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A New Approach for Solving the Disruption in Vehicle Routing Problem During the Delivery

A Comparative Analysis of VRP Meta-Heuristics

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This thesis is submitted to the Faculty of Computing at Blekinge Institute of Technology in partial fulfillment of the requirements for the degree of Master of Science in Computer Science. The thesis is equivalent to 20 weeks of full-time studies.

I declare that I am the sole author of this thesis and have not used any sources other than those listed in the bibliography and identified as references. I further declare that I have not submitted this thesis at any other institution to obtain a degree.

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Abstract

Context. The purpose of this research paper is to describe a new approach for solving the disruption in the vehicle routing problem (DVRP) which deals with the disturbance that will occur unexpectedly within the distribution area when executing the original VRP plan. The paper then focuses further on the foremost common and usual problem in real-time scenarios i.e., vehicle-breakdown part. Therefore, the research needs to be accomplished to deal with these major disruption in routing problems in transportation.
Objectives. The study first investigates to find suitable and efficient meta-heuristic techniques for solving real-time vehicle routing problems than an experiment is performed with the chosen algorithms which might produce near-optimal solutions. Evaluate the performance of those selected algorithms and compare the results among each other.
Methods. To answer research questions, firstly, a literature review has been performed to search out suitable meta-heuristic techniques for solving vehicle routing problems. Then based on the findings an experiment is performed to evaluate the performance of selected meta-heuristic algorithms.
Results. Results from the literature review showed that the meta-heuristic approaches such as. Tabu Search, Ant Colony Optimization and Genetic Algorithm are suitable and efficient algorithms for solving real-time vehicle routing problems. The performance of those algorithms has been calculated and compared with one another with standard benchmarks.
Conclusions. The performance of a Tabu Search algorithm is best among the other algorithms, followed by Ant Colony Optimization and Genetic Algorithm. Therefore, it has been concluded that the Tabu Search is the best algorithm for solving real-time disruption problems in VRP. The results are similar to the performance comparison of the selected algorithms and standard benchmarks are presented within the research.

Keywords: vehicle routing problem, disruption, vehicle breakdown, solution algorithms, meta-heuristics, Tabu Search.

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List of Abbreviations

DVRP - Disruption in Vehicle Routing Problem

VRP - Vehicle Routing Problem

CVRP - Capacitated Vehicle Routing Problem

TSP - Traveling Salesman Problem

CVRPLIB - Capacitated Vehicle Routing Problem Library

TS - Tabu Search

ACO - Ant Colony Optimization

GA - Genetic Algorithm

GRASP - Greedy Randomize Adaptive Search Procedure

OR - Operational Research

CO - Combinatorial Optimization

EV's - Extra Vehicles

ANOVA - Analysis of Variance

RQ - Research Question

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Chapter 1

Introduction

1.1 Context and Motivation

The future of the world is dedicated to automobiles and artificial intelligence. So, we can use them together to deal with minimizing the usage of scarce and valuable resources in the transport or logistics industry. The main goal of logistics is optimization. Optimization is performed by solving complex computing problems, routing, and many other instances related to problem-solving [1]. There are many ways to solve a problem that needs to be optimized, based on the type of problems such as standard and usual methods, techniques, strategies. In this thesis, research is performed regarding the disruption in vehicle routing problem. Determining the optimal solution to VRP is an NP-hard problem which means that it is almost difficult to obtain a perfectly optimized solution. So, the size of the problems, that can be solved, optimally, by using mathematical optimization or combinatorial optimization tasks. This paper further investigates all solution approaches and how they can be helpful being implemented real-time applications by comparing with other approaches that aim to solve disruption in VRP which have been proven to be highly effective and efficient [2].

There is a vast need for research on routing problems in a day to day life with numerous classifications and several factors. The demands and travel times are known and fixed for scheduling and routing problems, and many techniques have been developed to produce near-optimal or optimal solutions. Due to optimize routing solutions, many researchers have been working with scientific methods by combining and innovating new solutions for optimizing vehicle routing. Researchers expanding the solutions of disruption problems in VRP (DVRP) by using the standard techniques and combining them with a functional logic. As years passed by, research regarding these routing problems began to get more problematic and difficult due to the extension of various constraints to the problem like capacity limit, delays in delivery, non-uniform vehicles, annual cost, time limit, etc. These factors added more significance to vehicle routing problems, and researchers worldwide found interest in this area [2].

1.2 Disruption in Vehicle Routing Problem (DVRP)

What is Disruption?

Disruption is the disturbance or problem which interrupts an activity or process. The ability to deal with the disturbance that is going to happen without knowing in advance is the main feature of disruption management.

Disruption in Vehicle Routing Problems (DVRP) plays a significant role in the distribution area, because of unexpected events, such as [3] :

- Customer demand increases or order canceling,
- Time of delivery changes (pre or postponement),
- Disabled roads by traffic or accidents or blocking, and
- Vehicle breakdowns

The Disruptions has also been addressed with machine learning approaches [4]. DVRP aims to find a feasible solution to minimize the negative effect. It does not aim to increase customer satisfaction, but it attempts to minimize customer dissatisfaction. And, it does not aim to reduce the travel time, but it reduces the increase in travel time. It does not aim to reduce the total costs, but it minimizes the sum of annual costs. Schedulers will respond to different kinds of situations in disruptions when they are experienced. But they make spontaneous decisions for the solutions to make an adjustment simple, which may unsuitable for the large-scale problems and may not be a feasible solution. The distribution state constantly changes with the distribution process [5].

Figure 1.1 shows the distribution state constantly changes from distribution state at time t1, t2, and final. Let us assume, demand is increasing at time t1 and produced a new routing scheme for time t1. After the readjustment, the final solution is the disruption solution at time t2. At time t2 let us again assume there is a disruption problem with vehicle breakdown and provided the final solution for the routing scheme. Many different solutions and algorithms may be needed to solve the disruption problems in real-time. Therefore, developing a solution and algorithm by predefined with a specific disruption, which works for a feasible solution.

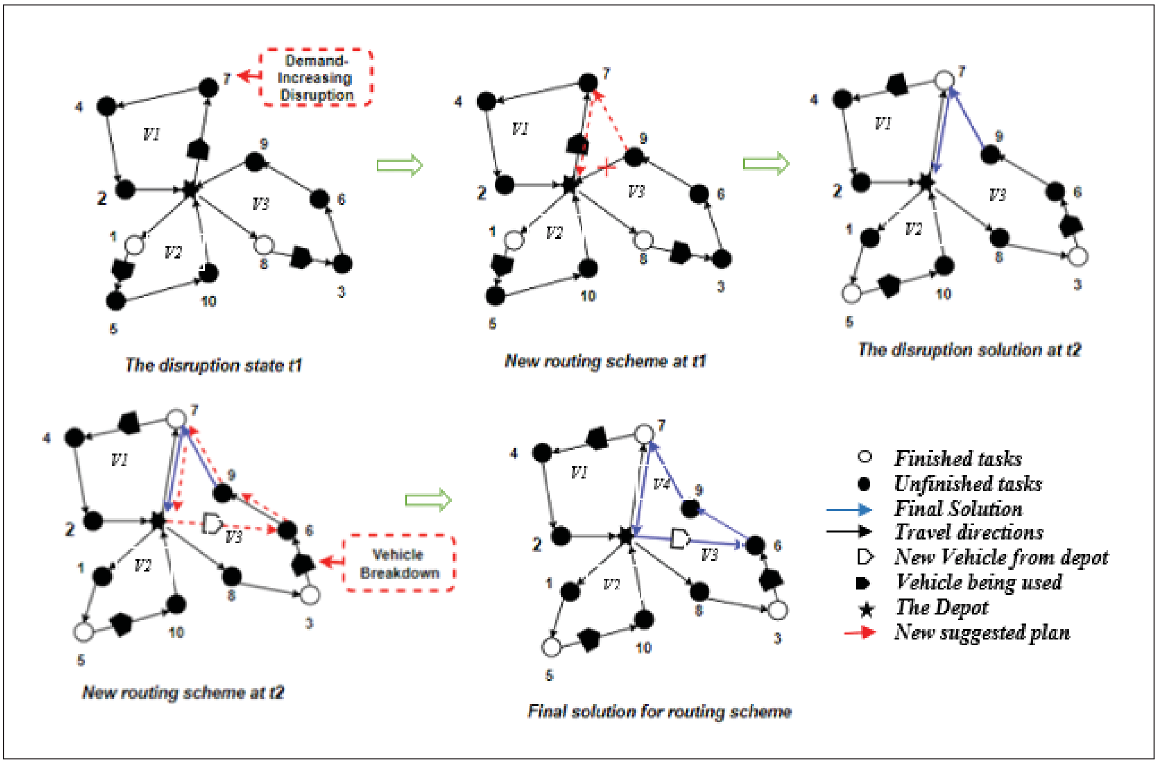

Figure 1.1: Example of the occurrence of disruption at various distribution states [5]

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1.3 Problem Statement

Though there are many solution approaches for solving different vehicle routing problems. But, when it comes to disruption problems, vehicle breakdown is one of the major and most common problems in many of the cases in transportation. In this research, disruption is defined as *"during the execution of the original operational plan, there might be deviations from that original plan which is adequately huge and that plan has to be immediately replaced to handle the negative effect"* [6]. When we are facing a problem with a vehicle breakdown, it is significant to give a fast response to all the vehicles to handle the disturbance that is caused and also to produce the new routing plan. But, most algorithms are not able to convict a solution in a short time. Therefore, there needs to be research carried out to evaluate the existing state-of-the-art of solution algorithms and identify the best algorithm for producing the optimal solutions in a shorter time for solving disruption in vehicle breakdown problem, as there is only a little research has been existed in this area of study, to date.

Several solution algorithms are previously used by a few researches for solving vehicle routing problems. Tabu search, Ant Colony Optimization, Genetic algorithm, Simulated Annealing, Neural Networks are some of the popular meta-heuristic solution approaches. These algorithms differ from each other majorly in their performance and evaluation, which depends on the constraints such as cost, distance, and time, etc... Hence, these models need to be evaluated as it is important to choose a suitable algorithm which can produce the best near-optimal solutions for solving routing problems.

1.4 Aim and Objectives

The main aim of this thesis is to find out the suitable meta-heuristic techniques for solving the disruption in vehicle routing problems during the delivery and evaluate their performance.

The following objectives are identified to fulfill the aim of this research:

- To identify suitable meta-heuristic solutions which can be used for solving the disruption in VRP.
- Implement and adopt the selected algorithm: Tabu Search algorithm is assessed with state-of-the-art algorithms ACO and GA.
- Evaluate and compare the performance of the selected algorithms among each other and also with standard benchmarks, present the results.

1.5 Research Questions

The following research questions have been formulated to achieve the objectives of the thesis:

RQ1. What are the suitable and efficient meta-heuristic algorithms that can be used to solve the disruption problems in the vehicle routing problem?

Motivation: This research question has been formulated to find suitable and efficient meta-heuristics that can be used to solve the problems caused by a disruption in real-time scenarios, which would be useful in the future research topics in developing some other disruption problems i.e., traffic jams, road blocking, accidents and other routing problems in transportation.

RQ2. Which one among the selected meta-heuristic solution algorithm has better performance in producing the near-optimal solutions for solving DVRP and why?

Motivation: The motivation for choosing this research question is to conduct a literature review, and from that obtain good knowledge about selected meta-heuristic solution algorithms i.e., Tabu Search, ACO and GA, among these algorithms one has been selected and the other two are considered as state-of-the-art algorithms.

RQ3. How can we measure the efficiency and performance of the selected meta-heuristic algorithms among each other in DVRP?

Motivation: The motivation for choosing this research question by conducting an experiment to evaluate the performance of selected algorithms among each other and comparing the results with standard benchmarks. Therefore, implementation and comparison are performed to answer this research question.

1.6 Thesis Outline

Chapter 2: Presents the background, describes all the basic information that is needed for this research.
Chapter 3: Related work section, which presents previously performed work by the other authors in the field of VRP using solution algorithms.
Chapter 4: Describes the methodology used in this research which is details about literature review and experiment.
Chapter 5: The literature review findings and results of the experiment are presented.
Chapter 6: Presents the analysis and discussion regarding the results of the literature review and experiment.
Chapter 7: Finally, the conclusion and future work of this research.

Chapter 2

Background

In this chapter, we are going to discuss the background work of this research.

2.1 Operational Research

Operational Research (OR) could be a discipline that deals with the appliance of scientific & mathematical methods to the study and involving complex systems for the analysis of problems. OR is generally concerned with determining the values of some real-world objectives: maximum (performance, profits) and minimum (risk, cost). It uses in a wide range of problem-solving methods in business, society, and industry. Today, OR plays a significant role in many industries such as airlines - scheduling crews and planes, tickets pricing, and making reservations; financial services - credit card scoring, and marketing; local government – providing urgent services; logistics companies - planning and routing [7]. OR is most often applied to analyze real-time complex problems to optimize and improve performance. In the area of transportation, there is one problem related to OR that has been given a lot of attention in the scientific literature is called the vehicle routing problem.

2.2 Optimization

In mathematics and computer science, optimization is a problem of finding the best optimal solution from all feasible solutions. The problems are classified into different types that use certain constraints which are solved by using standard techniques. Due to the complexity of NP-hardness, the optimized route requires much effort in real-time applications. Optimizing the routes, costs, and time is a great challenge for local optimization algorithms. An optimization algorithm is a procedure that is executed by comparing different solutions until an optimum solution is found and also designs the best shortest routes to reduce travel costs and time [8]. The research is about optimization which plays a very significant role in affecting the performance analysis of the algorithms.

2.3 Vehicle Routing Problem

2.3.1 What is VRP?

Vehicle Routing Problem (VRP) is a general name given to the class of problems in which a fleet of vehicles must be determined based on one or several depots for many geographically dispersed cities or customers. Dantzig and Ramser in 1959 were solved the truck dispatching problem which is about optimizing the fleet of gasoline delivery vehicle routes between a terminal at bulk and the service stations supplied by the terminal at a large number [9]. The main objective of the VRP is to reduce the total distance traveled, the number of vehicles used, and satisfy service requirements. VRP is a generalization of the famous traveling salesman problem (TSP) which is one of the most studied NP-hard problems and current solution methods have reached a very high level.

Traveling salesman problem aims to find the shortest route that visits each node at least once exactly and must return to the starting node. Many algorithms are proposed for TSP to solve other types of VRP variants [10].

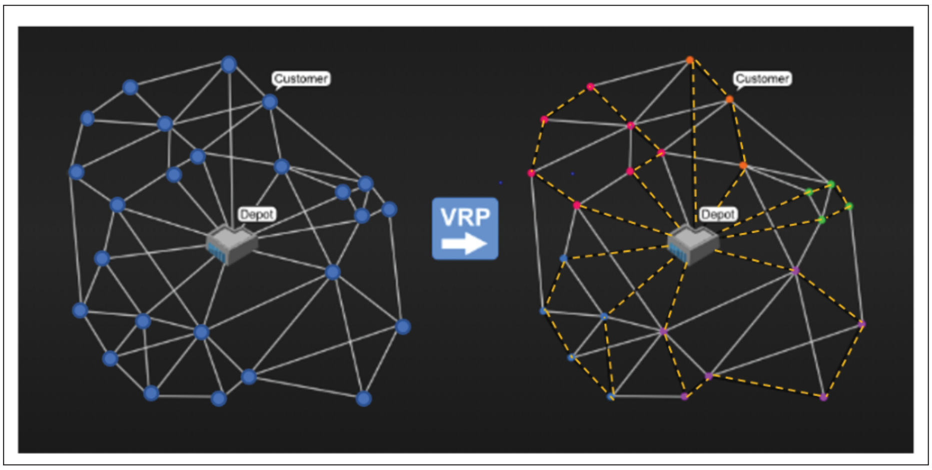

Figure 2.1: The basic structure of classic VRP [10]

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In figure 2.1, is the basic structure of the classic vehicle routing problem. In the middle of the figure, there is a depot from where the vehicles dispatch i.e. starting point. According to the right-side image, 25 customers need to be delivered and the total number of vehicles used is 5. Each color portrays the delivery points that the vehicles are covering which uses the shortest route which can be observed from dotted lines. The solution is that all the delivery points by traveling the shortest route that was covered by the vehicles. A figure also shows the routing before and after getting an optimal solution. The left side figure describes, all the nodes are connected to neighboring nodes to each other. The right-side figure is the solution part and describes, most of the connections are ignored because of decreasing the total distance covered by the vehicles.

Vehicle routing problems are difficult optimization problems, which have applications in many fields, transportation, logistics, and manufacturing. Because of wide usage, it has been one of the elementary problems in logistics. Improving the order of the route visits by optimizing the routes of vehicles, Cargo, delivery trucks, public transportation on the road. When compared to manual planning, this optimization reduces fuel consumption and also travel time of the vehicles. Many logistics enterprises face a vehicle routing problem daily: determine the optimal route to deliver many commodities to several locations with a fleet of vehicles [11].

2.3.2 Types of VRP Variants

The VRP arises naturally as a central problem in the fields of distribution, provision, and transportation. There are many VRP variants based on the problems we face in the real world are: [12] [10]

- Capacitated VRP (CVRP): Every vehicle must have a uniform capacity of a single commodity.
- VRP with Time Windows (VRPTW): Within a certain time every customer has to be delivered. Each vehicle route must be started and ended within the time window associated with the depot.
- Multiple Depot VRP (MDVRP): The logistics company's dealer may use several depots to supply the products to the customers.
- VRP with Pickup and Deliveries (VRPPD): The customers may return some goods to the company.
- Split Delivery VRP (SDVRP): It is a relaxation of the VRP to reduce overall annual costs, and it is allowed to serve the products to customers by different vehicles.
- VRP with Backhauls (VRPB): It is a VRP in which the customers can demand or return some commodities and is similar to VRPPD.
- Periodic VRP (PVRP): In VRP, typically the planning period is a single day. In the case of PVRP, the classical VRP is generalized by extending the planning period to M days.

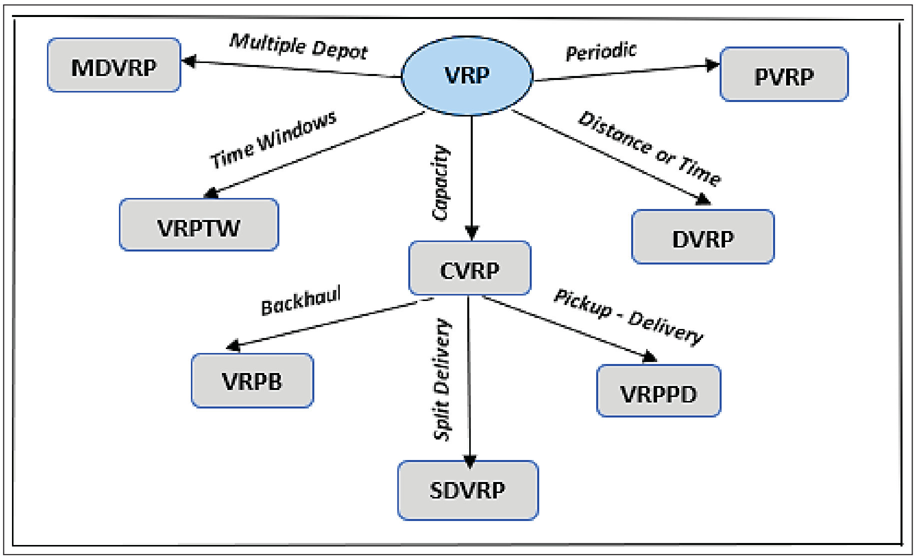

Figure 2.2: Types of VRP variants

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The above figure 2.2 is the different variant types of vehicle routing problems, and the description of each variant is also described. The instances of VRP are the combination of different variants.

2.3.3 Solution Algorithms for Solving VRP

The most usually used algorithms for solving VRP are listed. When the number of cities is large then no exact solution algorithm can be guaranteed to produce the optimal solutions within reasonable computing time. This is mainly because of the NP-hardness of the problem.

From figure 2.3, exact algorithms are only able to solve the small scale routing problems and may take a longer time, depending on the problem size. They were the first solutions to VRP and known to solve the problem to an optimal extent. One of the disadvantages of the exact optimization approaches doesn't work efficiently to provide an appropriate solution with a high-dimensional search space in solving problems. Approximate heuristics are suitable for very large-scaled routing problems and takes a shorter time when compared with exact approaches, solution dependent (not dependent on problem size). These heuristics perform a relatively limited analysis of the search space and produce good quality solutions within moderate computing times. Simple heuristics are both construction and improvement methods to develop the route in which usually one at the time, until a complete route is developed and also trying to improve the solution for a more efficient solution. Meta-heuristics are to find their initial solution and will be continuing the search for a better global optimal solution.

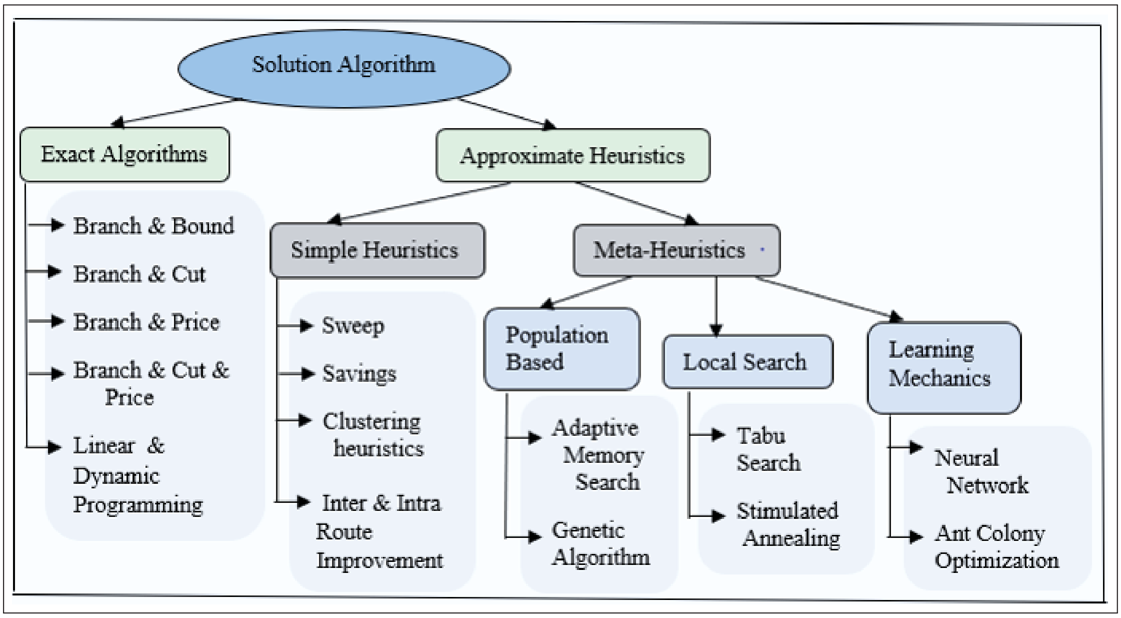

Figure 2.3: Solution algorithms and methods for solving routing problems

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2.4 Meta-Heuristics

Meta-heuristics are improvement algorithms that they start with one or more feasible solutions to the routing problem and suggest more techniques for improving solutions.

Why Meta-heuristics?
Meta-heuristics are used for solving the routing and scheduling problems in real-life scenarios. For route optimization e.g. selecting the shortest and quality route to a destination in routing problems. The meta-heuristic approach is important for generating an optimum set of test data in software testing.

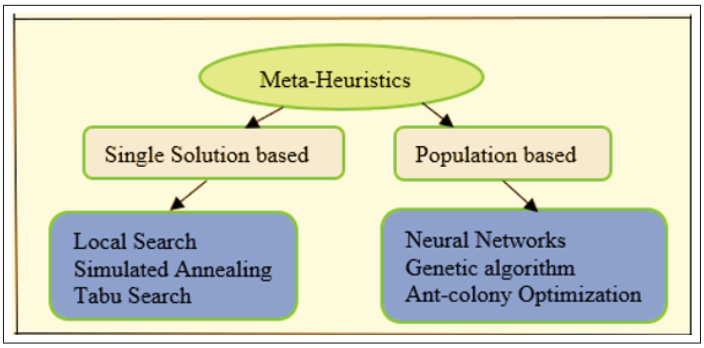

Figure 2.4: Meta-Heuristic Algorithms

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Figure 2.4, is the solutions of meta-heuristics include local search, tabu search, simulated annealing, ant colony optimization, neural networks, and genetic algorithm. The simulated Annealing, Greedy Randomize Adaptive Search Procedure, Neural Networks are not selected in this research as there is a lack of research on these algorithms for solving scheduling and vehicle routing problems. The main disadvantage of Simulated Annealing is that the methods are computation-intensive and is not widely used, and are not as quite easy to code for solving problems [13]. In paper [14] the author compares the TS and GRASP for solving instances of the discrete-hub location problem, a problem in airline applications and package delivery systems, and some telecommunications network design problems. Based on his work the author concludes that the TS was about twice as fast as the GRASP code in producing the best solution, and GRASP found solutions having the best-known value more often. Though 'Neural Networks' are also being preferred more for solving complex problems, but it is not as straight forward as other algorithms. The algorithm implementations will also be tricky for solving VRP. [15].

2.4.1 Tabu Search (TS)

Tabu Search is one of the successful meta-heuristics for the application to combinatorial optimization and is a dynamic neighborhood search method. It is also a direct searching algorithm for optimizing very complex problems. The basic concept of tabu search is described by Taillard in [16] worked on a TS heuristic for VRP with time windows. In the TS, a neighborhood of the current solution is produced through an exchange procedure that swaps sequences of customers between two routes [10].

TS is a global optimization algorithm and a meta-heuristic for controlling an embedded heuristic technique. The main feature of TS is always moved to the best available neighborhood solution point, even if the solution is worse than the current solution.

1. Basic Steps for TS Algorithm

The TS general algorithm steps can be stated as follows [17]:

Where, i, j = solution indexes; k = number of iterations; v^*= subset of solution; $N(i, k)$ = neighbourhood solution 'i' at iteration 'k'; $f(i)$ = objective function value for solution 'i'

- *Step 1: Select an initial solution i in S. Set $i^* = i$ and the Tabu List x.*
- *Step 2: Set a value for tabu list size $x = x + 1$ and a subset v^* generates a solution in $N(i, x)$ in which either one of the tabu conditions may disrupt*

or the aspirations condition holds.

- *Step 3: Choose the best feasible and suitable move j in i^* and set $i = j$.*
- *Step 4: If $f(i^*) > f(i)$ then update the solution, set $i^* = i$.*
- *Step 5: Update the Tabu List and Aspiration Condition.*
- *Step 6: If the Stopping Criterion is met stop and report the solution. Else go to Step 2.*

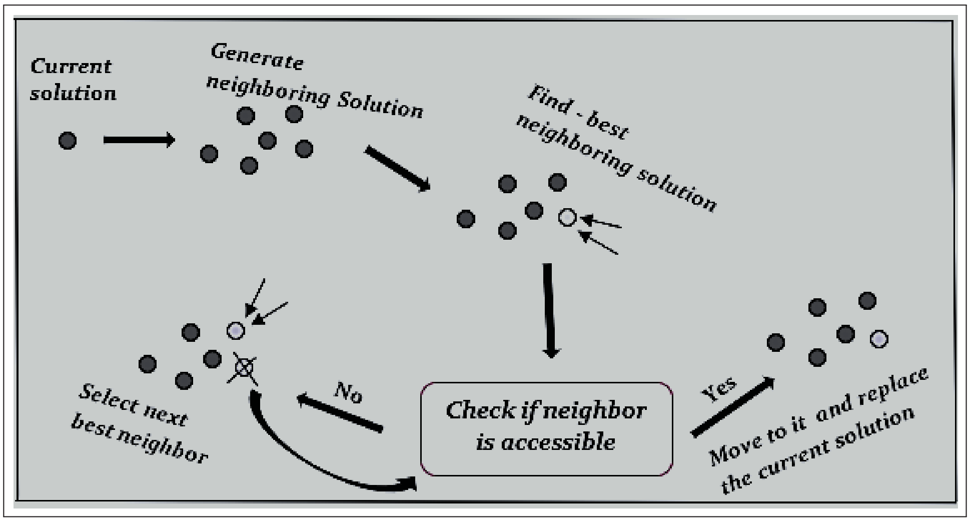

Figure 2.5: Tabu search example of neighbor selection [18]

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From the above simple steps of the tabu search algorithm and figure 2.5, TS starts with an initial solution in which 'i' is considered as a first step for the algorithm. The notion of using memory to certain moves that are forbidden can be assigned by saying that the neighborhood solution depends on time, So x is the number of iterations i.e., instead of $N(i)$, we refer as $N(i, x)$ which denotes neighborhood solution i at iteration k. It may also accept a move from i to i^* (in v^*) even if $f(i^*) < f(i)$. Then update the best solution in tabu and aspiration conditions. Finally, if the best solution has been found after the max number of iterations then terminate the algorithm which is called stopping criteria.

2. TS Optimization Process for Solving DVRP

In the 1990s, the meta-heuristic solutions like tabu search algorithm became very popular in solving vehicle routing problems and optimization problems in an accurate and exact behavior. Nowadays, TS is one of the most extensive meta-heuristics. The feature of tabu search represents the use of memory, which stores in the formation of the related search process. The main parameters that TS uses during the optimization procedure are local search, neighborhood structure, aspiration condition, or criteria. Besides, we use some more parameters like tabu moves, the maximum size of tabu, tabu list, and stopping rule or criteria.

TS is an improvement heuristic based on local search which escapes from local optima even all the neighboring nodes do not improve the solutions. As in local search, it replaces the current solution when a better neighbor is found [10]. Initially, TS starts with a current solution for the problem we are working on, which is the current solution, and then it searches for the best solution in a suitable neighborhood node (a collection of routes that can be easily reachable from the current node) of the solution. The complete dynamic change of the neighborhood may be considered as TS. Then it designates the solution which is best in the nearest neighborhood node as the current solution and it starts the searching process again. This procedure may produce cycles, i.e., the previous solutions which are already visited once could be selected again. To avoid these cycles, the solutions that it has visited in recent iterations, the TS maintains a list of neighbor nodes generation moves that it considers forbidden, or tabu (hence name tabu or taboo) and ignores the solutions that are reached by using those tabu moves while searching the neighborhood of the solution [19].

TS controls the moves that are applied recently or the memory of the solutions which are called tabu list and this establishes the short-term memory. As soon as a move enters the list of moves in tabu, then it will stay there for a given number of iterations of tabu search (which is called tabu tenure of the move). The short-time memory will be updated at each iteration of tabu Search. Storing all visited neighbor node solutions are space and time-consuming. Certainly, we need to check at each iteration of a solution that is generated and does not belong to the list of solutions which are all visited once. The constant number of tabu moves are included and the attributes of moves are stored in the tabu list. By proposing the concept of move features in the tabu list, some data may be lost about the search memory. The solutions which have not yet been generated in the list can be rejected. A non-generated solution should be forbidden since the tabu list may be prohibitive. But, the tabu solutions may be accepted for some conditions called aspiration criteria. The solution may run forever because of the unknown optimum solution. Hence, to avoid the repetition of the process the max number of iterations up to 10000 is given to stop the condition. The stopping criteria are needed since the algorithm is open-ended [20].

Several researchers have been adding more features that have the basic steps for the tabu search algorithm and have intermediate-term and long term memory structures, and aspiration criteria that have been used widely and that applied to tabu search implementations for most of vehicle routing problems.

3. Algorithm Procedure

The below algorithm provides a pseudo-code implementation for minimizing the cost function of the tuned tabu search algorithm.

1. $Input : tabuList_{size}$
2. $Output : S_{best}$
3. $S' \leftarrow S_0$
4. $S'_{best} \leftarrow S'$
5. $tabuList \leftarrow \emptyset$
6. $while(\neg\ stoppingCondition(\ ))$
7. $\quad customerList \leftarrow \emptyset$
8. $\quad for(S'_{customer} \in S'_{bestNeighborhood})$
9. $\quad\quad if(\neg\ containsTabuElements(S'_{customer}\ ,\ tabuList))$
10. $\quad\quad\quad customerList \leftarrow S'_{customer}$
11. $\quad\quad end\ if$
12. $\quad end\ for$
13. $\quad S'_{customer} \leftarrow LocateBestCustomer(customerList)$
14. $\quad if(cost(S'_{customer}) \leq cost(S'_{best}))$
15. $\quad\quad S'_{best} \leftarrow S'_{customer}$
16. $\quad\quad tabuList \leftarrow featureDifferences(S'_{customer}\ ,\ S'_{best})$
17. $\quad\quad while(size(tabuList) > maxTabuListSize)$
18. $\quad\quad\quad ExpireFeatures(tabuList)$
19. $\quad\quad end\ while$
20. $\quad end\ if$
21. $end\ while$
22. $return(S'_{best})$

Pseudo-code of tuned TS for Cost Function [21].

2.4.2 Ant Colony Optimization (ACO)

Ant colony optimization was first introduced in Dorigo and successively extended by Dorigo et at. These algorithms are called swarm intelligence algorithms, and they are inspired by the behavior of real ants looking for good sources of food to their nest. Real ants can communicate information regarding the sources of food via an aromatic essence called pheromone. As soon as an ant finds a source of food, it carries some of this food to the nest and determines the quality and quantity of the food. In general, the ACO algorithms try to solve CO problems by iterating the following: Solutions are constructed using the pheromone model, which is a parameterized distribution of probability over the solution space. And the solutions are used to modify the pheromone values in the way it considered to search the high-quality solutions [22]. The following code shows the ACO meta-heuristic algorithm.

1. $Input : CO\ problem\ of\ an\ instance\ n$
2. $Output : S_{best}, customer\ to\ an\ optimal\ solution\ for\ n$
3. *while* (¬ *met termination condition*) *repeat while*
4. $\quad ScheduleActivites$
5. $\qquad AntBasedSolutionConstruction(\ )$
6. $\qquad PheromoneUpdate(\ )$
7. $\qquad DaemonActions(\ )$
8. $\quad$ *end ScheduleActivities*
9. $\quad S_{best} \leftarrow best\ solution\ in\ the\ population\ of\ solutions$
10. *end while*

Pseudo-code of Ant Colony Optimization [22].

2.4.3 Genetic Algorithm (GA)

Genetic Algorithm is most widely and very likely to be known meta-heuristic algorithms, today receiving exceptional attention all over the world. It is based on the process of evolution which has a biological path on its own. GA algorithm is a natural selection mechanism these algorithms are applied for a given number of iterations and output is the best solution that will be found in the population or found during the evolution of the algorithm. The most well-known operators that are used in the algorithm are reproduction, crossover, and mutation. Therefore, this technique tries to move toward the optimal solution of the problem which is used to develop various solution sets of feasible solutions [23]. Below are the general steps of the genetic algorithm.

```
Genetic Algorithm {
    Generate initial population P_o
    Evaluate population P_o
    while (¬ satisfied, stopping GA criteria) Repeat {
      For 1 to (number of events) {
            Select N_t chromosomes for events
            Find a chromosome with the lowest fitness
            Remove chromosome with the lowest fitness
            Crossover (Create new chromosome)
            Evaluate new chromosome
         }
         Mutation
         Evaluate (mutated chromosomes)
    }
}
```

Pseudo-code of Genetic Algorithm [24]

2.4.4 Advantages and Disadvantages

The following table 2.1 describes the advantages and disadvantages of the selected meta-heuristics algorithms in this research.

S.No	Algorithm	Advantages	Disadvantages
1	ACO	1. Robustness, scalability, and flexibility in dynamic environments. 2. Good for graph-based problems.	1. Parameter initializations by using errors and trials. 2. Not easy to code. 3. For discrete search space, the original method has been designed. 4. Tough theoretical analysis.
2	GA	The ability of: 1. Solving many types of optimization problems. 2. Easy to be combined with other algorithms. 3. Finding the best solution to many problems. 4. Design the binary search space.	1. Finding a sub-optimal solution. 2. Convergence rate is slow. 3. The crossover and mutation rates are dependent on the convergence and stability. 4. Local search is weak. 5. Hard encoding strategy.
3	TS	1. Can able to solve large scale and more complex problems. 2. Applied to both discrete and continuous solutions. 3. Limited effort. 4. Saving time. 5. Conflict Solution.	1. Too many parameters to be determined. 2. Sometimes global optimum may not be found, depends on parameter settings.

Table 2.1: Advantages and disadvantages of selected algorithms [25].

2.5 Disruption in VRP - Causes and Factors

A formal definition of disruption management is found in [26][27] *" By using optimization models and solution schemes, optimal or near-optimal operational plans are obtained. Disruptions may occur, due to internal or external constraints which are uncertain factors while executing operational plans. Thus, the original operational plan will not remain feasible or optimal. Due to these conditions, consequently, the original plan has to be revised and should obtain a new plan that* *reflects the constraints and objectives of the evolved environment by reducing the negative impact of disruption. Hence this problem is called disruption management ".* Disruptions during the execution of an original VRP plan are caused by a vehicle breakdown, departures delayed from the service terminal, blocking and canceled orders or new orders, etc. In those scenarios, routes should be quickly revised as that may affect the logistics company and customers. When dealing with disruptions a proper decision-making process should be made therefore with adequate algorithms that can find a new plan as quickly as possible [3].

(a) (b)

(c) (d)

Figure 2.6: Examples of causing disruption problems

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From figure 2.6, in the image (a) the reason for causing disruption is climatic/environmental conditions. Image (b) is the reason for causing disruption, road car accidents. Images (c) & (d) are caused by the disruption and the reason is due to earthquakes and tsunami.
The following are the factors that are involved in the disruption management [27]:

- There will be very limited time for the re-planning of the vehicle. This will be usually happening in many of the cases. For this situation, it is important to produce an optimized plan for recovery by using any algorithms.

- The time needed to communicate with each other for the operational plan for those to implement it and to receive information back about disruption should also be considered into account.

- Maybe the restriction in the new plan that was not in the original VRP plan. These may be the consequence of the disruption that has happened, as the road may be blocked due to the accident or unavailability of the vehicle, vehicle breakdown.

- The original VRP plan of the vehicle before disruption may be helpful for the new plan as a starting point. When producing the newly developed plan, there is no need to find out a plan from scratch.

- It may be appropriate to involve the new annual costs that are related to the deviations caused by the original VRP plan.

Chapter 3

Related Work

In this chapter, a set of papers have been selected and described each of them:

Vehicle Routing Problem (VRP) was first introduced by Dantzig and Ramser in 1959 as a traveling salesman problem (TSP) and he described VRP is an integer programming and combinatorial optimization problem to supply the goods to the number of customers with a fleet of vehicles [9]. Several papers are studied on disruption management and problems with vehicle routing problems. Li et al. [28] described when a public transport vehicle breaks down, one or more vehicles are needed to re-planned to serve and other service plans originally scheduled for the vehicle which is disabled. The author describes the rescheduling problem of the vehicle is investigated to calculate the costs of scheduled disruption and operating costs and the cost of trips for cancellation and a lagrangian relaxation-based insertion heuristic is developed.

In the paper [29], the author described the meta-heuristic methods for rich vehicle routing problems and addresses the periodic VRP with time windows (PVRPTW) which states the classical VRP with time windows (CVRPTW). Performance of the suggested methodology compared to the literature with solutions requiring fewer vehicles and the cost of travel to perform efficiently.

Baker in paper [30] the study considers the application of a genetic algorithm to the basic VRP. The results are given for hybrid GA with neighborhood search methods. The author showed GA is competitive with tabu search and simulated annealing in terms of cost and time.

In the article [31], the author introduces a parallel iterated tabu search heuristic for solving four different routing problems they are: the classical VRP, multi depot VRP, the periodic VRP, and the site-dependent VRP which applies to the time window variant of these problems. By adopting the iterated local search method, the tabu search heuristic method combines with a simple perturbation method to ensure a deep analysis of the search space. To take advantage of multi-core processors the author also described the implementation of heuristic in parallel.

Jia and Li [32], the author discusses the importance of disruption management. In this paper, the author described and performed a new tabu search algorithm by proposing the mixed local search and mutation approaches for reducing the current TS weakness. The author also has done the comparison of improved tabu search with other algorithms and the performance of improved TS is shown. In the paper [33] the author proposed a new set of benchmark instances ranging from 100 to 1000 customers, and reported the results with state-of-the-art exact and heuristic methods i.e., iterated local search based meta-heuristic, unified hybrid genetic search, and also branch-cut-and-price approaches for the capacitated vehicle routing problem (CVRP).

The author in [34] describes the vehicle scheduling problem which involves designing a given set of goods for customers with known distribution areas, and by considering the capacity constraints time, distance, and cost of the tours. Considering three methods of solutions i.e., Savings approach, branch-and-bound approach, and 3-optimal tour method.

Feng et al. in the paper [35] introduced local search in a structural form of the individual learning phase of the memetic algorithm and also involved based on genetic programming. The results showed that this memetic algorithm creates highly robust and scalable algorithms. Hence for generating and improving the results, the author has considered much existing and human-developed state-of-the-art memetic algorithm and meta-heuristic benchmark sets for solving capacitated vehicle routing problems.

Korayem et al. in the paper [36] use a bio-inspired grey wolf algorithm to solve the Capacitated Vehicle Routing Problem. The main aim is to minimize the total cost or distance traveled by vehicles. The author of the paper developed two new clustering heuristic solutions for solving CVRP which are: cluster-fist and route-second method and also combining grey wolf algorithm with traditional K-means algorithm. These developed algorithms are tested on benchmarks to get better results.

The author in [37] addresses the VRP with delivery and pick-up (VRPDP) and he proposed multi-phase constructive heuristic using shrink wrap algorithm and generalized assignment procedure. For the final intensive search, he has used the genetic algorithm for making trials on large-scale problems.

Chapter 4

Research Methodology

In this research, the well-suited methodology is performed to answer the research questions and to achieve the objectives of the research are to perform a literature review and by experimenting.

4.1 Literature Review

For any research, the literature review is the preparatory work that needs to be done to identify, formulate an idea or concept. This method has been selected because to answer the RQ.1 and RQ.2 research questions. When considering those questions, a literature review can give the desired answer.

In this research, the literature review has been carried out to gain knowledge in the topics below:

- To gain a good knowledge of disruption problems in vehicle routing problems and its variants.
- To obtain knowledge and a deep understanding of various types of meta-heuristic solution algorithms.

4.1.1 Search process

The list of articles for the literature review is obtained to find all the papers by the search strings: "disruption", "VRP", and "meta-heuristics" have been mentioned. Therefore, search strings such as "Disruption AND VRP AND Meta-heuristics" have been used for the search process. It has been carried out on Google Scholar, IEEE Xplore, Science Direct, and Springer Link databases. After selecting the list of articles with a clear goal have been discussed in subsection 4.1.2 which is the inclusion and exclusion criteria selection. The listed articles have been filtered by reading the title of the paper, followed by reading the abstract of the selected articles.

4.1.2 Inclusion and Exclusion Criteria

The following are the inclusion and exclusion criteria have been used to filter the related papers for this literature review:

- Articles that are discussed only about the routing problems in VRP and meta-heuristic solution methods are included.
- Articles that are related to our study are selected by looking at the title and reading the abstract of the articles.
- The language of the selected paper is written in English is included for understand-ability purposes.
- If the articles Articles related to types of VRP using other heuristic solution approaches are excluded.
- If the article doesn't contain the availability of full text is excluded.

4.2 Experiment

An Experiment has been selected as the research method to answer RQ.3. It is chosen as a research method because it is the best approach for evaluation to see how the model is affected by different variables. The main goal of this experiment is to evaluate the selected meta-heuristics solution algorithms i.e., TS, ACO and GA for solving the real-time disruption problems in VRP. The experiment is performed in a controlled environment.

4.2.1 Independent and Dependent Variables

The variables which can be changed with different scenarios and environments are the independent variable. And the variables which depend on independent variables are the dependent variable. Problem size is the independent variable in this experiment. The annual cost is the dependent variable to be considered in this experiment. The annual cost may vary with the changes in the problem size and so they are considered as dependent variables.

4.2.2 Initial setup

The following steps are performed that are essential for the implementation of the algorithm.

- **Software Environment:** Java (Java 8 update 20) with both JDK and JRE (Java Development Kit and Java Run-time Environment) with libraries has been selected as the programming language as it is a high-level programming language, which is easy to learn and code, and used widely for developing AI and machine learning algorithms.

- **Hardware Environment:** The system hardware specifications in which the selected algorithm has been implemented are shown in table 4.1

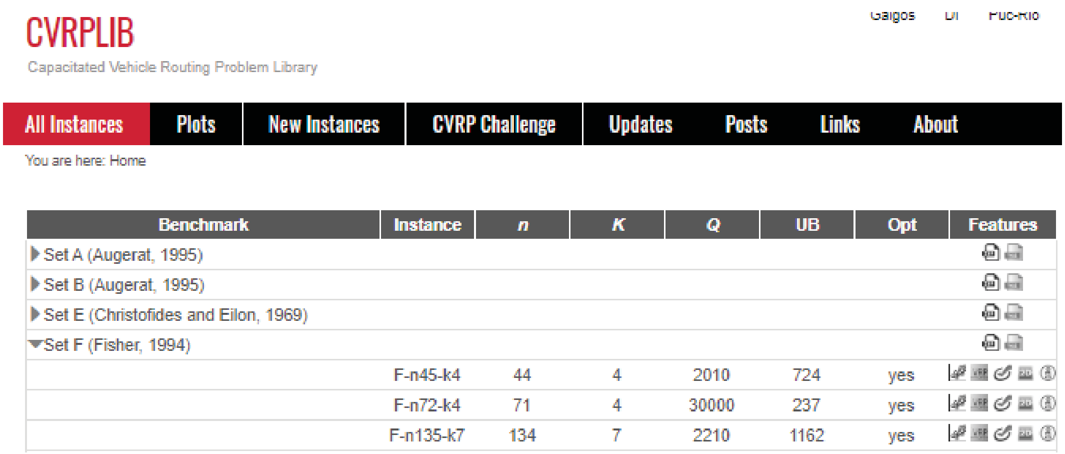
System	HP Zbook 14u G6 14
GPU	Intel(R) UHD Graphics 630
CPU	Intel Core i7-9850H
speed (GHz)	1.80
Installed Memory (RAM)	16 GB
Operating System (OS)	Windows 10

Table 4.1: Hardware Environment

- **Datasets (Benchmark Instances):** In this research, the major source is the datasets (benchmarks). The datasets considered in this experiment has 50 standard benchmark instances adopted from the public domain CVRPLIB [38]. These instances are widely used by most of the authors who worked on implementing solution algorithms to solve the routing problems. The instances have been collected in such a way that each instance has an optimal value for the cost. To get the optimal value for the cost function, the dataset is given as input for the implementation of the algorithm. These datasets contain the following basic information as input:

  - The coordinates in the graph represent the position of the delivery points and position of the depot.
  - The number of vehicles used and the problem size (number of delivery points).

  The main benefit that comes from these benchmark instances is that most of the researchers and authors use these instances to implement their solution technique algorithms and become easier for them to measure and compare the performance of the results of the implemented algorithm determined with other algorithms that use the same instances. The following figure 4.1, shows example data sets of cost metric from the CVRP library:



Benchmark	Instance	n	K	Q	UB	Opt	Features
Set A (Augerat, 1995)							
Set B (Augerat, 1995)							
Set E (Christofides and Eilon, 1969)							
Set F (Fisher, 1994)							
	F-n45-k4	44	4	2010	724	yes	
	F-n72-k4	71	4	30000	237	yes	
	F-n135-k7	134	7	2210	1162	yes	

Figure 4.1: Example format of benchmark instance by Fisher [38]
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From the above 4.1 shows the dataset in the format of F-n45-k4 which means 'F' represents the set F, 'n45' is problem size (number of customers), and 'k4' is the number of vehicles used to deliver the customers.

4.2.3 Experimental Process

In this thesis paper, the experiment is done to implement and adopted a tabu search algorithm with the suited tabu parameters for solving DVRP. Based on the data sets the results are calculated and gathered. The next step is to compare the results of the adopted algorithm based on results calculated from the selected meta-heuristics. The one advantage of VRP is that the computational results are accurately compared to efficiently and accurately with some existing relevant benchmark instances and can be considered as an input for developing solutions. By doing a comparison between the selected algorithms, we cannot only determine how the performance of the selected algorithm is working better when compared to other algorithms by using different approaches, but also will know which one gives better results for optimal or near-optimal solutions.

The benchmark instances are provided as an input data file (with .zip file) from the CVRP Library [38] contains the constraints of the problem size, annual cost, the distance between two nodes, and time traveled. The other algorithms are chosen based on the type or variant of VRP it solves the problem and considers various methods like exact, simple, and meta-heuristics. Most importantly, all these adopted algorithms must be using the same data sets to compare the performance.

The implementation of the experiment procedure is followed in this research is as visualized in figure 4.2

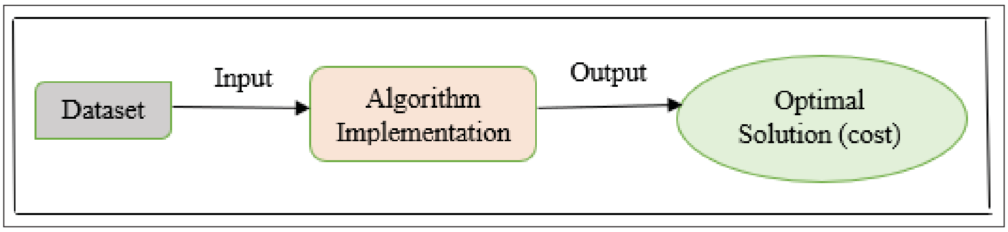

Figure 4.2: An overview of the experiment procedure

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4.2.4 Experimental Design

This experiment is divided into two parts. In the first part, we develop a tabu search with suited tabu parameters and adopted two state-of-the-art algorithms ACO, GA. In the second part, we evaluate the performance of the selected algorithm with each other by giving some of the inputs considered from the benchmark instances.

The following are the steps to be performed for experimental design for this research method:

- Windows 10 is the development environment in my laptop which I have used for this experimental design.
- Complete Java software is required for this research and that needs to be installed.
- Since the experiment, implementation of an algorithm is coded in the programming Java for that Eclipse IDE is downloaded and set up.
- The benchmark instances act as an input for the algorithm that is downloaded from the online CVRP library which contains zip files.
- The computational results of the algorithm performance are compared with the standard benchmark solutions.
- Tabulate the results and show the performance of results via bar diagrams.
- Finally, statistical analysis should be done to compare the analysis of algorithms with each other to see which algorithm performs good and produce near-optimal solutions for an annual cost.

Chapter 5

Results

In this section, the results are gathered from the literature and the experiment.

5.1 Literature Review Results

There is very limited research about disruption management in vehicle routing problems with the vehicle breakdown part. The literature review is based on routing problems in many different papers that have been implemented by combining with various solution techniques of VRP.

The results obtained from the literature review are tabulated in the tables 5.1 and 5.2.

5.2 Experiment Results

In this section, we discuss and analyze the results gathered from the experiment. After completion of the implementation and execution process, the algorithms have been evaluated on several data-sets containing the values of Optimal cost and the number of vehicles used. Results consisting of the three selected algorithms - TS, GA, and ACO, and comparison have to be done to evaluate the performance of algorithms.

- For the collection of near-optimal solutions every each data-set has been tested on three selected algorithms which are essential to evaluate the performance.
- Figure 5.1, is the screenshot of one of the data-set "A-n37-k6" which is used on TS, GA, and ACO to show the results of the experiment.
- The shortest routes of each vehicle traveled to deliver the number of customers can be observed in the figures 5.2, 5.3, and 5.4.

S.No	Solution approaches	Findings from the article
1.	A Lagrangian relaxation based insertion heuristic algorithm	The results of the article [28] show that selected heuristic performs well for solving real-time vehicle rescheduling problem and the metrics involved are operating costs, disruption costs, and trip cancellation costs.
2.	Population-based meta-heuristic - Hybrid generational Genetic Algorithm	From the Experiment in the article [29] confirms that the proposed method works well in giving best solutions on large instances for solving rich VRP with the goal that requiring fewer vehicles and travel costs.
3.	Genetic algorithm, Tabu Search, and Simulated Annealing	From the results of the article [30] shows that GA approach is competitive with tabu search and simulated annealing for the VRP in terms of solution quality and time.
4.	Improved tabu search approach	In the article [32], the solutions of designed algorithm for solving VRP is very good with the size of problems is big or small and also the convergent speed is fast with high efficiency.
5.	Parallel iterated local search, and Tabu Search heuristic	From the computational results of the paper [31] shows that the proposed heuristic algorithm performs good, which are used for the VRP and several variants: VRP with time windows, Multi-Depot VRP, Periodic VRP, and Site-Dependent VRP.

Table 5.1: (i) Results of a Literature Review.

- From figures 5.1, 5.2, 5.3, and 5.4, we can clearly see that among all selected meta-heuristic algorithms, TS solutions are good at producing the best near-optimal solutions than compared to state-of-the-art algorithms i.e., ACO and GA for an annual cost.

S.No	Solution approaches	Findings from the article
1.	Heuristics:- Iterated local search, Unified hybrid genetic search and Exact solutions:- Branch-Cut-and-Price	In the article [33], the authors propose a new set of benchmark instances. The report results with state-of-the-art methods for both heuristic and exact solution approaches for the Capacitated VRP.
2.	Savings approach, Branch-and-bound, and 3-optimal tour method	From the results of the article [34], among the three proposed approaches, 3-optimal tour method is better than the other two methods to minimize the constraints for the vehicles, and a distance(or time) with cost, for the vehicle dispatching problem.
3.	Local searches in memetic algorithms and Linear genetic programming	Results of the paper [35] showed that the memetic algorithm with local search gives good results when bench-marking against the human-designed or many existing adaptive state-of-the-art memetic algorithms and meta-heuristics for solving Capacitated VRP.
4.	Bio-inspired grey wolf optimizer, K-means clustering algorithm	The article [36] concludes the methods employed in solving Capacitated VRP is the cluster-first route-next method. The traditional K-means algorithm combined with a bio-inspired grey wolf, the optimizer has proven to be efficient in solving optimization problems which minimize the total cost or distance traveled by the vehicles.
5.	Clustering approach, shrink-wrap algorithm, and genetic algorithm	From the article [37] findings, the author proposes a multi-phase constructive heuristic based on proximity of the cluster nodes and generalized procedure and for a final intensive search he used genetic algorithm to solve the VRP with delivery and pick-up.

Table 5.2: (ii) Results of a Literature Review.

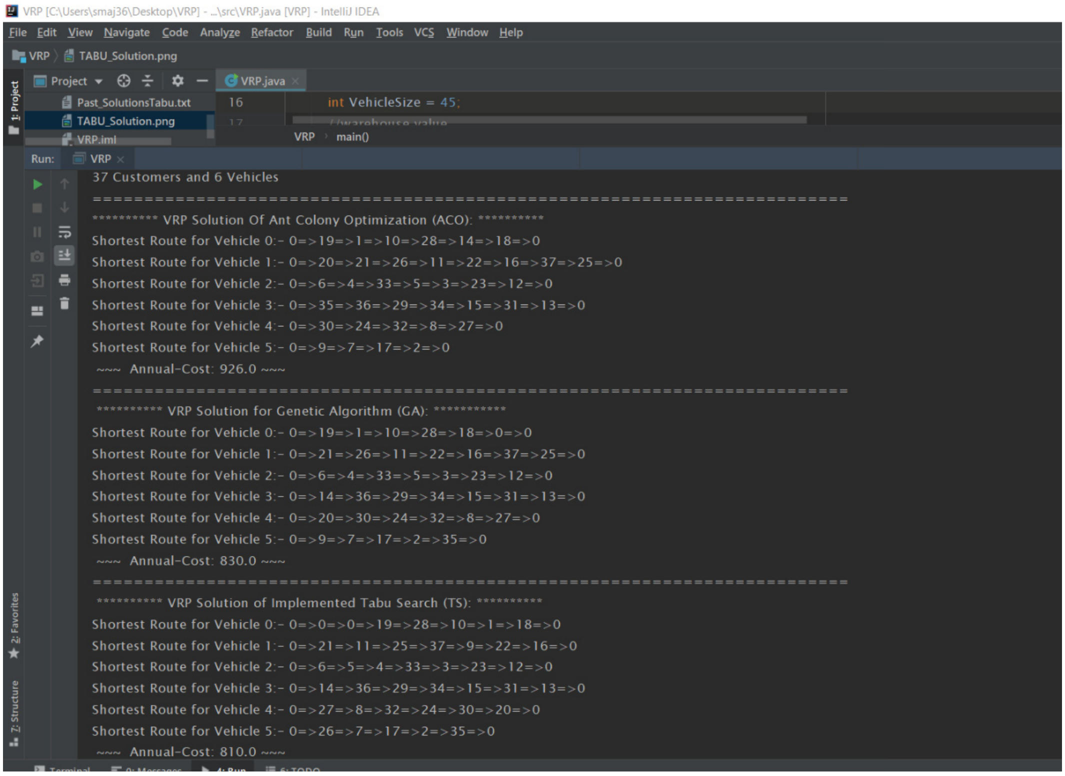

Figure 5.1: Annual cost solution of algorithms for the dataset "A-n37-k6".

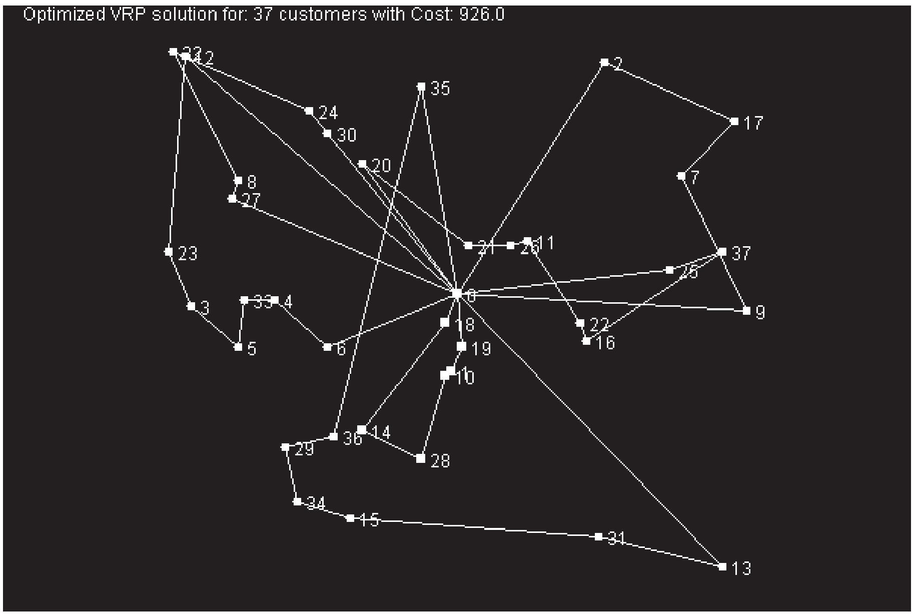

Figure 5.2: Shortest routes of each vehicle traveled - ACO solution.

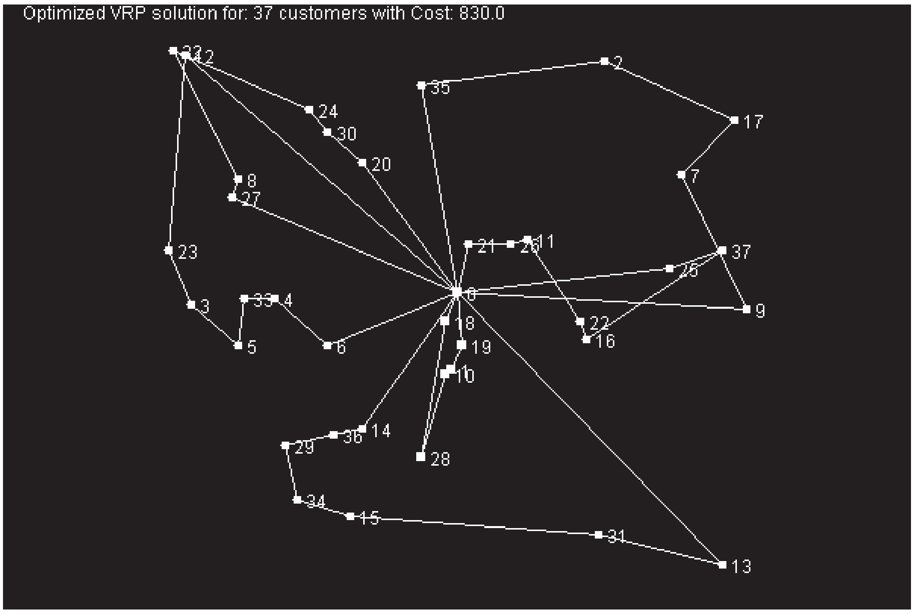

Figure 5.3: Shortest routes of each vehicle traveled - GA solution.

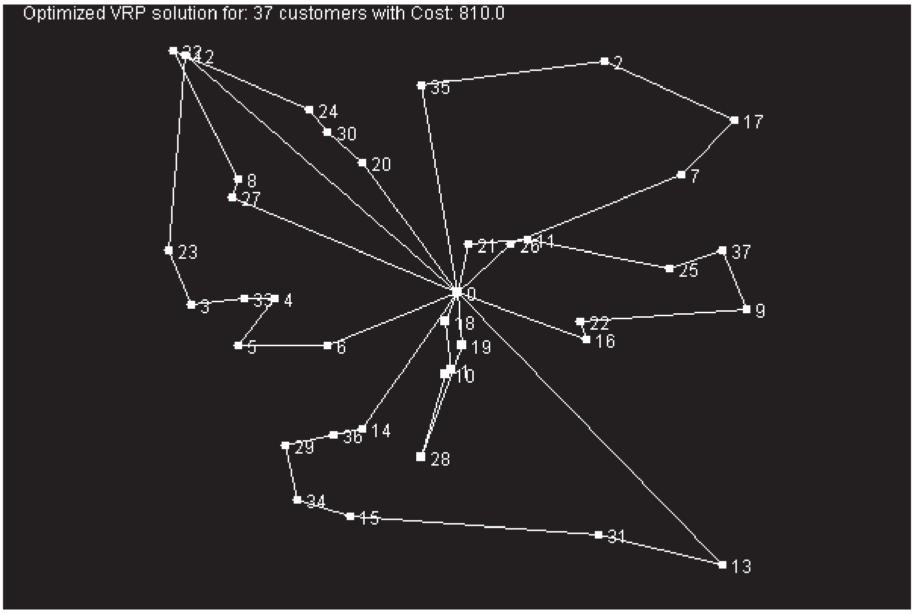

Figure 5.4: Shortest routes of each vehicle traveled - TS solution.

5.2.1 Comparison of all obtained results

To evaluate the performance of selected algorithms the comparison has made with each other and also compared with standard benchmarks that were considered from public domain CVRPLIB. The reason for selecting these five papers is that cost is a metric in my research. The results are shown in the tabular form.

Note: The reported values presented in all the below tables 5.3, 5.4, 5.5, 5.6, 5.7, and 5.8 are the annual cost of selected algorithms.

The first paper shows the set of benchmarks for a cost that is collected from the solution algorithms that were proposed by Augerat et al. in 1995 paper [33]. The author has solved CVRP problems and got very good results and have been tested instances from six different classes and sets. The data sets are created by 27 instances. From the paper, two sets of instances are gathered which are set A and Set B, and the results of set A are shown in table 5.3.

Instances	ACO	GA	TS	Augerat et al. set A
A-n32-k5	810	678	671	784
A-n33-k6	837	751	736	742
A-n34-k5	741	715	683	778
A-n36-k5	830	789	723	799
A-n37-k6	859	795	786	949
A-n38-k5	808	744	687	730
A-n39-k5	837	774	703	822
A-n46-k7	940	862	851	914
A-n55-k8	1176	1072	1062	1073
A-n62-k8	1291	1076	1051	1288
A-n69-k9	1462	1218	1200	1259
A-n80-k10	1526	1284	1259	1763

Table 5.3: Comparison of results with solutions by Augerat et al. - set A.

The first paper extends the solution algorithm with set B and the comparison of results of set B are shown in table 5.4.

Instances	ACO	GA	TS	Augerat et al. set B
B-n35-k5	788	716	665	955
B-n38-k6	893	808	785	805
B-n41-k6	930	810	807	829
B-n50-k8	1063	976	964	1312
B-n57-k9	1207	1087	1076	1598
B-n63-k10	1436	1168	1167	1496
B-n66-k9	1319	1274	1256	1316
B-n68-k9	1446	1151	1121	1272

Table 5.4: Comparison of results with solutions by Augerat et al. - set B.

The second paper shows the set of benchmarks for a cost that is collected from the solutions that were proposed by Christofides et al. in 1969 paper [34]. The author in this paper used exact approaches and heuristic approaches for solving the vehicle-dispatching problem. I have gathered the benchmarks of this paper and compared it with the selected algorithm which showed in the below table 5.5.

Instances	ACO	GA	TS	Christofides et al. set E
E-n22-k4	646	521	356	375
E-n23-k3	606	551	450	569
E-n30-k3	644	516	491	534
E-n31-k7	840	671	537	379
E-n33-k4	736	674	658	835
E-n51-k5	915	834	638	521
E-n76-k10	909	843	830	830

Table 5.5: Comparison of results with solutions by Christofides et al. - set E.

The third paper shows the set of benchmarks of the cost that are collected from the solutions that were proposed by Feng et al. [35]. The authors in this paper made conceptual modeling of evolvable local searches in memetic algorithms by using linear genetic-based programming for solving CVRP problems. From this paper, the two sets (set A and set B) of benchmarks are gathered and compared with tabu search which can see in table 5.6.

Instances	ACO	GA	TS	Feng et al. set A & B
A-n32-k5	756	692	685	784
A-n54-k7	1111	1111	992	1169
A-n60-k9	1484	1294	1142	1355
A-n69-k9	1277	1165	1151	1163
A-n80-k10	1555	1439	1402	1776
B-n57-k7	1266	1006	1004	1140
B-n63-k10	1530	1301	1258	1537

Table 5.6: Comparison of results with solutions by Feng et al. - Set A & B.

In the fourth paper, the author Korayem et al. was used a very unique method to formulate the results [36]. The solution results of this paper were also compared with the selected algorithm and the comparison is shown in the below table 5.7.

Instances	ACO	GA	TS	Korayem et al. set A & B
A-n33-k6	837	751	721	742
A-n34-k5	741	715	700	778
A-n36-k5	774	774	761	799
A-n39-k6	916	814	785	831
B-n31-k5	761	644	637	672
B-n41-k6	910	813	809	829
B-n44-k7	1003	884	873	909
B-n50-k8	1165	1074	1062	1312

Table 5.7: Comparison of results with solutions by Korayem et al. - set A & B.

In the final paper, the author Ganesh et al. in the paper [37] used a shrink-wrap algorithm, and allotted vehicles used generalized assignment procedures. They have used cluster and search heuristic and genetic algorithms to get the final search for solving vehicle routing problems with delivery and pickup. The solutions of this paper are gathered and compared with selected algorithms which were shown in the below table 5.8

Instances	ACO	GA	TS	Ganesh et al. set A
A-n53-k7	1135	1061	970	1017
A-n54-k7	1201	1060	1056	1172
A-n55-k9	1230	1063	1062	1073
A-n60-k9	1340	1268	1265	1358
A-n62-k8	1412	1127	1107	1288
A-n63-k10	1386	1386	1289	1322
A-n64-k9	1282	1130	1083	1410
A-n65-k9	1290	1153	1114	1177
A-n69-k9	1289	1159	1148	1163
A-n80-k10	1622	1572	1401	1780

Table 5.8: Comparison of results with solutions by Ganesh et al. - set A.

Chapter 6

Analysis and Discussion

This section describes the discussion and statistical analysis of the results compared in the above section. And also, motivation for research questions.

6.1 Analysis of Literature Review

By the literature review conducted in section 5, we can strongly recommend that the implementation of various meta-heuristics techniques plays an important role in solving DVRP problems and has very satisfactory solutions. And also proven that the performance of algorithms by reducing annual costs by implementing in the right way. From the literature review, we can motivate the answers for the research questions RQ.1 and RQ.2.

6.2 Analysis and Discussion of Experimental results

For answering the third research question the main motive is to compare the cost performance of the selected algorithms. In this paper, the performance of the algorithm is based on problem size which we take as the X-axis, and the solution is based on cost value which we take in the Y-axis that can be shown in the form of bar diagrams in the results selection. In the paper, three sets of benchmark instances are chosen which they are starting with letters A, B, and E. Every instance increases with the size of the problem. Therefore, the analysis should be made based on the size of the problem and its increment. Below is the discussion about each paper considered in the results section and the type of instance is as follows:

Analysis and discussion about the first paper: From the first paper, the results which are used for analysis are taken from both sets 'set A' and 'set B' by Augerat et al. [33]. From figures 6.1 and 6.2 in the results section, if we consider the performance analysis for this case almost similar values for tabu search and genetic algorithms but there are huge differences with ant colony and Augerat et al. We can also observe that if the problem size increases then the annual cost is also increased. After the comparison of results with the paper by Augerat et al. we can clearly, see that the tabu search performs well when compared with the other three algorithms.

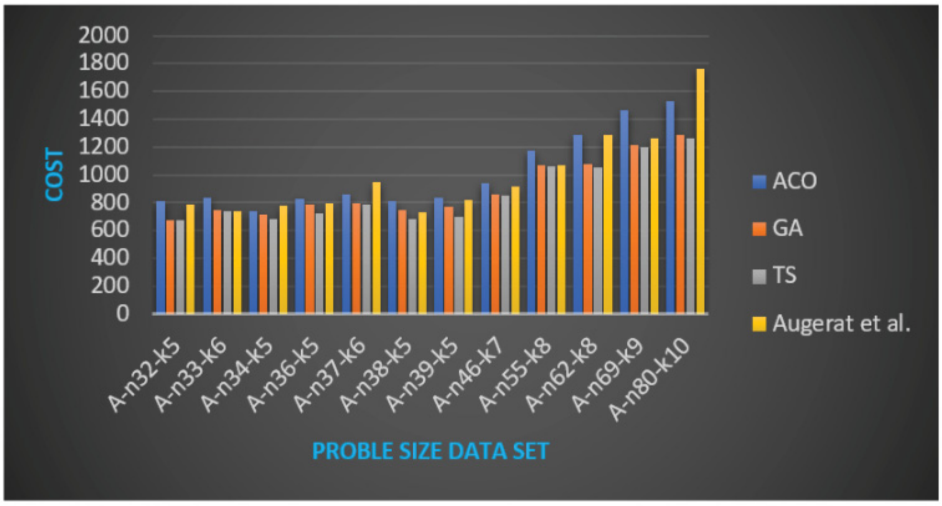

Figure 6.1: Bar representation of results with Augerat et al. Set A

Figure 6.2: Bar representation of results with Augerat et al. Set B

Analysis and discussion about the second paper: The results which are used for analysis are taken from the 'set E' from the second paper by Christofides et al. [34]. From figure 6.3, we can see that there are almost similar values for tabu search and genetic and Christofides for first problem size but when we observe in the second one the size of the problem increased, Christofides solution is also increased. Hence, we can again see that the tabu search performs well when compared with the other three algorithms.

Figure 6.3: Bar representation of results with Christofides et al. Set E

Analysis and discussion about the third paper: Coming to a third paper, we have used both sets 'set A' and 'set B' by Feng et al [35]. Figures 6.4 and 6.5, the performance analysis is a minor difference between each algorithm solutions. The performance of Feng et al. solutions is almost more when compared to the performance of tabu search in all the cases.

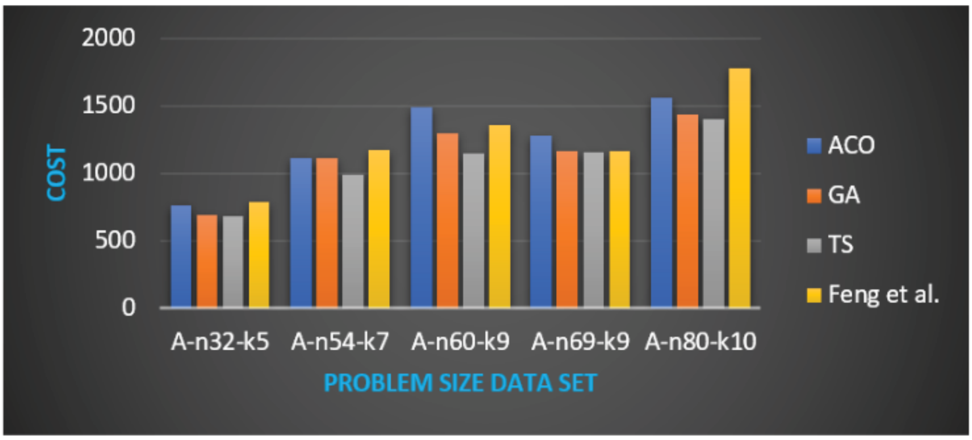

Figure 6.4: Bar representation of results with Feng et al. Set A

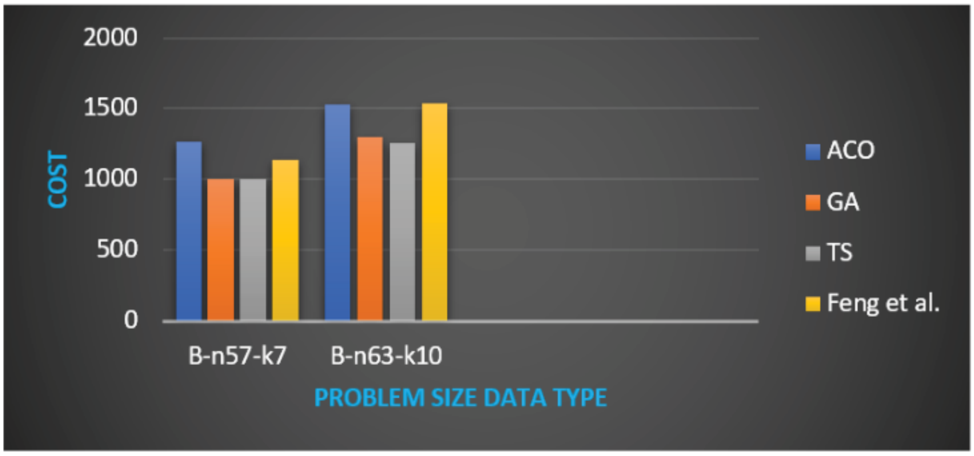

Figure 6.5: Bar representation of results with Feng et al. Set B

Analysis and discussion about the fourth paper: From the fourth paper, the results used for analysis are considered both sets 'set A' and 'set B' by Korayem et al [36]. Figures 6.6 and 6.7 shows that the Korayem solutions are almost near to the performance of tabu search in maximum cases. Even though when there is a slight difference between each other algorithms, among all tabu search shows more effective solutions when compared to other algorithms.

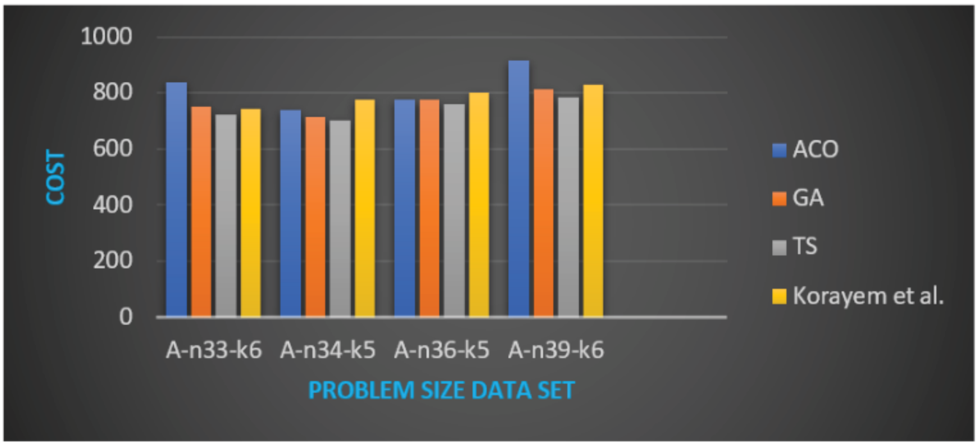

Figure 6.6: Bar representation of results with Korayem et al. Set A

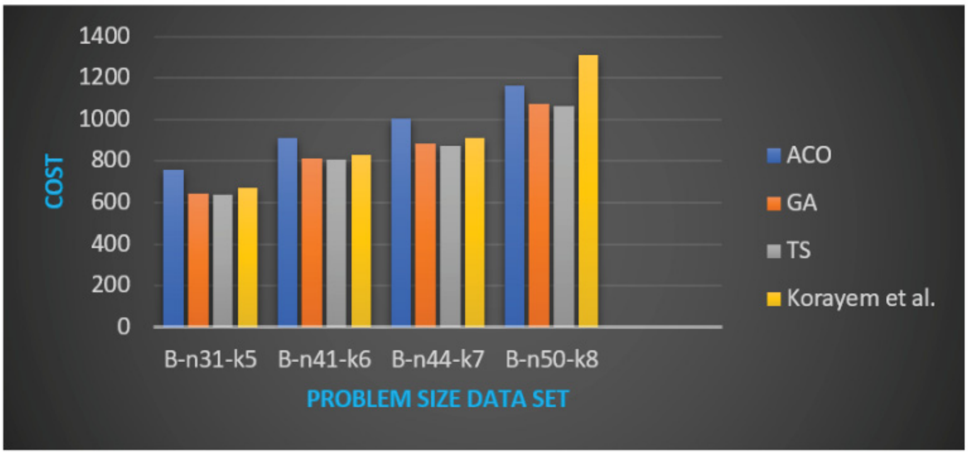

Figure 6.7: Bar representation of results with Korayem et al. Set B

Analysis and discussion about the fifth paper: Coming to the last paper, from figure 6.8, the comparison has been done between ACO, GA, tabu search, and Ganesh at al. [37]. We can see that Ganesh et al. has very high solutions compared to all the other three algorithms. The analysis shows that the tabu search performs a lot better than compared to the remaining algorithms.

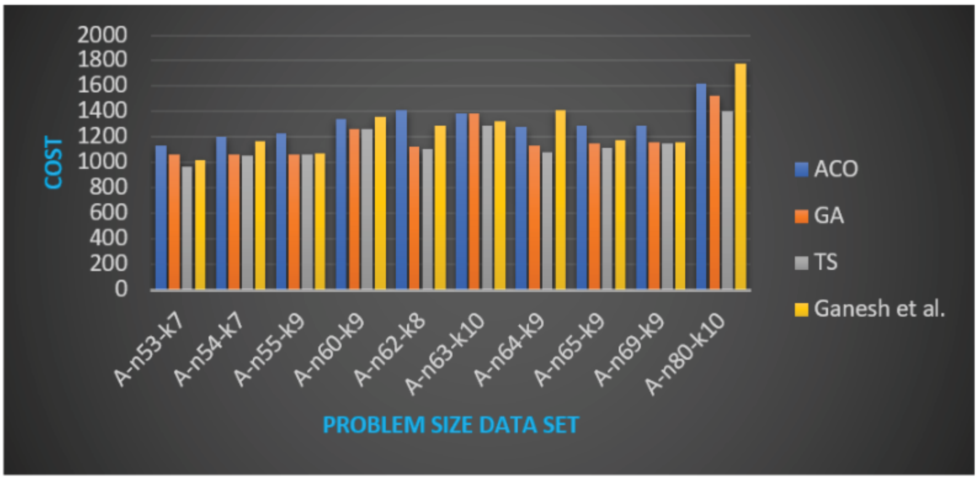

Figure 6.8: Bar representation of results with Ganesh et al. Set A

6.3 Statistical Analysis

To perform statistical analysis to the collected data I have used ANOVA (Analysis of Variance) two-factor without replication method has been used as it is suitable for the data used for this thesis paper. For analyzing experimental results, ANOVA is a widely used statistical hypothesis testing tool. Microsoft Excel is used for analyzing the data using the data analysis tool. This provides the values of variance and standard deviation. After the final analysis, the tool provides the source of variance in rows and columns based on the excel sheet. From the values obtained, we can determine the hypothesis statistically whether to approve or reject.

Why ANOVA?

The Most Common statistical tests for three or more data sets is the Analysis of Variance, or ANOVA. To use this test, the data must meet certain criteria which should be as followed:

- First, the data should be numerical. Ordinal data - such as 5-point scale ratings, are not numerical data, and the ANOVA will not yield accurate results if used with ordinal data.
- Second, the data should be normally distributed in a bell curve.

If these assumptions are met, the ANOVA test can be used for a single dependent variable across three or more samples or data sets to analyze the variance. Shapiro-Wilk test has been used to test the normality of the data and the test proved that the data was normally distributed. From the paper [39] Shapiro-Wilk test results are only dependable on several observations > 2000, and the current number of observations i.e., data sets are lesser than 2000.

Why Two Way ANOVA in Excel without Replication?

The population testing in statistics can be performed using an ANOVA test. While the t-test compares the means, ANOVA compares the variance between the populations. Comparing a group of individuals performing more than one task a Two-Way ANOVA without replication is used.

For example, we should use

- ANOVA two factor with replication, if we are comparing the performance of each algorithm based on a single instance.
- ANOVA two factor without replication, if we are comparing the performance of three or more algorithms based on several instances.

Three or more sample tests:

The efficiency of three or more heuristic algorithms for comparison, the data is derived on the same problem set from the execution of several algorithms. When the populations assumed to be normal, the parametric two-way analysis of variance test is used to compare three or more other heuristic algorithms. When all (three or more) algorithms have equal mean costs, then it is the null hypothesis and if all (three or more) algorithms do not have equal mean costs then it is an alternative hypothesis [40]. Below stated are the performed statistical analysis for the results:

From table 5.3 and figure 6.1, below is the statistical analysis for the first paper by the author Augerat et al. Set A.

Anova: Two-Factor Without Replication				
SUMMARY	Count	Sum	Average	Variance
32	4	2943	735.75	5122.9166
33	4	3066	766.5	2247
34	4	2917	729.25	1618.9166
36	4	3141	785.25	2026.9166
37	4	3389	847.25	5657.5833
38	4	2969	742.25	2509.5833
39	4	3136	784	3638
46	4	3567	891.75	1789.5833
55	4	4383	1095.75	2886.9166
62	4	4706	1176.5	17131
69	4	5139	1284.75	14572.9166
80	4	5832	1458	55842
ACO	12	12117	1009.75	77290.932
GA	12	10758	896.5	43609.545
TS	12	10412	867.66667	46610.061
Augerat et al.Set A	12	11901	991.75	95835.659
ANOVA RESULTS				
Source of Variation	SS	F	P-value	F crit
Data-sets (rows)	2727591.667	48.35683872	3.92453E-17	2.093254411
Algorithms (columns)	175913.5	11.43534171	2.68296E-05	2.891563517
Error	169216.5			
Total	3072721.667			

Table 6.1: Statistical Analysis of results with Augerat et al. Set A.

Since all the table discussions are similar, so described at the end of all tables (To avoid repeated information).

From table 5.4 and figure 6.2, below is the statistical analysis for the first paper by the author Augerat et al. Set B.

Anova: Two-Factor Without Replication				
SUMMARY	Count	Sum	Average	Variance
35	4	3124	781	16002
38	4	3291	822.75	2297.58
41	4	3376	844	3382
50	4	4315	1078.75	26126.25
57	4	4968	1242	59847.33
63	4	5267	1316.75	30300.91
66	4	5165	1291.25	974.25
68	4	4990	1247.5	21772.33
ACO	8	9082	1135.25	64649.07
GA	8	7990	998.75	41121.92
TS	8	7841	980.125	43953.83
Augerat et al. Set B	8	9583	1197.875	90122.69
ANOVA RESULTS				
Source of Variation	SS	F	P-value	F crit
Data-sets (rows)	1464886	20.53129	4.68179E-08	2.487577
Algorithms (columns)	268061.25	8.76644	0.000578	3.072466
Error	214046.75			
Total	1946994			

Table 6.2: Statistical Analysis of results with Augerat et al. Set B.

Since all the table discussions are similar, so described at the end of all tables (To avoid repeated information).

From table 5.5 and figure 6.3, below is the statistical analysis for the second paper by the author Christofides et al. Set E.

Anova: Two-Factor Without Replication				
SUMMARY	Count	Sum	Average	Variance
22	4	1898	474.5	18505.66
23	4	2176	544	4451.33
30	4	2185	546.25	4557.583
31	4	2427	606.75	38422.916
33	4	2903	725.75	6436.25
51	4	2908	727	32383.33
76	4	3412	853	1431.33
ACO	7	5296	756.571	17214.619
GA	7	4610	658.571	19334.285
TS	7	3960	565.714	24560.904
Christofides et al. Set E	7	4043	577.571	35937.9
ANOVA RESULTS				
Source of Variation	SS	F	P-value	F crit
Data-sets (rows)	427163.428	8.261116	0.000215	2.66130
Algorithms (columns)	163442.10	6.321768	0.004062	3.15990
Error	155123.14			
Total	745728.67			

Table 6.3: Statistical Analysis of results with Christofides et al. Set E.

Since all the table discussions are similar, so described at the end of all tables (To avoid repeated information).

From table 5.6 and figures 6.4 and 6.5, below is the statistical analysis for the third paper by the author Feng et al. Set A and B.

Anova: Two-Factor Without Replication				
SUMMARY	Count	Sum	Average	Variance
32	4	2917	729.25	2352.916
54	4	4383	1095.75	5531.583
60	4	5275	1318.75	20158.25
69	4	4756	1189	3480
80	4	6172	1543	28376.66
57	4	4416	1104	15714.66
63	4	5626	1406.5	21821.66
ACO	7	8979	1282.714	80505.23
GA	7	8008	1144	59842
TS	7	7634	1090.571	52169.28
Feng et al. Set A & B	7	8924	1274.857	101521.80
ANOVA RESULTS				
Source of Variation	SS	F	P-value	F crit
Data-sets (rows)	1664705.71	50.1798	2.86736E-10	2.6613
Algorithms (columns)	192782.96	11.6222	0.000180	3.1599
Error	99524.28			
Total	1957012.96			

Table 6.4: Statistical Analysis of results with Feng et al. Set A and B.

Since all the table discussions are similar, so described at the end of all tables (To avoid repeated information).

From table. 5.7 and figure 6.6 and 6.7, below is the statistical analysis for the fourth paper by the author Korayem et al. Set A and B.

Anova: Two-Factor Without Replication				
SUMMARY	Count	Sum	Average	Variance
33	4	3051	762.75	2608.25
34	4	2934	733.5	1167
36	4	3108	777	252.666
39	4	3346	836.5	3169.666
31	4	2714	678.5	3253.666
41	4	3361	840.25	2236.916
44	4	3669	917.25	3494.916
50	4	4613	1153.25	13315.583
ACO	8	7107	888.375	20650.83
GA	8	6469	808.625	16648.553
TS	8	6348	793.5	16896
Korayem et al. Set A & B	8	6872	859	38316
ANOVA RESULTS				
Source of Variation	SS	F	P-value	F crit
Data-sets (rows)	605645.5	43.32822	4.46095E-11	2.48757
Algorithms (columns)	46561.75	7.77245	0.001119581	3.07246
Error	41934.25			
Total	694141.5			

Table 6.5: Statistical Analysis of results with Korayem et al. Set A and B.

Since all the table discussions are similar, so described at the end of all tables (To avoid repeated information).

From table 5.8 and figure 6.8, below is the statistical analysis for the final paper by the author Ganesh et al. Set A.

Anova: Two-Factor Without Replication				
SUMMARY	Count	Sum	Average	Variance
53	4	4183	1045.75	4920.916
54	4	4489	1122.25	5646.916
55	4	4428	1107	6748.666
60	4	5231	1307.75	2324.25
62	4	4934	1233.5	20725.666
63	4	5383	1345.75	2341.583
64	4	4905	1226.25	22218.916
65	4	4734	1183.5	5715
69	4	4759	1189.75	4418.25
80	4	6330	1582.5	25529.666
ACO	10	13187	1318.7	18244.233
GA	10	11934	1193.4	24169.155
TS	10	11495	1149.5	16906.944
Ganesh et al. set A	10	12760	1276	46959.11
ANOVA RESULTS				
Source of Variation	SS	F	P-value	F crit
Data-sets (rows)	832006.1	20.04690	9.36754E-10	2.25013
Algorithms (columns)	177260.6	12.8131	2.15589E-05	2.9603
Error	124508.9			
Total	1133775.6			

Table 6.6: Statistical Analysis of results with Ganesh et al. Set A.

In the above tables: where, ' SS ' = Sum of squares ; F = F-Value ; ' α '= 0.05 (Constant); P-value = significance level; F-crit = F critical value.

Considering two hypothesis: null and alternate hypotheses

1. Null Hypotheses:- The null hypothesis is that all the algorithms have a similar performance.

2. Alternate Hypothesis:- The alternative hypothesis is there is a significant difference in the performance of all algorithms and one algorithm performs better than others.

From the above, all tables 6.1, 6.2, 6.3, 6.4, 6.5, and 6.6, which represent the descriptive statistic values i.e., SUMMARY, Count, Sum, Average, and Variance of each data sets and it also shows the different factors or the qualifying tests that the data sets have to take. So, coming to the results of ANOVA represents inferential part i.e., Source of Variation, SS, F, P-Value, F crit. Under the source of variation, there are two rows Data-sets (rows) and Algorithms (columns) and both have the values SS, F, P-value, F crit. We can observe that 'F' value and 'F critical' value is not equal and F $>$ F critical (Which means there is a huge difference in the performance between each individual data-set and algorithm). The standard alpha value is considered which is the value of 0.05. If the P-value is greater than alpha value then it says that there is no statistically significant difference. But, if we observe algorithms (column) the P-value is less than the alpha value then it determines that the differences are statistically significant in the performance of algorithms with each other. From all the above analysis tables it was clearly seen that F $>$ F critical and $\alpha >$ P-value.

The main aim of the research is to compare the performances of the selected meta-heuristic algorithms with each other. From the statistical analysis, it proves to us that there is a significant difference in the performance of all algorithms and one algorithm performs better than others. Also, it determines that we can clearly reject the null hypothesis.

After observing all the results and conducting analysis it is clear that the results are highly effective for a conclusion. The results also show us the tabu search algorithm has given a better performance than all the five selected papers (Solution algorithms) and also better than selected state-of-art algorithms.

6.4 Answers to Research Questions

RQ1. What are the suitable and efficient meta-heuristic algorithms that can be used to solve the disruption problems in the vehicle routing problem?

Answer: To answer this research question, I have highly performed a literature review to obtain knowledge about various meta-heuristic solution algorithms that are suitable for solving routing problems. There is limited research on the usage of applying the meta-heuristics solution algorithms on the disruption problems, but for solving the VRP the results of meta-heuristic algorithms attend to an intensive performance that is proved by some researchers. When considering the implementation and performance of these algorithms on standard benchmarks, Tabu Search, Ant Colony Optimization and Genetic Algorithm have been identified as the most suitable and efficient meta-heuristic algorithms to solve disruption problems in real-time vehicle routing problems.

RQ2. Which one among the selected meta-heuristic solution algorithm has better performance in producing the near-optimal solutions for solving DVRP and why?
Answer: A literature review is an important part to answer this type of research question. From the literature study, we can conclude that ACO and GA are the most used solutions for solving routing and scheduling problems. So, ACO and GA algorithms are considered as the two state-of-the-art algorithms in this research. Among this selected meta-heuristics Tabu Search has a lack of research for solving the disruption problems in VRP. Also, when compared to other algorithms the TS algorithm is simple, very effective, easy to implement and, finds a relatively good solution in very less time. So, I have considered the TS algorithm is the best suited for producing the optimal solutions. TS can be able to solve very large-scaled and more difficult routing problems and gives better optimal solutions in less computational time.

RQ3. How can we measure the efficiency and performance of the selected meta-heuristic algorithms among each other in DVRP?
Answer: To answer this research question, an experiment has been performed to evaluate the efficiency and performance of these selected algorithms. Comparing the selected algorithms among each other by using the standard benchmarks shows the results of the best algorithm that gives the near-optimal solutions for solving the disruption problems in VRP. Also, it will not only prove one algorithm is better than others but also to make interest for researchers on the strategies used in approaches. Also, to encourage them to be able to further optimize the solutions for solving many vehicle routing and scheduling problems.

6.5 Validity Threats

6.5.1 Internal Validity

Internal validity refers to how well research has been performed [41]. The threat could be a possibility to perform or repeat iterations many times in algorithm which leads to worse the solution is mitigated by defining a maximum number of iterations in the algorithm.

6.5.2 External Validity

The extent to which we can generalize our experimental results is known as external validity [42]. External validity is achieved in this research by collecting data that has been collected from multiple papers (From CVRPLIB) and can be used to evaluate the algorithm and performance of the selected meta-heuristic algorithms.

6.5.3 Conclusion Validity

Conclusion validity checks whether the data and results obtained from the experiment are right and justified. These validity threats arise when the experiment of the research is conducted without proper procedures and methods. This threat is mitigated by following proper procedures and methods while conducting the research. By choosing proper metrics to analyze and evaluate the solution algorithms (meta-heuristics).

Chapter 7

Conclusions and Future Work

In this research, Tabu Search, Genetic Algorithm, and Ant Colony Optimization algorithms are suitable meta-heuristic algorithms for solving the disruption in vehicle routing problems. The implementation of the selected meta-heuristic algorithms have been presented to determine good approximate and near-optimal solutions. These algorithms take the asset of the original plan and within a limited time, they generate a new routing plan. Tabu Search algorithm includes suitable parameters and strategies which are easy, flexible, and always produce an optimal solution. They were tested on different standard benchmarks that were gathered from CVRPLIB. The experiment results demonstrate the efficiency and effectiveness of the selected algorithm, for which we provide better results than the existing best-known results for data sets. Moreover, the selected TS algorithm obtains promising results on tested instances, which shows the stability of the algorithm. From this research paper, we can conclude the importance of meta-heuristics solutions is very enormous from the literature studies and the experiment conducted for solving disruption in vehicle routing problems. These algorithms with the combination of other solution algorithms have a high scope of reaching further optimal solutions.

Many relative domains need to be considered in a future study, disruption problem in vehicle routing problems may cause further from traffic jams, accidents, road blocking, environmental conditions, etc... which needs to be investigated in future work. Also, the possibilities of implementing the meta-heuristic algorithms and further metrics for solving the related routing problems by considering the objectives like capacity, changes of a service request to customers, time windows, usage number of vehicles, size of the vehicle (small, medium, large). Finally, the algorithms should be tested with very large-scale benchmark instances. There is still a long way to go on the track to connect the vehicle routing problems with sustainable issues. We hope this research may lead to new opportunities and circumstances for sustainable management of logistics industries and will encourage more researchers and make interests in choosing topic VRP.

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