ISSN: 2182-2069 / E-ISSN: 2182-2077

A Detailed Review of the Capacitated Vehicle Routing Problem: Model, Computational Complexity, Solutions, and Practical Applications

Asaad Shakir Hameed[1*], Haiffa Muhsan B. Alrikabi[2], Abeer A. Abdul–Razaq[3], Huda Karem Nasser[4], Modhi Lafta Mutar[5], and Hala Hilal Katea[6]

[1*]Artificial Intelligence Engineering Department, Engineering College, Al-Ayen Iraqi University, Thi-Qar, 64001, Iraq; Presidency of the University, Shatrah University, Thi-Qar, 64001, Iraq. asaad.shakir@alayen.edu.iq, https://orcid.org/0000-0001-5979-6232

[2]Department of Mathematics, College of Education for Pure Sciences, University of Thi-Qar, Thi-Qar, 64001, Iraq. hai8aa123@gmail.com, https://orcid.org/0000-0003-4049-1417

[3]Department of Mathematics, College of Computer Science and Mathematics, Thi-Qar University, Thi-Qar, Iraq. a4393981@gmail.com, https://orcid.org/0000-0003-3384-0471

[4]Department of Mathematics, General Directorate of Thi-Qar Education, Ministry of Education, Thi-Qar, 64001, Iraq. h700387@gmail.com, https://orcid.org/0000-0002-0654-5031

[5]Presidency of the University, Shatrah University, Thi-Qar, 64001, Iraq; Education College, Al-Ayen Iraqi University, Thi-Qar, 64001, Iraq. modhi@alayen.edu.iq, https://orcid.org/0000-0002-3038-8507

[6]Biomedical Engineering Department; Engineering College, Al-Ayen Iraqi University, Thi-Qar, 64001, Iraq. hala.hlal@alayen.edu.iq, https://orcid.org/0009-0006-0833-3127

Received: November 28, 2024; Revised: January 07, 2025; Accepted: January 25, 2025; Published: February 28, 2025

Abstract

An instance of a combinatorial optimization problem (COP) is the “Capacitated Vehicle Routing Problem (CVRP)”. When the CVRP is big, locating a top-quality answer is very tough. An extensive variety of real-life scenarios, consisting of garbage series, avenue cleansing, and bus schedules may be modelled as CVRP, with the model's objective being to pinpoint a series of a fleet's routes of motors that need to provide service to customers from a centralized depot. It is believed that automobiles have identical capabilities and that the departure and return points of each automobile are equal. Since every consumer has a consistent demand, the vehicle's capacity cannot be exceeded. More specifically, CVRP seeks to reduce the overall expense necessary to serve a certain group of clients. To this goal. To address CVRP, two main approaches exact and approximate "heuristic and metaheuristic" algorithms have been presented. The precise algorithms are focused on providing a worldwide optimal solution for CVRP of small size within a suitable period, whereas the approximation algorithms are focused on identifying the near-optimal or optimal solution for large-scale CVRP. This study aims at (i) conducting a thorough analysis of the approaches that have been used to solve the CVRP model, (ii) investigating the ACO family of algorithms, and (iii) identifying the best algorithm that can improve CVRP model solutions depending on how accurate the algorithm is, in an acceptable length of time. Our findings indicate that ACO-based approaches, particularly

Journal of Internet Services and Information Security (JISIS), volume: 15, number: 1 (February), pp. 218-235.
DOI: *10.58346/JISIS.2025.I1.014*

*Corresponding author: Artificial Intelligence Engineering Department, Engineering College, Al-Ayen Iraqi University, Thi-Qar, 64001, Iraq; Presidency of the University, Shatrah University, Thi-Qar, 64001, Iraq.

the Ant Colony System (ACS), offer significant improvements in solving large-scale CVRP instances efficiently. Specifically, the ACS algorithm evaluated the high-quality performance of computational efficiency and solution quality, making it a promising approach for realistic packages.

Keywords: Capacitated Vehicle Routing Problem, Metaheuristic Algorithms, Combinatorial Optimization Problem, Ant Colony System.

1 Introduction

Combinatorial Optimization Problems (COPs) are an area in theoretical computer technology and carried out mathematics which involves the identity of a most excellent item from a finite set of gadgets (Cook & Cunningham, 1998; Hameed et al., 2018; Sheldon et al., 2020). Most of the time, it is impossible to achieve a complete search for solutions to those problems. The way it works is determined by the optimization problems' domain, where the set of viable solutions is discrete or reducible to discrete, to find the optimal solution. As a subset of mathematical optimization, combinatorial optimization is associated with algorithm theory, operations research, and computational complexity (Babenko et al., 2021). COPs have several relevant applications in different fields like auction theory, artificial intelligence, software engineering, and machine learning (Barhoumi et al., 2024).

The COPs class is important to researchers in computer science and operations research (OR) (Diaby et al., 2021; Hameed et al., 2020; Ayoola et al., 2020). Its importance stems from the fact that many applications of a daily nature can be framed within it, and can be described using known mathematical models and symbolized by a graph with weights “G = (V, E)” with positive weights, and requires the search for an element which is the optimal solution among a large number of separate candidate solutions in a limited set, but this set is too large to be enumerated and implicitly given by its combinatorial structure. Usually, this element is an integer, a subset, a switch operation, or a graph structure. More so, combinatorial problems are important in the sense that the objective function and constraints are naturally not the same in many problems of daily nature, and the function *f* enables the classification of optimization problems into two different categories (Pishvaee & Rabbani, 2011; Archetti & Speranza, 2014; Korte, 2017) as follows: Problems of continuous optimization, this category represents the first category of Optimization Problems and consist of problems with continuous variables whose solutions are encoded with real variables.

Problems of discrete optimization, represent the second category of Optimization Problems in the case of discrete variables. Here, the focus is on discrete optimization and those whose solutions are encoded with discrete variables (Suhail & Kokila, 2024). The COPs have belonged to problems of discrete optimization, and most of the applications of a daily nature have problems of a discrete nature. Numerous specialised COPs exist, including the "Vehicle Routing Problem (VRP), Facilities Problem (FP), Scheduling Problem (SP), and Travelling Salesman Problem (TSP)" (Pintea, 2014; Choong et al., 2019; Cheikh-Graiet et al., 2020). The vehicle routing problem (VRP) which is a fleet of vehicles with restricted capability routed to visit a group of customers at a minimal cost, has received considerable attention in recent times (Punriboon et al., 2019). VRP is aimed at reducing the total duration of a given route or the total distance traversed, the total amount of vehicles required to serve customers. Although these are the major objectives, there are still other objectives.

Typically, a VRP can be defined as the problem associated with the design from one depot to a collection of physically separated locations, including clients, of low-cost routes, warehouses and cities with much ease. The interest in the applications of VRP in supply-chain management has necessitated the extensive studies that have been carried out on VRP. Also, a great number of extensive studies have been conducted because the VRP is widely known as a complex combinatorial problem (Wang, 2013; Mutar et al., 2017; Speranza, 2018; Vidal et al., 2019). There is an extensive variety of VRPs which might be constant with constraints variance, consisting of the multi-depot vehicle routing problem (MDVRP), the open vehicle routing problem (OVRP), the vehicle routing problem with time windows (VRPTW), and the capacitated vehicle routing trouble (CVRP) etc. With distinct constraints (Kheirkhahzadeh & Barforoush, 2009; Messaoud & Alaoui, 2017; Adewumi & Adeleke, 2018; Beresneva & Avdoshin, 2018; Syahputra et al., 2018; Bhuvaneswari et al., 2018).

The Capacitated Vehicle Routing Problem (CVRP) is a type of VRP, so named because of the restriction of limited vehicle capacity. Furthermore, the CVRP problem entails determining a collection of routes that a fleet of cars should take to serve a specific number of clients from a central depot. It is assumed that all of the vehicles have the same capacity and that they leave and arrive at the same depot. Each customer's demand quantity is the known constant in this case, and no demand exceeds the vehicle's capacity (Rosnelly et al., 2022). In essence, CVRP seeks to lower the overall cost necessary to serve a specific number of clients. The total cost is a weighted function of the number of automobiles and the distance they must travel to serve a group of customers. The course must be designed so that each customer can only be visited once with the best car. The CVRP is a common combination issue that falls under the category of NP-hard problems (Madhan & Shanmugapriya, 2024; Stodola et al., 2014; Kuo & Zulvia, 2017; Farhanna et al., 2018; Mutar et al., 2020; Ngisomuddin & Satyananda, 2020). Great attention has been given to the CVRP because of how complex and important it is, as well as its vast applications of daily nature. In theory, The CVRP, taken into consideration NP-hard, extends upon advance studies efforts and is diagnosed as an important focus in the field of optimization. Its complexity and relevance make it a huge subject matter for researchers aiming to develop efficient algorithms and answers. On the other hand, in practice, the majority of the results of such researchers have been applied in different fields like logistic services, industry, and strategic decision-making (Janjarassuk & Masuchun, 2016; Lima & Schimit, 2018; Mutar et al., 2019; Redi & Satyananda, 2020). The CVRP can be solved using two approaches, which are exact algorithms and approximate algorithms. The approximate algorithms include “ant colony optimization (ACO), local search algorithms (LSAs), Tabu Search (TS), and Genetic algorithms (GAs)”, whereas, the exact algorithms include branch and cutting, and branch and bound algorithm.

The approximate algorithms cannot find the best solution; however, they can find the solution that is closest to the best within the acceptable time frame, especially when the problem size is large (Madhan & Shanmugapriya, 2024). Meanwhile, the exact algorithms can find the best solution for small-sized problems within a reasonable time frame (Laporte & Martello, 1990; Boltužić, 2012; Satyananda & Wahyuningsih, 2019; Davim & Joshi, 2019; Hameed et al., 2019; Ayop et al., 2020). The CVRP is aimed at determining the routes that should be followed by each of the vehicles to arrive at their final destinations within a distributed network. The aim of this is to reduce the total distance travelled or the number of vehicles.

The CVRP is regarded as COPs because an increase in the number of clients to be served leads to an increase in the number of candidate routing solutions. In other words, the number of candidate routing solutions grows exponentially with the number of clients to be served. This exponential growth immediately goes beyond the processing capacity of current computers. For this reason, it is recommended that approximate methods be used since they do not find optimal solutions, instead, they find near-best solutions that are good enough. Meanwhile, the use of exact algorithms is not advisable due to the high amount of computational time required; this problem has been addressed by many researchers using single objectives (Janjarassuk & Masuchun, 2016; Kuo & Zulvia, 2017; Qiu-ping, 2017; Dhanya et al., 2018; Gupta & Saini, 2018; Aggarwal & Kumar, 2019; Gokalp & Ugur, 2020). Due to the truth that the CVRP is categorized as an NP-difficult trouble, there are not any to be had precise algorithms which could efficiently clear up huge size times inside an affordable computational time. Thus, numerous meta-heuristic and heuristic algorithms have been mainly designed to find approximate methods to the CVRP, along with GAs, ACO, SA, and TS. With the exact algorithms, finding an optimal solution within a reasonable time frame is guaranteed. Here, the solution space is searched systematically to discover the most advantageous solution. Generally, a precise set of rules is not able to find superior answers to massive length issues inside a reasonable time body. Recently, the interest of researchers in phrases of fixing the VRP using ACO has persisted to grow (Janjarassuk & Masuchun, 2016; Kuo & Zulvia, 2017; El Bouyahyiouy & Bellabdaoui, 2017; Chitty et al., 2019). As a metaheuristic, the ACO is inspired using nature, following the metaphor of real ants that have efficiently discovered the shortest paths among their nest and meal sources (Necula et al., 2017; Gupta & Saini, 2018; Dhanya et al., 2018; Xu et al., 2018; Wu et al., 2020).

This research is geared toward: (i) carrying out an extensive survey of strategies that have formerly been used in fixing the CVRP model, (ii) surveying the algorithms that fall beneath the ACO circle of relatives, and (iii) exploring the most suitable algorithm that may be used to decorate the solutions of CVRP model inside an inexpensive time according to the algorithm's accuracy. The structure of the paper is as follows: the review of related literature is introduced in Section 2, in Section 3, the mathematical model for CVRP, section 4 includes a critical analysis of the literature review, CVRP model solutions have been presented in Section 5, whilst, section 6 presents the conclusion.

2 CVRP Model, Complexity, Applications, and Solutions

This phase highlights a thorough assessment of research that focused on the CVRP. These studies have scenarios; the first one provides an overview of the literature on CVRP, while the second scenario reviews the literature on earlier research. This section is organized using the following subsections.

Information Sources

The following databases were searched for the literature examined in this study: "IEEE Xplore, Web of Science, Science Direct, and the Scopus" database. The CVRP model has been discussed in the selection's reasoning, Complexity of the CVRP model, Applications of the CVRP model, and Methods to solve the CVRP model. In addition, presented a critical analysis of the studies that related.

Study Selection

Different types of reports were not included in the examination of the literature, which instead focused on conference papers and journal articles because they likely contain more appropriate and cutting-edge scientific research that is connected to and pertinent to the current survey. The survey employed 876 items in all, and Figure 1 depicts the search procedure using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram as follows.

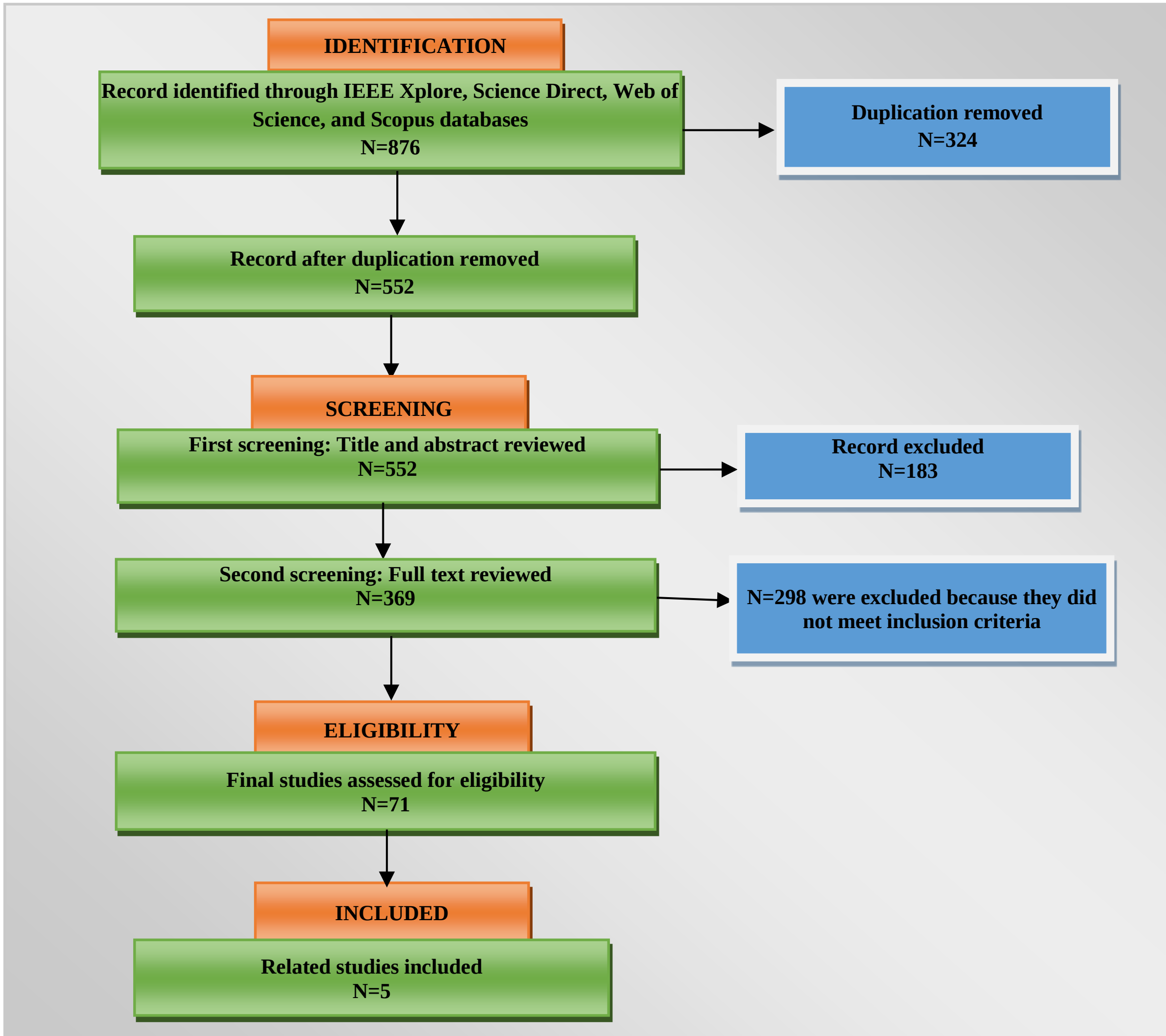

Figure 1: PRISMA Flow Diagram

Initially, 876 records were identified through databases such as "IEEE Xplore, Science Direct, Web of Science, and Scopus". 552 records were left for additional screening after 324 duplicates were eliminated. After reviewing the titles and abstracts of these records, 183 articles that were disqualified for failing to meet the inclusion criteria. This left 369 articles for full-text screening. Out of these, 298 articles were excluded for various reasons: 108 articles discussed types of VRP not relevant to the survey, 47 focused on the ACO algorithm without meeting other inclusion criteria, and 143 were excluded for other reasons. Consequently, 71 studies were assessed for eligibility, from which 5 related studies were included in the final review.

3 Mathematical Model for CVRP

The CVRP is an NP-Hard combinatorial problem that is widely used (Yu et al., 2009). More specifically, it refers to the full range of issues that arise when a collection of automobiles is stationed at one or more depots and follows a set of routes. Typically, there is a maximum carrying capacity for these vehicles and frequently serve clients in various geographic locations. VRP and CVRP are solved using the same methods; the primary distinction is that CVRP has a vehicle capacity limit. It is possible to compare

CVRP to VRP if the total number of customer requests does not go over the vehicles' capacity. The primary goal of the VRP and CVRP is to reduce the overall expense of travelling to serve a group of clients whose needs are known. Because of this, the routes must be planned so that a single truck can visit each customer just once.

- Data on all client demands must be identified early in the traditional CVRP version.
- The fleet of uniformed vehicles comes from a single station.
- The orders cannot be separated, and a customer can only be served by one vehicle.

CVRP refers to a problem whereby the optimal route must be found, and through that route, a set of customers will be visited so that their demands are met; this is subject to several constraints. The basic elements of the following are the CVRP in figure 2:

A complete graph $G = (V, E)$ where $n = |V|$ Denotes number of nods, $V = \{1,2, \ldots, n\}$ represents a set of nodes and $E = \{(i, j): i, j \in V; i \neq j\}$ the collection of edges connecting all of the nodes, and $D = (d_{ij})$ Represents the distance matrix between each node and the depot, and the relationship between each two nodes i, j is computed in Euclidean space by $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$, note that each edge $(i, j) \in E$related to cost d_{ij}, $C = (c_{ij})$ The cost Matrix and the two matrixes (cost, and distances) are related to E, and the Cost function $C: E \to Z^+$ And the major depot is represented by node 0, and the main depot's demand is $d_0 = 0$. The demands of the customers are represented by the rest of the nodes, and each customer i has a demand of a non-negative weight, which is denoted by the demand function $d: V \to Z^+$ And m the set of the vehicles symmetrical existing in the main depot (Xia, 2009) under the following conditions (Kuo & Zulvia, 2017), (Janjarassuk & Masuchun, 2016):

- A vehicle visits a customer just once.
- The capacity of a given vehicle is not exceeded by the total demand for any route.
- The tour begins and ends at the depot.

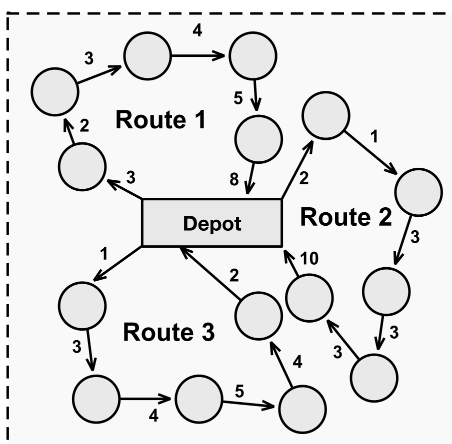

Figure 2: Routes for CVRP that have a Single Central Vehicle Fleet Depot (Boltužić, 2012)

Assumptions

- "The Customer's demand q_i is already established $0 \leq qi \leq$ Q".
- The capacity of the vehicle is limited.

Variables and Barometers

- "Customers V: the number of representatives they have, denoted by $V = \{v_0, v_1, v_2, \ldots, v_n\}$"
- "C_{ij}: the transport cost from the node i to node$j$".
- "Length of road D: must not go beyond a given limit".
- "Q: the total capacity of the vehicle".
- "*m*: total number of vehicles".
- "v_0: the major centre of distribution is the node from the tour starts and ends".
- "*K*: total number of identical vehicles **K**= $\{k1, k2, \ldots, km\}$ based in the main distribution center v_0".

For the first time in 1959, J.H Ramser introduced the mathematical model of the VRP and defined it as follows:

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

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

Subject to the following restrictions:

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

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

$$\sum_{k=1}^{m} \sum_{\substack{i=0 \\ j\neq i}}^{n} x_{ij}^{k} = 1 \quad ; \ j \in \{1, \ldots, \mathrm{n}\} \quad (5)$$

$$\sum_{k=1}^{m} \sum_{\substack{j=0 \\ i\neq j}}^{n} x_{ij}^{k} = 1 \quad ; \ i \in \{1, \ldots, \mathrm{n}\} \quad (6)$$

$$\sum_{j=1}^{n} x_{0j}^{k} \leq 1 \ \forall \ \mathrm{k} \in \mathbf{K} \quad (7)$$

$$\sum_{i=1}^{n} x_{i0}^{k} \leq 1 \ \forall \ \mathrm{k} \in \mathbf{K} \quad (8)$$

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

Equation (1) & (2) represents the function that, given a vehicle constraint as shown in Equation (3), minimizes the overall distance travelled. All the vehicles that leave deport are controlled using

Constraint Equation (4), and they are expected to return once they finish serving customers. With constraints Equatiom (5) and (6), all customers that can be served just once can be observed. More so, to ensure that all vehicles can depart from and return to the depot just once during the entire service period, constraints Equation (7) and (8) can be used. Equation (9) is the main equation used to solve the CVRP, whereby the capacity of the vehicle is assigned according to the goods to be carried, ensuring that the loading capacity of each vehicle is not exceeded.

Complexity of CVRP

The TSP is a special case of CVRP when $m = 1$. In practice, the vehicle routing problem is difficult to resolve compared to the TSP of the same measurement (Lenstra & Kan, 1981; Ramos, 2011; Sun et al., 2017; Isnanto & Nurhayati, 2018). The complexity of the vehicle routing problem has been studied by scientists (Magnanti, 1981; Golden & Wong, 1981) has shown that the CVRP is often unsolvable. The CVRP increases as the number of nodes increases. Since any increase in the number of nodes will exponentially increase their computing time, the problem will be harder to solve, regardless of the use of high-potential computers. Also, given this situation, it may even be impossible to solve the problems due to the large number of calculations required to solve them. Due to the complexity of CVRP which is a popular combinatorial problem, a good number of researchers have increasingly shown interest in researching the problem. The initial proposal of VRP by (Dantzig & Ramser, 1959) was among the most expansively calculated combinatorial optimization problems (Stodola et al., 2014; Khachay & Ogorodnikov, 2018; Gokalp & Ugur, 2019).

Applications of the CVRP of a Daily Nature

Recent developments in technology have allowed the development of a new set is wide and important in our daily lives, including (Wang, 2016; Zhang & Yin, 2017):

- **Services:** Maintenance Services, Emergency Patient Services, Collection of solid industrial waste, Street cleaning and Logistic Services.
- **Transport and Distribution:** includes express Mail Service, Transmission and distribution of energy, transfer of information within networks, bringing staff to work and bringing them home and goods are picked up and delivered.
- **Move people:** Routing the school bus, routing aircraft, routing ambulances to the affected areas and Routing salespeople.
- **Decision support:** It has many other vital applications and all the problems that can be formulated as VRP situations.

Methods Solved by CVRP

There are two categories of approaches that have been used in solving the CVRP; they are referred to as approximate and exact algorithms.

- **Exact Algorithms**

Exact algorithms are the algorithms that always produce the optimal solution set within specific conditions and measurements; several exact algorithms have been designed to solve the CVRP. However, they are only able to work out small-scale cases in an acceptable amount of time. Even though exact methods can be used to generate the ideal solutions to CVRP, an expensive and huge amount of time is required for their computation (Sun et al., 2017; Hameed et al., 2018) Among all the exact algorithms, the most relevant ones are the Branch and cut, and Branch and bound.

- **Approximate Algorithms**

The development of the approximate algorithms by researchers has been necessitated by the inability of the exact algorithms to produce an ideal solution for CVRP by an acceptable time. The aim of this is to overcome the complexity associated with NP-hard problems so that good, approximate, and relatively low-cost solutions can be obtained. However, optimal solutions cannot be achieved within a reasonable. Therefore, in this study, finding solutions that are good enough and effective is preferred (Sun et al., 2017; Golden & Wong, 1981; Hameed et al., 2018). The algorithms that can be used to achieve optimal solutions include “heuristic algorithms and meta-heuristic algorithms”.

Heuristic Algorithms

With “heuristic algorithms”, solutions for optimum approximations can be obtained for large-scale cases in a fast manner and within a reasonable time. Therefore, when these algorithms are used, good solutions can be obtained within a reasonable time frame. However, the solutions are not sufficient enough to hinder the occurrence of local optimization (Wang, 2016), (El Bouyahyiouy & Bellabdaoui, 2017). The three most relevant kinds of heuristic algorithms include the savings algorithm, nearest neighbour algorithm, and Greedy heuristic algorithm.

Metaheuristic Algorithms

This category consists of methods and approaches that are used in finding solutions to COPs based on a certain amount of randomness. Recently, a good number of researchers have directed their research efforts towards designing meta-heuristic algorithms with higher efficiency than the typical extension algorithms. More so, the recently designed algorithms produce solutions of high quality and can be used to solve a wide range of complex problems that are encountered daily. Apart from that, they are also efficient in preventing the occurrence of local optimization (Janjarassuk & Masuchun, 2016; Kuo & Zulvia, 2017; Lu et al., 2017). The algorithms behind the extension include many parameters that need to be well-controlled for each problem before the application process. The metaheuristic has been divided into three categories (Abdel-Basset et al., 2018) as follows:

- Evolutionary such as “Genetic Algorithm (GA)”;
- Physic - Based such as “Simulated Annealing Algorithm (SAA)”; and
- Swarm Intelligence like “Ant colony optimization (ACO)”.

Through the analysis of the related literature which was carried out to find an approach that can be used in solving the problem, the swarm intelligence category was found to be the most suitable for solving the problem, especially when ACO is being used. This is because it corresponds to nature. There is a wide range of algorithms that can be classified under the ACO family including, “Ant Colony System (ACS), Ant System (AS), Max-Min Ant System (ASMM), Elitist Ant System (EAS), and Rank-Based Ant System”. Table 1 below shows these types of algorithms in addition to the differences between:

Table 1: Variations Among the ACO Family of Algorithms

"Type of Algorithm"	**"Construction of Tour"**	**"Evaporation of the Pheromone"**	**"Update of the Pheromone"**
"AS"	The randomness of the probability equation	Every edge is diminished using a fixed parameter ρ	The pheromone is deposited on each edge that an ant visit.
"EAS"	The probability equation is arbitrary.	A constant parameter ρ is used to minimize all edges.	The best tour to date is available with Pheromone.
"AS_{rank}"	The probability equation is unpredictable.	Using a constant parameter ρ, all edges are decreased.	The ants are grouped based on how long the tour lasts, and the pheromone is placed based on each ant's rank.
"ASMM"	The randomness of the probability equation	The constant parameter ρ is used to decrease all edges	In the domain [τ_{mim} τ_{max}], through the greatest ant version or the best ant to date
"ACS"	Semi-random probability equation	The edges that belong to the greatest tour to date are diminished	The edges of the greatest tour to date have pheromones placed on them

The recent ACO family algorithms that have been employed to enhance CVRP model solutions have been looked at in this literature review and are listed in Table 2.

Table 2: Recent Algorithms from the ACO Family

Reference	**Title**	**Algorithm**
(Sedighpour et al., 2011)	"An Optimization Algorithm for the Capacitated Vehicle Routing Problem Based on Ant Colony System"	ACS
(Lee et al., 2012)	"Solved CVRP using the Ant Colony Optimization"	Rank-Based Ant System Algorithm
(Stodola et al., 2014)	"Solved the CVRP through the use of the Ant Colony Optimization Algorithm"	Ant System Algorithm
(Lee et al., 2010)	"An enhanced ant colony optimization (EACO) applied to capacitated vehicle routing problem"	ACS Algorithm
(Gupta & Saini, 2018)	"Employed the use of an Enhanced Ant Colony Optimization Technique to solve the CVRP"	Rank-Based Ant System Algorithm

4 Critical Analysis of the Literature Review

The above table includes relevant research projects that have addressed the CVRP (single objective) and the CVRPs were solved using an ACO algorithm. The critical analysis has been presented as follows:

- All algorithms were used to deal with CVRP with a single objective (distance) although there are other objectives such as reducing the number of vehicle, reducing of emission of CO2, ...etc.
- Most studies found initialized solutions using heuristic methods such as the nearest neighbour heuristic.
- Most of the studies used the original transition equation, and others improved this equation through the use of algorithms such as saving heuristics.
- There are two studies that addressed the ACS; one of them used the original local pheromone update without improvement and the other improved it.

- In the local search section, some techniques were used such as 2-opt, 3-opt, and swap.
- The global pheromone update was improved in two studies.
- Although there are many techniques used to adjust parameters, these methods have not been taken up by the related studies.
- The number of solutions reached by the related studies was 50 out of 263, although most of those studies provided improvements to the methods that were used for CVRP.
- The process of the structure of the solution depends on moving from one node to another by benefiting from the experience of the complete solution from previous iterations, and the use of the experience of the sub-paths was not addressed.

5 CVRP Model Solutions

The studies that were taken into consideration in the literature review part and listed in Table 2 are covered in this section. Furthermore, this section is divided into two subsections: the analysis is presented in the first subsection, and the comparison and discussion are presented in the second. Furthermore, after analyzing and discussing the results of earlier research, a comparison based on accuracy (best gap) was conducted to identify the most effective strategy.

Analysis Process

The CVRP database cases in CVRPLIB (http://vrp.atd-lab.inf.puc-rio.br/index.php/en/) were used to test all of the algorithms in Table 2, and the CVRP database mentions two different kinds of solutions. Optimal Solution (OPT) is the first type, while the Best-Known Solution (BKS) is the second. However, CVRPLIB contains two sets of difficulties that make any suggested approach difficult to solve. Thirteen OPT cases and sixteen BKS instances are included in this study. The accuracy of the algorithms has been determined using the following equation (10):

$$Gap = (CBest - C^*) / C^* \times 100 \qquad (10)$$

Where C^* is the most well-known value extracted from CVRPLIB, and C is the best solution value discovered by the suggested algorithm. Furthermore, the quality of the solutions obtained by applying the algorithms can be influenced by the set of algorithm parameters. To determine the most suitable collection of parameter values that yield desired outcomes, a significant number of experiments must be conducted.

Comparison and Discussion

In this section, a discussion on the results that were obtained by the following algorithms has been discussed:

- **EACO-L** refers to the algorithm which was presented by (Lee et al., 2010).
- **ACS-S** means the algorithm which was suggested by (Yousefikhoshbakht & Sedighpour, 2011).
- **ACO-L** means the algorithm which was proposed by (Lee et al., 2012).
- **ACO-S** refers to the algorithm that had been introduced by (Stodola et al., 2014).
- **ACO-G** means the algorithm which was suggested by (Gupta & Saini, 2018).
- **ACS** means the algorithm which was suggested (Mutar et al., 2020).

The outcomes of applying these algorithms are reviewed and shown for both the "Best-Known Solution (BKS) and the optimal solutions (OPT)". As seen in Table 2, 50 instances of the CVRP database were subjected to the algorithms suggested in the literature. The EACO-L algorithm got from CTM case 8 OPT out of 13, but it did not obtain BKS. Furthermore, this algorithm addressed the Golden case but failed to obtain OPT, and from this case, one instance of BKS was obtained. The ACS-S algorithm reached 4 instances OPT out of 13 OPT and was unable to get BKS of the CTM case, while the same algorithm got 8 instances OPT out of 12 OPT and was unable to get BKS also from the Tai case.

The ACO-S algorithm obtained one instance OPT out of 13 OPT, but this algorithm was unable to reach a BKS of the CTM case. The ACO-G algorithm took 13 instances out of 13 OPT and got one instance OPT of it, but this algorithm did not reach the BKS to CTM case, while this algorithm got 2 instances OPT out of 3 OPT of set F. ACO-L algorithm got 2 OPT out of 13, and also it did not obtain BKS of CTM case. Finally, the ACS algorithm presented in the study of (Mutar et al., 2020) obtained 12 OPT out of 13 OPT and 1 BKS out of 1 BKS from the case CTM, while it got 6 OPT out of 6 OPT from the Golden case, got 12 BKS out of 14 BKS from the same case, set F obtained 3 OPT out of 3 OPT, got 12 OPT out of 12 OPT and 1 BKS out of 1 BKS from the case Tai.

Table 3: Optimal and Best-Known Solutions obtained by the studies in Table 2

No.	Name of Problem	Number of OPT	Number of BKS	EACH-L		ACS-S		ACO-L		ACO-S		ACO-G		ACS	
				OPT	BKS	OPT	BKS	OPT	BKS	OPT	BKS	OPT	BKS	OPT	BKS
1	CTM	13	1	8	-	4	-	2	-	1	-	1	-	12	1
2	Golden	6	14	-	-	-	-	-	-	-	-	-	-	6	12
3	Set F	3	-	-	-	-	-	-	-	-	-	2	-	3	-
4	Tai	12	1	-	-	8	-	-	-	-	-	-	-	12	1
Sum		**34**	**16**	**8**	**-**	**12**	**-**	**2**	**-**	**1**	**-**	**3**	**-**	**33**	**14**

Table 3 is graphically represented as follows in Figure 3:

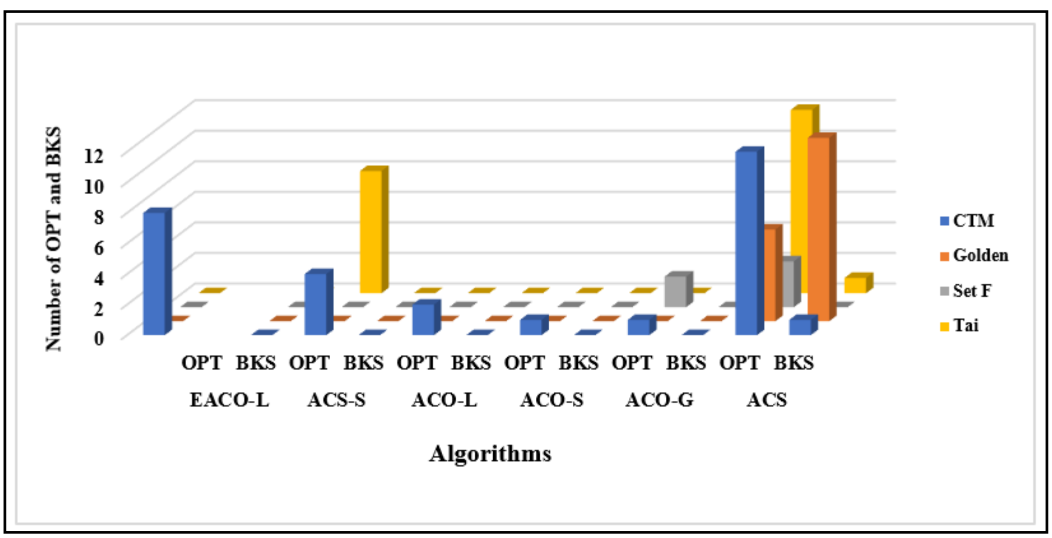

Figure 3: Graphical Representation of Table 3

6 Conclusion

In this look, a survey of the Capacitated Vehicle Routing Problem (CVRP) has been performed, and the CVRP model has been analysed as nicely. More so a number of the packages of the CVRP version have been highlighted, imparting a clean photograph of the techniques that have been used to remedy the CVRP model. The criterion for comparison between the algorithms covered in this study is the accuracy (gap) of those algorithms which were applied to 50 instances of CVRP data. The results of these comparisons show that the performance of the Ant Colony System (ACS) was better than the other algorithms. About the future, it is suggested that the ACS algorithm for multi-Objective should be improved to solve the multi-objective capacitated vehicle routing problem.

References

[1] Abdel-Basset, M., Manogaran, G., Rashad, H., & Zaied, A. N. H. (2018). A comprehensive review of quadratic assignment problem: Variants, hybrids, and applications. *Journal of Ambient Intelligence and Humanized Computing, 9*(4), 1207–1232. https://doi.org/10.1007/s12652-018-0917-x

[2] Adewumi, A. O., & Adeleke, O. J. (2018). A survey of recent advances in vehicle routing problems. *International Journal of System Assurance Engineering and Management*, *9*, 155-172. https://doi.org/10.1007/s13198-016-0493-4

[3] Aggarwal, D., & Kumar, V. (2019). Performance evaluation of distance metrics on firefly algorithm for VRP with time windows. *International Journal of Information Technology*, *13*(6), 2355-2362. https://doi.org/10.1007/s41870-019-00387-7

[4] Archetti, C., & Speranza, M. G. (2014). A survey on matheuristics for routing problems. *Operational Research*, *14*(3), 223–246. https://doi.org/10.1007/s13675-014-0030-7

[5] Ayoola, J. A., Asani, E. O., Okeyinka, A. E., & Ayegba, P. O. (2020, March). Towards Comparative Analysis of Branch-And-Bound and Nearest Neighbour Algorithms. In *2020 International Conference in Mathematics, Computer Engineering and Computer Science (ICMCECS)* (pp. 1-5). IEEE. https://doi.org/10.1109/ICMCECS47690.2020.240901

[6] Ayop, S. F. M., Othman, L. S., & Yusuf, M. M. (2020). Ant colony optimization using different heuristic strategies for capacitated vehicle routing problem. *IOP Conference Series: Materials Science and Engineering*, 864, 012082. https://doi.org/10.1088/1757-899x/864/1/012082

[7] Babenko, V., Danilov, A., Vasenin, D., & Krysanov, V. (2021). Parametric Optimization of the Structure of Controlled High-voltage Capacitor Batteries. *Archives for Technical Sciences*, *1*(24), 9–16. https://doi.org/10.7251/afts.2021.1324.009B

[8] Barhoumi, E. M., Charabi, Y., & Farhani, S. (2024). Detailed guide to machine learning techniques in signal processing. *Progress in Electronics and Communication Engineering*, *2*(1), 39–47. https://doi.org/10.31838/PECE/02.01.04

[9] Beresneva, E., & Avdoshin, S. (2018). Analysis of mathematical formulations of capacitated vehicle routing problem and methods for their solution. *Proceedings of the Institute for System Programming of the Russian Academy of Sciences* , *30*(3), 233-250.

[10] Bhuvaneswari, M., Eswaran, S., & Rajagopalan, S. P. (2018). A survey of vehicle routing problem and its solutions using bio-inspired algorithms. *International Journal of Pure and Applied Mathematics*, *118*(9), 259-264.

[11] Boltužić, F. (2012). A hybrid ant colony system approach for the capacitated vehicle routing problem and the capacitated vehicle routing problem with time windows. *Vehicle Routing Problem*, 57–70.

[12] Cheikh-Graiet, S. B., Dotoli, M., & Hammadi, S. (2020). A Tabu Search based metaheuristic for dynamic carpooling optimization. *Computers & Industrial Engineering*, *140*, 106217. https://doi.org/10.1016/j.cie.2019.106217

[13] Chitty, D. M., Wanner, E., Parmar, R., & Lewis, P. R. (2019, July). Scaling ACO to large-scale vehicle fleet optimisation via Partial-ACO. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion* (pp. 97-98). https://doi.org/10.1145/3319619.3322048

[14] Choong, S. S., Wong, L. P., & Lim, C. P. (2019). An artificial bee colony algorithm with a modified choice function for the traveling salesman problem. *Swarm and Evolutionary Computation, 44,* 622–635. https://doi.org/10.1016/j.swevo.2018.08.004

[15] Cook, W. J., & Cunningham, W. H. (1998). Book reviews. *Bulletin of the Menninger Clinic, 75*(11), 273–274. https://doi.org/10.1521/bumc.2011.75.1.94

[16] Dantzig, G. B., & Ramser, J. H. (1959). The truck dispatching problem. *Management science*, *6*(1), 80-91. https://doi.org/10.1287/mnsc.6.1.80

[17] Davim, J. P., & Joshi, S. N. (2019). Advances in computational methods in manufacturing. *Lecture Notes on Multidisciplinary Industrial Engineering*.

[18] Dhanya, K. M., Kanmani, S., & Hanitha, G. (2018). Hybrid crow search-ant colony optimization algorithm for capacitated vehicle routing problem. *Springer Singapore*. https://doi.org/10.1007/978-981-13-1936-5

[19] Dhanya, K. M., Kanmani, S., Hanitha, G., & Abirami, S. (2018). Hybrid crow search-ant colony optimization algorithm for capacitated vehicle routing problem. In *Soft Computing Systems: Second International Conference, ICSCS 2018, Kollam, India, April 19–20, 2018, Revised Selected Papers 2* (pp. 46-52). Springer Singapore. https://doi.org/10.1007/978-981-13-1936-5_5

[20] Diaby, M., Karwan, M. H., & Sun, L. (2021). On modelling hard combinatorial optimisation problems as linear programs: refutations of the 'unconditional impossibility' claims. *International Journal of Operational Research*, *40*(2), 261-278. https://doi.org/10.1504/IJOR.2021.113505

[21] El Bouyahyiouy, K., & Bellabdaoui, A. (2017). An ant colony optimization algorithm for solving the full truckload vehicle routing problem with profit. *2017 International Colloquium on Logistics and Supply Chain Management (LOGISTIQUA)*, 142–147. https://doi.org/10.1109/LOGISTIQUA.2017.7962888

[22] Farhanna, M., Firdaus, W., & Mahmudy, W. F. (2018). An improved simulated annealing for the capacitated vehicle routing problem (CVRP). *International Journal of Advanced Engineering and Science*, 9(3).

[23] Gokalp, O., & Ugur, A. (2019). A multi-start ILS–RVND algorithm with adaptive solution acceptance for the CVRP. *Soft Computing*, *24*(4), 2941–2953. https://doi.org/10.1007/s00500-019-04072-6

[24] Golden, B. L., & Wong, R. T. (1981). Capacitated arc routing problems. *Networks*, *11*(3), 305-315. https://doi.org/10.1002/net.3230110308

[25] Gupta, A., & Saini, S. (2018). On solutions to capacitated vehicle routing problem using an enhanced ant colony optimization technique. In *Networking Communication and Data Knowledge Engineering: Volume 1* (pp. 257-266). Springer Singapore. https://doi.org/10.1007/978-981-10-4585-1_21

[26] Hameed, A. S., Aboobaider, B. M., Choon, N. H., & Mutar, M. L. (2018). Review the methods to solve combinatorial optimization problems particularly the quadratic assignment model. *International Journal of Engineering & Technology, 7*, 15–20.

[27] Hameed, A. S., Aboobaider, B. M., Choon, N. H., Mutar, M. L., & Bilal, W. H. (2018). A comparative study between the branch and cut algorithm and ant colony algorithm to solve the electric meter reader problem in rural areas. *Opcion, 34*(86), 1525-1539.

[28] Hameed, A. S., Aboobaider, B. M., Mutar, M. L., & Choon, N. (2019). An efficient crossover operator for quadratic assignment problem based on discrete differential evolution algorithm. *International Journal of Advanced Science and Technology*, 28(8), 591–601.

[29] Hameed, A. S., Mohd, B., Hea, N., & Lafta, M. (2018). Improved discrete differential evolution algorithm in solving quadratic assignment problem for best solutions. *International Journal of Advanced Computer Science and Applications, 9*(12), 434–439. https://doi.org/10.14569/ijacsa.2018.091261

[30] Hameed, A., Aboobaider, B. M., Mutar, M. L., & Choon, N. H. (2020). A new hybrid approach based on discrete differential evolution algorithm to enhancement solutions of quadratic assignment problem. *International Journal of Industrial Engineering Computations*, *11*(1), 51-72. https://doi.org/10.5267/j.ijiec.2019.6.005

[31] Isnanto, R. R., & Nurhayati, O. D. (2018, March). Using CVRP model in designing decision support system for optimizing distribution route and amounts of utilized vehicles. In *2018 International Conference on Information and Communications Technology (ICOIACT)* (pp. 789-792). IEEE. https://doi.org/10.1109/ICOIACT.2018.8350799

[32] Janjarassuk, U., & Masuchun, R. (2016, December). An ant colony optimization method for the capacitated vehicle routing problem with stochastic demands. In *2016 International Computer Science and Engineering Conference (ICSEC)* (pp. 1-5). IEEE. https://doi.org/10.1109/ICSEC.2016.7859921

[33] Khachay, M., & Ogorodnikov, Y. (2018, July). Efficient PTAS for the Euclidean CVRP with time windows. In *International Conference on Analysis of Images, Social Networks and Texts* (pp. 318-328). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-11027-7_30

[34] Kheirkhahzadeh, A. A., & Barforoush, M. (2009). A hybrid algorithm for the vehicle routing problem. In *2009 IEEE Congress on Evolutionary Computation* (pp. 1791–1798). https://doi.org/10.1109/CEC.2009.4983158

[35] Korte, B. (2017). *Combinatorial optimization*. Springer.

[36] Kuo, R. J., & Zulvia, F. E. (2017). Hybrid genetic ant colony optimization algorithm for capacitated vehicle routing problem with fuzzy demand: A case study on garbage collection system. *2017 4th International Conference on Industrial Engineering and Applications (ICIEA)*, 244–248. https://doi.org/10.1109/IEA.2017.7939215

[37] Laporte, G., & Martello, S. (1990). The selective capacitated vehicle routing problem. *Operations Research*, 26, 193–207.

[38] Lee, C. Y., Lee, Z. J., Lin, S. W., & Ying, K. C. (2010). An enhanced ant colony optimization (EACO) applied to capacitated vehicle routing problem. *Applied Intelligence*, *32*, 88-95. https://doi.org/10.1007/s10489-008-0136-9

[39] Lee, L. S., Majid, Z. A., & Seow, H. V. (2012). Ant colony optimization for capacitated vehicle routing problem. *Applied Mathematical Modelling*, *36*(6), 846–852.

[40] Lenstra, J. K., & Kan, A. R. (1981). Complexity of vehicle routing and scheduling problems. *Networks*, *11*(2), 221-227. https://doi.org/10.1002/net.3230110211

[41] Lima, P. H. T., & Schimit, S. J. A. (2018). A hybrid approach based on genetic algorithm and nearest neighbor heuristic for solving the capacitated vehicle routing problem. *Acta Scientiarum - Technology*, 40. https://doi.org/10.4025/actascitechnol.v40i1.36708

[42] Lu, D. N., Nguyen, T. H., Nguyen, D. N., & Nguyen, H. N. (2017, January). A novel traffic routing method using hybrid Ant Colony System based on genetic algorithm. In *2017 International Conference on Information Networking (ICOIN)* (pp. 584-589). IEEE. https://doi.org/10.1109/ICOIN.2017.7899563

[43] Madhan, K., & Shanmugapriya, N. (2024). Efficient Object Detection and Classification Approach Using an Enhanced Moving Object Detection Algorithm in Motion Videos. *Indian*

Journal of Information Sources and Services, *14*(1), 9–16. https://doi.org/10.51983/ijiss-2024.14.1.3895

[44] Magnanti, T. L. (1981). Combinatorial optimization and vehicle fleet planning: Perspectives and prospects. *Networks*, *11*(2), 179-213. https://doi.org/10.1002/net.3230110209

[45] Messaoud, E., & Alaoui, A. E. (2017, April). Hybrid ant colony system algorithm for the vehicle routing problem with dynamic customers and traffic factors. In *2017 Intelligent Systems and Computer Vision (ISCV)* (pp. 1-4). IEEE. https://doi.org/10.1109/ISACV.2017.8054979

[46] Mutar, A. Y., Lafta, M., Aboobaider, B. M., & Hameed, A. S. (2019). Enhancing solutions of capacity vehicle routing problem based on an improved ant colony system algorithm. *International Journal of Advanced Science and Technology*, 11, 1362–1374.

[47] Mutar, M. L., Aboobaider, B. M., & Hameed, A. S. (2017). Review paper on vehicle routing problem and future research trend. *International Journal of Engineering & Technology*, *12*(22), 12279–12283.

[48] Mutar, M. L., Burhanuddin, M. A., Hameed, A. S., Yusof, N., & Mutashar, H. J. (2020). An efficient improvement of ant colony system algorithm for handling capacity vehicle routing problem. *International Journal of Industrial Engineering Computations*, 11(4), 549–564. https://doi.org/10.5267/j.ijiec.2020.4.006

[49] Necula, R., Breaban, M., & Raschip, M. (2017, June). Tackling dynamic vehicle routing problem with time windows by means of ant colony system. In *2017 IEEE Congress on Evolutionary Computation (CEC)*, 2480-2487. https://doi.org/10.1109/CEC.2017.7969606

[50] Ngisomuddin, M. A. R., & Satyananda, D. (2020). Perturbation operator analysis on ILS-RVND algorithm to solve CVRP. *AIP Conference Proceedings*, 2215, 1–7. https://doi.org/10.1063/5.0000549

[51] Pintea, C. M. (2014). *Advances in bio-inspired computing for combinatorial optimization problems*. Springer Berlin Heidelberg.

[52] Pishvaee, M. S., & Rabbani, M. (2011). Advances in engineering software: A graph-theoretic-based heuristic algorithm for responsive supply chain network design with direct and indirect shipment. *Advances in Engineering Software*, *42*(3), 57–63. https://doi.org/10.1016/j.advengsoft.2010.11.001

[53] Punriboon, C., So-In, C., Aimtongkham, P., & Rujirakul, K. (2019). A Bio-Inspired Capacitated Vehicle-Routing Problem Scheme Using Artificial Bee Colony with Crossover Optimizations. *Journal of Internet Services and Information Security*, *9*(3), 21-40.

[54] Qiu-ping, Y. T. N. I. (2017). An ant colony algorithm for capacitated vehicle routing problem. *International Conference on Social Science and Management*, 570–575.

[55] Ramos, J. A. (2011). *Solving the Extended Vehicle Scheduling Problem with Metaheuristics* (Master's thesis, Universidade do Porto (Portugal)).

[56] Redi, A. A. N. P., & Satyananda, D. (2020). Simulated annealing algorithm for solving the capacitated vehicle routing problem: A case study of pharmaceutical distribution. *Jurnal Sistem dan Manajemen Industri*, 4(1), 41–49. https://doi.org/10.30656/jsmi.v4i1.2215

[57] Rosnelly, R., Riza, B.S., Wahyuni, L., Haryanto, S.E.V., & Prasetio, A. (2022). Vehicle Detection Using Machine Learning Model with the Gaussian Mixture Model (GMM). *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*, *13*(4), 233-243. https://doi.org/10.58346/JOWUA.2022.I4.016

[58] Satyananda, D., & Wahyuningsih, S. (2019, October). VND in CVRP, MDVRP, and VRPTW cases. In *Journal of Physics: Conference Series* (Vol. 1320, No. 1, p. 012025). IOP Publishing. https://doi.org/10.1088/1742-6596/1320/1/012025

[59] Sheldon, F., Cicotti, P., Traversa, F. L., & Di Ventra, M. (2020). Stress-testing memcomputing on hard combinatorial optimization problems. *IEEE Transactions on Neural Networks and Learning Systems*, *31*(6), 2222–2226. https://doi.org/10.1109/TNNLS.2019.2927480

[60] Speranza, M. G. (2018). Trends in transportation and logistics. *European Journal of Operational Research*, *264*(3), 830–836. https://doi.org/10.1016/j.ejor.2016.08.032

[61] Stodola, P., Mazal, J., Podhorec, M., & Litvaj, O. (2014). Using the Ant Colony Optimization algorithm for the capacitated vehicle routing problem. *Proceedings of the 16th International Conference on Mechatronics (Mechatronika 2014)*, 503–510. https://doi.org/10.1109/MECHATRONIKA.2014.7018311

[62] Suhail, P., & Kokila, G. (2024). Security Documents: Facial Periocular Region-based Unique Id Generation and One-to-one Verification. *International Journal of Advances in Engineering and Emerging Technology*, *15*(2), 1–15.

[63] Sun, X., Fu, Y., & Liu, T. (2017, March). A hybrid ACO algorithm for capacitated vehicle routing problems. In *2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)* (pp. 510-514). IEEE. https://doi.org/10.1109/IAEAC.2017.8054067

[64] Syahputra, R. H., Komarudin, K., & Destyanto, A. R. (2018). Optimization of distribution route with vehicle routing problem with transshipment facilities (VRPTF). *Proceedings of the 3rd International Conference on Computational Intelligence and Applications (ICCIA 2018)*, 11–15. https://doi.org/10.1109/ICCIA.2018.00010

[65] Vidal, T., Laporte, G., & Matl, P. (2019). A concise guide to existing and emerging vehicle routing problem variants. *Transportation Research Part B: Methodological*, *123*, 1–37.

[66] Wang, X. C. (2016). Novel ant colony optimization methods for simplifying solution construction in vehicle routing problems. *IEEE Transactions on Intelligent Transportation Systems*, *17*(11), 3132–3141. https://doi.org/10.1109/TITS.2016.2542264

[67] Wang, Y. P. (2013). Adaptive ant colony algorithm for the vrp solution of logistics distribution. *Research Journal of Applied Sciences, Engineering and Technology*, *6*(5), 807-811.

[68] Wang, Z. (2016, April). Application of VRP Model in the Transport of Water Resources in Henan Province. In *2016 3rd International Conference on Materials Engineering, Manufacturing Technology and Control* (pp. 696-698). Atlantis Press. https://doi.org/10.2991/icmemtc-16.2016.139

[69] Wu, Y., Pan, F., Li, S., Chen, Z., & Dong, M. (2020). Peer-induced fairness capacitated vehicle routing scheduling using a hybrid optimization ACO–VNS algorithm. *Soft Computing*, *24*(3), 2201–2213. https://doi.org/10.1007/s00500-019-04053-9

[70] Xia, M. (2009, November). A modified Ant Colony Algorithm with local search for capacitated vehicle routing problem. In *2009 Asia-Pacific Conference on Computational Intelligence and Industrial Applications (PACIIA)* (Vol. 2, pp. 84-87). IEEE. https://doi.org/10.1109/PACIIA.2009.5406543

[71] Xu, H., Pu, P., & Duan, F. (2018). Dynamic vehicle routing problems with enhanced ant colony optimization. *Discrete Dynamics in Nature and Society*, *2018*(1), 1295485. https://doi.org/10.1155/2018/1295485

[72] Yousefikhoshbakht, M., & Sedighpour, M. (2011). An optimization algorithm for the capacitated vehicle routing problem based on ant colony system. *Australian Journal of Basic and Applied Sciences*, *5*(12), 2729-2737.

[73] Yu, B., Yang, B., & Yao, Z. Z. (2009). An improved ant colony optimization for vehicle routing problem. *European Journal of Operational Research*, *196*(1), 171–176. https://doi.org/10.1016/j.ejor.2008.02.028

[74] Zhang, X., & Yin, Y. (2017, July). Research on the application of genetic algorithm in logistics location. In *2017 4th International Conference on Information, Cybernetics and Computational Social Systems (ICCSS)* (pp. 435-438). IEEE. https://doi.org/10.1109/ICCSS.2017.8091454

Authors Biography

Asaad Shakir Hameed B.Sc. Degree in Education/sciences of Mathematics from the College of Education, University of Basrah, Iraq, in 2001. Master of Mathematics Science, specialization in Mathematical analysis from the College of Science, University of Tishreen, Syria, in 2012 and a PhD in Mathematics / Modelling from Universiti Teknikal Malaysia Melaka (UTeM), Malaysia, in 2021. Currently job as Deputy Dean for Administrative Affairs of the Engineering College at Al-Ayen Iraqi University. Research interests include: Operations Research (OR); Reliable Communication Network Design (RCND); Metaheuristic Algorithms (MAs); and Combinatorial Optimization Problems (COPs).

Haiffa Muhsan B. Alrikabi B.Sc. Degree in Education/sciences of Mathematics from the College of Education, University of Basrah, Iraq, in 2001. Master of Mathematics Science, specialization in Differenational Equation from the College of Education, University of Al-Mustansirirya, in 2005 and a Ph.D. in Functional analysis from University of Mazandaran, in 2019. Currently job as Assistant Professor at the College of Education for Pure Sciences, Thi-Qar University.

Abeer A. Abdul–Razaq B.Sc. Degree in Mathematics from Thi-Qar University in 2001 Master of Mathematics from the University of Baghdad, College of Education Ibn Al-Haytham 2005. PhD in Mathematics from the University of Babylon, College of Education for Pure Sciences 2021 General specialization Mathematics Subspecialization Reliability of network.

Huda Karem Nasser B.Sc. Degree in Education/sciences of Mathematics from the College of Education for Pure Sciences, University of Thi-Qar, Iraq. Master of Mathematics Science, specialization in Fiinite Element from The College of Education for Pure Sciences, in 2018 and a Ph.D. in Mathematics / Mathematical statistics from University of Kufa, Iraq, in 2024. Currently job as Teacher at the Iraqi Ministry of Education.

Modhi Lafta Mutar B.Sc. Degree in Education/sciences of Mathematics from the College of Education, University of Basrah, Iraq, in 2001. Master of Mathematics Science, specialization in Mathematical analysis from the College of Science, University of Tishreen, Syria, in 2012 and a Ph.D. in Mathematics / Modelling from Universiti Teknikal Malaysia Melaka (UTeM), Malaysia, in 2021. Currently job as Deputy Dean for Administrative Affairs of the College of Education at Al-Ayen Iraqi University. Research interests include: Operations Research (OR); Ant Colony Optimization (ACO); and Combinatorial Optimization Problems (COPs).

Hala Hilal Katea B.Sc. Degree in Biomedical Engineering 2023 from Thi-Qar University - Iraq. Current position: Research Assistant in the Department of Biomedical Engineering at Ayen Iraqi University.