be visited). It is important to note that the transitional equation in the previous studies was dependent on terms supporting exploitation, and in this study, we introduce a new term through which the passage of the same sub-paths that were visited in previous solutions is avoided and this supports the exploration mechanism in the transitional equation. In the case of the multi-objectives problem, the transitional equation depends on more than one experience of the pheromone to achieve more than one objective, namely the objective of reducing the distance and the objective of reducing the number of vehicles and it is determined random weights ratios for these experiences to ensure the diversity of solutions and the formation of solutions for the Pareto Front achieve the property of spread (extent of expansion). The MACS-P depends on the experience of sub-paths that was adapted to a multi-objective problem, and improved way of solving CVRP was achieved, where the transition is either in the form of a node by node transition or a transition to sub-paths as follows:

$$S = \begin{cases} S_C^M(j) & if \quad h > a \\ S_P^M(j) & if \quad h < a \end{cases} \tag{4}$$

Where $S_C^M(j)$ is the multi–objective transition equation of node by node, while $S_P^M(j)$ is the multi -objective transition equation from node to sub-path, and given as follows:

$$S_C^M(j) = \begin{cases} arg\, max_{l \in U} \{[w_1. \tau_{il}^d + w_2. \tau_{il}^v]^\alpha [\eta_{il}]^\beta [\xi_{il}]^\gamma [\varphi_{il}^k]^\delta\} & if\ q \leq q_0 \\ J^M & otherwise \end{cases} \tag{5}$$

Where $\varphi_{il}^k = \frac{1}{\psi_{il}^k}$, ψ_{il}^k is the maximum number of continuously visited nodes from the beginning of the solution k until l ,which exist partly or completely on one of the recorded previous sub-paths, such that, as the number of nodes in the chosen sub-path ψ_{il}^k increases, the value of φ_{il}^k decreases, and therefore the probability of choosing it later decreases, and then the probability of exploring other sub-paths increases. 0<w1, w2 <1 random coefficients and w1+ w2=1 and $\tau_0^v, \tau_0^d > 0$, while $\alpha, \beta, \gamma, \delta, q, q_0$ are the parameters defined previously, J^M is the random variable that is determined depending on the multi –objective probability equation from node to another node, which is applied based on the experience of sub-paths as follows:

$$J^M: p_{ij}^k = \begin{cases} \frac{[w_1.\tau_{ij}^d + w_2.\tau_{ij}^v]^\alpha [\eta_{ij}]^\beta [\xi_{ij}]^\gamma [\varphi_{ij}^k]^\delta}{\sum_{l\in U}[w_1.\tau_{il}^d + w_2.\tau_{il}^v]^\alpha [\eta_{il}]^\beta [\xi_{il}]^\gamma [\varphi_{il}^k]^\delta} if\ j \in U \\ 0 \quad otherwise \end{cases} \quad (6)$$

The transition rule for multi-objective that depends on sub-paths is given as the follows:

$$S_P^M(r) = \begin{cases} arg\ max_{l\in G} \left\{[w_1.\tau_{P_{il}}^d + w_2.\tau_{P_{il}}^v]^\alpha [\eta_{P_{il}}]^\beta [\xi_{P_{il}}]^\gamma\right\} if\ q \le q_0 \\ J_r^M \quad otherwise \end{cases} \quad (7)$$

J_r^M is the random variable that is specified according to the multi–objective probability transition rule from node to sub-path which is applied based on the experience of sub-paths as follows:

$$J_r^M: p_{ir}^k \begin{cases} \frac{[w_1.\tau_{P_{ir}}^d + w_2.\tau_{P_{ir}}^v]^\alpha [\eta_{P_{ir}}]^\beta [\xi_{P_{ir}}]^\gamma}{\sum_{l\in W}[w_1.\tau_{P_{il}}^d + w_2.\tau_{P_{il}}^v]^\alpha [\eta_{P_{il}}]^\beta [\xi_{P_{il}}]^\gamma} if\ r \in G \\ 0 \quad otherwise \end{cases} \quad (8)$$

(i) Local pheromone update

For a multi-objective solution to the problem under study with the improved algorithm, the pheromone which is related to the experience of the objective in distance reducing is evaporated, and also, the pheromone which is related to experience of the objective in reducing the number of the vehicles is evaporated to ensure that new solutions that support improving distance and the number of vehicles are explored one or both where the local update in the case of a multi-objectives is given by the following relationship:

$$\tau_{P_{ij}}^d(t+1) = (1-\rho).\tau_{P_{ij}}^d(t) + \rho\tau_0^d \quad (9)$$

$$\tau_{P_{ij}}^v(t+1) = (1-\rho).\tau_{P_{ij}}^v(t) + \rho\tau_0^v \quad (10)$$

Where $0 \le \rho \le 1$ is a user-defined parameter called evaporation coefficient, and $\tau_0 = (n \times L_{NN})^{-1}$ is the initial pheromone level of edges, where n is the number of nodes and L_{nn} is the tour length produced by the Nearest Neighbor algorithm (NN).

Step III: Local Search

At this stage, after building the solution, local re-search is applied to improve these solutions by applying 3-opt to the complete sub-tour and k-opt on the sub-paths from the previous iteration, taking into account the installation of the first and last node in each sub-path as in a single objective. In this phase local re-search is applied so as to improve solutions and local search in the case of multi-objectives that resembles in his work from a single objective, where in the multi-objectives more than one objective are involved. However, in this section, the focus is not on the objective of the number of vehicles, because, as earlier mentioned, local search is applied within sub-tours.

Step V: Global Pheromone Update

The pheromone is updated globally by using the rank system based on the arrangement of ants according to the quality of the solution by finding the best solutions, and in the case of more than one objective, a set of solutions based on the Pareto concept must be used. Then in the case of the objective of the number of vehicles, there is only a limited number of diversities in the number of vehicles. For example, from seven to eleven vehicles; that limits the number of solutions on the Pareto front to a maximum of five solutions. This called for the introduction of another concept, which is the Pareto Sort, which allows selecting a greater number of solutions on the Pareto front, which in turn allows the updating of the pheromone globally through the experience of a greater set of the solutions. This was, the best solutions can be found. The global updating rule is described as follow:

$$\tau_{ij}^d(t+1) = \rho\ \tau_{ij}^d(t) + \Delta\tau_{ij}^d + \Delta\tau_{ij}^{d^*} \quad (11)$$

Where: $\Delta\tau_{ij}^d = \sum_{\mu^d=1}^{\sigma^d-1} \Delta\tau_{ij}^{\mu^d}$

$$\Delta\tau_{ij}^{\mu^d} = \begin{cases} (\sigma^d - \mu^d)\frac{Q}{L_{\mu^d}} if\ \ \mu^d - th\ best\ ant\ on\ edge \\ (i,j)\ depending\ on\ experience\ of\ distance \\ 0 \quad otherwise \end{cases} \quad (12)$$

$$\Delta\tau_{ij}^{d^*} = \begin{cases} \sigma^d \frac{Q}{L^{d^*}}\ if\ edge\ (i,j)\ is\ part\ of\ best\ solution \\ found\ depending\ on\ experience\ of\ distance \\ 0 \quad otherwise \end{cases} \quad (13)$$

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

Where: $\Delta\tau_{ij}^v = \sum_{\mu^v=1}^{\sigma^v-1} \Delta\tau_{ij}^{\mu^v}$

$$\Delta\tau_{ij}^{\mu^v} = \begin{cases} (\sigma^v - \mu^v)\frac{Q}{L_{\mu^v}}\ if\ \mu^v - th\ best\ ant\ on \\ edge(i,j)\ depending\ on\ experience\ of\ vehicles \\ 0 \quad otherwise \end{cases} \quad (15)$$

$$\Delta\tau_{ij}^{v^*} = \begin{cases} \sigma^v \frac{Q}{L^{v*}} if edge(i,j)\ is\ part\ of\ best\ solution \\ found\ depending\ on\ experience\ of\ vehicles \\ 0 \quad otherwise \end{cases} \quad (16)$$

Where μ^d is ranking index, , $\Delta\tau_{ij}^{\mu^d}$ denotes increase of trail level on edge (i, j) caused by the μ^d – *th* best ant depending on experience of distance, $L_\mu{}^d$ is tour length of the μ^d – *th* best ant depending on

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experience of distance, increase of trail level on edge (i, j) caused by the elitist ants depending on experience of distance, number of elitist ants depending on experience of distance, L^* tour length of best solution found depending on experience of distance, t iteration counter, $\rho \in (0, 1]$ parameter to regulate the reduction of τ_{ij}^{d} . $\Delta\tau_{ij}^{\mu^v}$ increase of trail level on edge (i, j) caused by the $\mu^v - th$ best ant depending on experience of vehicles, L_{μ^v} tour length of the $\mu^v - th$best ant depending on experience of vehicles, $\Delta\tau_{ij}^{d^*}$ increase of trail level on edge (i, j) caused by the elitist ants depending on experience of vehicles, σ^v number of elitist ants, L^{v*} tour length of best solution found depending on experience of vehicles, t iteration counter, $\rho \in (0, 1]$ parameter to regulate the reduction of τ_{ij}^{v} . Figure 3 shows the flowchart MACS-P algorithm as follows:

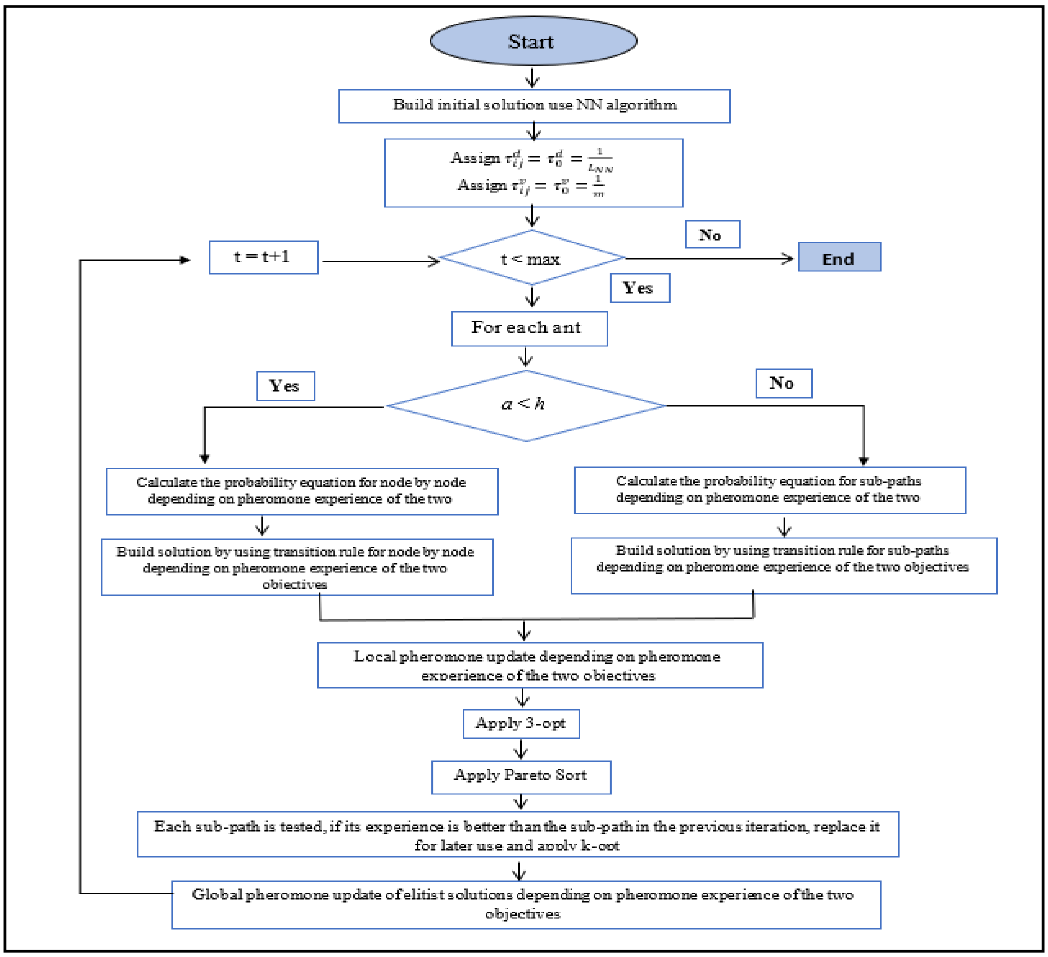

Figure 3: Flowchart of MACS-P algorithm

4. COMPUTATIONAL RESULTS

After analyzing the dataset of the Capacitated Vehicle Routing Problem (CVRP) which can be accessed through the following link: http://vrp.atd-lab.inf.puc-rio.br/index.php/en/, some cases which were found in this dataset made it possible to reduce the number of vehicles in it. The mechanism of applying the proposed algorithm to solve a multi-objective (distance, number of vehicles) is presented by structuring the solution depending on the experience of the sub-paths, and then use the Pareto concept by choosing one of the selection methods represented by NSGA-II to determine the best solutions and sort the non-dominated solutions from the dominated solutions by crowding metric in an effort to reduce the total distance traveled by the fewest numbers of vehicles. Table 2. shows the results of single objective instances with the best distance (which makes it possible to decrease the number of vehicles in it) as follows:

Table 2 Instances have a number of a vehicle not optimum

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No.	Group	Instances	Distance	Number of Vehicle
1	Set M	M-n200-k17	1275	17
2	Set CTM	CMT5	1291.29	17
3	Set CTM	CMT6	555.43	6
4	Set CTM	CMT7	909.68	11
5	Set CTM	CMT8	865.94	9
6	Set CTM	CMT9	1162.55	14
7	Set CTM	CMT10	1395.85	18
8	Set CTM	CMT13	1541.14	11
9	Set CTM	CMT14	866.37	11

4.1 Parameters Setting

Grid Search Technique has been used to find the best parameters by which to increase the efficiency of the proposed algorithm. The grid search technique is the most unpretentious optimization technique which depends on an exhaustive search during a manually specific set of the parameter area of classification technique. The benefit of using the grid search technique is that the candidate parameter settings are systematically created. For that, every dataset is used to test all datasets [36]. Grid search is made up of three steps as follows:

I. Generating of candidate parameter settings depend on a given budget threshold consistently. For instance, a budget threshold of five will limit the number for candidate settings of every parameter to five. So, for a despotic classifier with three parameters and a budget threshold of five, the grid search technique creates five *five * five = a hundred twenty-five mixtures of parameter settings.

II. Evaluation of every candidate parameter setting.

III. Identification of the optimal parameter settings.

Table 3 shows the parameters used in the proposed algorithm.

Table 3: Parameters Setting

Parameters	Value
β	2
q_0	0.9
α	2
ρ	0.98
τ_0	$(L_{nn})^{-1}$
γ	2
σ	6
Number of iterations N	1000
Q	According to the benchmark results table
Number of vehicle m	According to the benchmark results table
artificial ants n=m	According to the benchmark results table

4.2 Implementations

The improved multi-objective algorithm MACS-P was applied to the cases from the CVRP dataset for a multi-objective solution (distance, number of vehicles) found in table 4 in order to find the optimal number of vehicles based on the experience of the sub-paths and the Pareto concept.

Table 4: Solve two objectives distances and vehicles by MACS-P from dataset of CVRP

No.	Group	Instances	Two-Objectives		Time (s)
			Vehicle	Cost	
1	Set M	M-n200-k17	16	1809	3876.389
			17	1275	
2	Set CTM	CMT5	16	1291.29	339.359
			17	1416.43	
			18	1827.56	

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3	Set CTM	CMT6	5	562.9	510.241
			6	555.43	
4	Set CTM	CMT7	10	911.68	1385.011
			11	909.68	
			12	966.02	
5	Set CTM	CMT8	8	929.89	1404.229
			9	865.94	
6	Set CTM	CMT9	12	1265.84	998.097
			13	1180.08	
			14	1162.55	
7	Set CTM	CMT10	17	1525.8	2031.931
			18	1395.85	
8	Set CTM	CMT13	7	1541.16	678.886
			8	1541.14	
			9	1552.45	
			10	1542.02	
			11	1541.14	
9	Set CTM	CMT14	10	867.09	1752.648
			11	866.37	

Instance M-n200-k17 (Euclidian Distances, 200 customers, 1 depot, vehicle capacity = 200), minimum number of vehicle or routes = 17, the value of optimum distance = 1373. The results of this case for multi-objective were a number of vehicles 16 with a distance in 1809 as a non-dominated solution and other non-dominated solution with a number of vehicles 17 with a distance 1275. Instance CMT5 (Euclidian Distances, 200 customers, 1 depot, vehicle capacity = 200), minimum number of vehicle or routes = 17, the value of optimum distance = 1291.29. The results of this case with multi-objective were a number of vehicles 16 with a distance 1291.29 as a non-dominated solution while the dominated solutions were represented by a solution that has a number of vehicles 17 and a distance 1416.43 and other dominated solution with a number of vehicles 18 and a distance 1827.56. Instance CMT6 (Euclidian Distances, 51 customers, 1 depot, vehicle capacity = 160), minimum number of vehicle or routes = 6, the value of optimum distance = 555.43. The results of this case with multi-objective were a number of vehicles 5 with a distance in 562.9 as a non-dominated solution and other non-dominated solution with a number of vehicles 6 with a distance 555.43. Instance CMT7 (Euclidian Distances, 76 customers, 1 depot, vehicle capacity = 140), minimum number of vehicle or routes = 11, the value of optimum distance = 909.68. The results of this case for multi-objective were a number of vehicles 10 with a distance 911.68 as a non-dominated solution and other non-dominated solution with a number of vehicles 11 with a distance 909.68 while the dominated solutions were represented by a solution that has a number of vehicles 12 and a distance 966.02. Instance CMT8 (Euclidian Distances, 101 customers, 1 depot, vehicle capacity = 200), minimum number of vehicle or routes = 9, the value of optimum distance = 865.94. The results of this case with multi-objective were a number of vehicles 8 with a distance 929.89 as a non-dominated solution and other non-dominated solution with a number of vehicles 9 with a distance 865.94. Instance CMT9 (Euclidian Distances, 151 customers, 1 depot, vehicle capacity = 200), minimum number of vehicle or routes = 14, the value of optimum distance = 1162.55. The results of this case with multi-objective were a number of vehicles 12 with a distance 1265.84, a number of vehicles 13 with a distance 1180.08, and a number

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of vehicles 14 with a distance 1162.55 as a non-dominated solution. The results of this case with multi-objective were a number of vehicles 12 with a distance 1265.84, a number of vehicles 13 with a distance 1180.08, and a number of vehicles 14 with a distance 1162.55 as a non-dominated solution. Instance CMT10 (Euclidian Distances, 200 customers, 1 depot, vehicle capacity = 200), minimum number of vehicles or routes = 18, the value of optimum distance =1395.85. The results of this case with multi-objective were a number of vehicles 17 with a distance 1525.8 as a non-dominated solution and other non-dominated solution with a number of vehicles 18 with a distance 1395.85. Instance CMT13 (Euclidian Distances, 121 customers, 1 depot, vehicle capacity = 200), minimum number of vehicle or routes = 11, the value of optimum distance = 1541.14. The results of this case with multi-objective were a number of vehicles 7 with a distance 1541.16 as a non-dominated solution and other non-dominated solution with a number of vehicles 8 with a distance 1541.14 while the dominated solutions were represented by a solution that has a number of vehicles 9 and a distance 1552.45, a number of vehicles 10 with a distance 1542.02 and a number of vehicles 11 with a distance 1541.14. Instance CMT14 (Euclidian Distances, 101 customers, 1 depot, vehicle capacity = 200), minimum number of vehicle or routes = 11, the value of optimum distance = 866.37. The results of this case with multi-objective were a number of vehicles 10 with a distance 867.09 as a non-dominated solution and other non-dominated solution with a number of vehicles 11 with a distance 866.37. Figures below show the pareto front for instances of table 4 as follows:

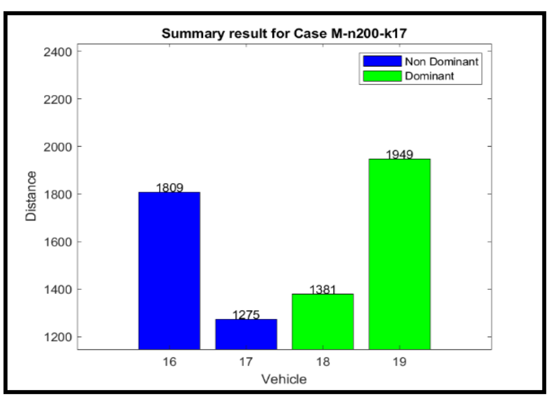

Figure 4: Solve instance M-n200-k17

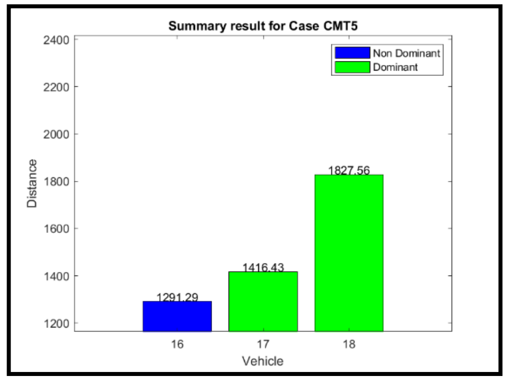

Figure 5: Solve instance CMT5

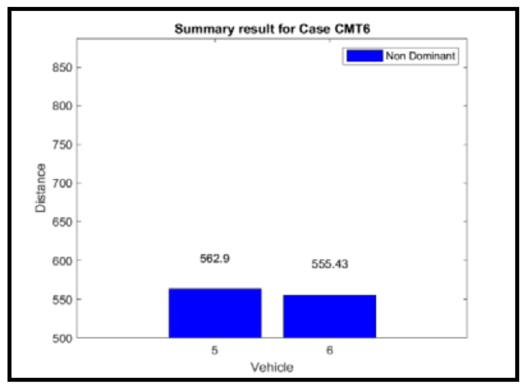

Figure 6: Solve instance CMT6

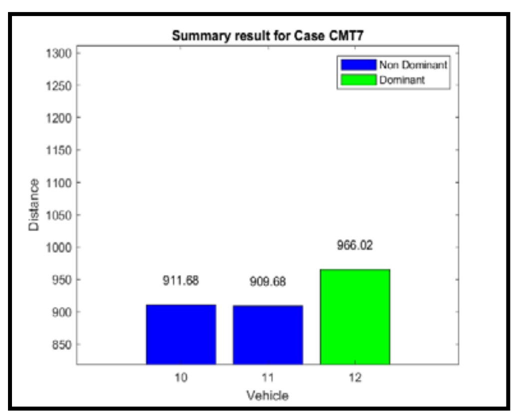

Figure 7: Solve instance CMT7

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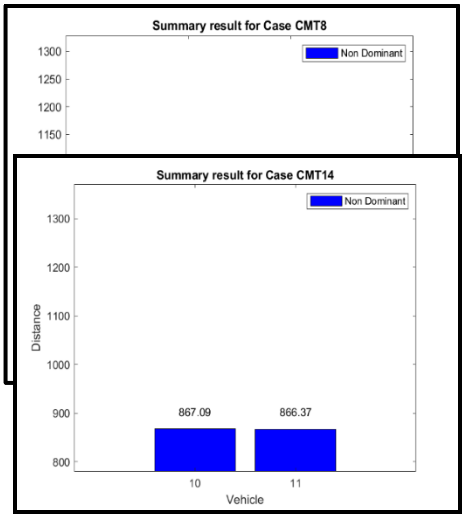


Figure 8 Solve instance CMT8

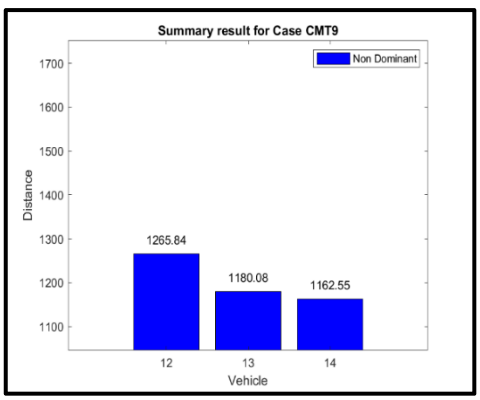


Figure 9 Solve instance CMT9

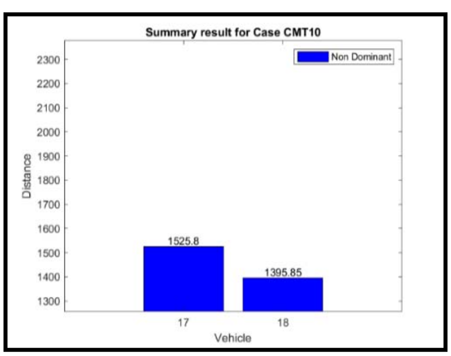
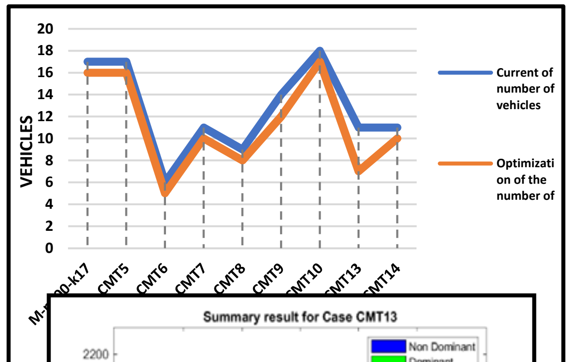


Figure 10: Solve instance CMT10

Figure 11: Solve instance CMT13

Figure 12: Solve instance CMT14

The following figure shows the summarized the number of vehicles optimized by the proposed algorithm as follows:



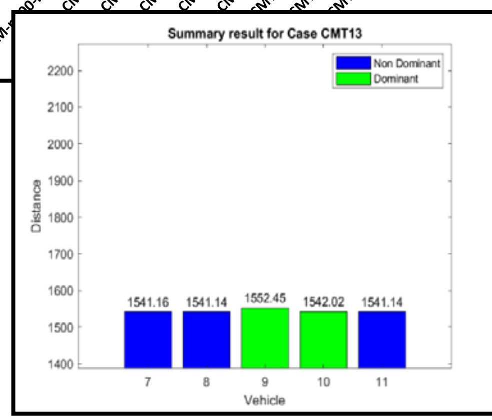


Figure 13: Number of vehicles optimized by the proposed algorithm

5. CONCLUSION

This paper introduces the ACS algorithm that depends on the experience of sub-paths for solving the CVRP multi objective. The model of CVRP considers the reduction of total distance traveled by all vehicles and the total number of vehicles used as multi-objective functions, based on vehicle capacity constraint. The proposed method contributed to minimizing the number of vehicles in some cases of the database of CVRP since after analyzing this database, it was found that some cases in the CVRP the dataset have optimal distance, but with the number of vehicles no optimal which is possible to reduce the number of vehicles in it. Another contribution of this study is to develop the ACS algorithm to a multi-objective ACS algorithm based on the experience of sub-paths and the Pareto concept, where was identified the most preferred

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solutions after obtaining the approximation of Pareto-optimal solutions by algorithm, NSGA-II. The proposed method was tested on some instances of standard benchmarks for CVRP, which was found to be so effective and competitive. Extra improvements might be possible to test different variants of the vehicle routing problem and by considering other objectives optimization.

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