AN OPTIMIZATION MODEL FOR MULTI-OBJECTIVE VEHICLE ROUTING PROBLEM FOR PERISHABLE GOODS DISTRIBUTION

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Degree of Master of Science

Department of Transport and Logistics Management

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STATEMENT OF THE SUPERVISOR

The above candidate has carried out research for the Degree of Master of Science under my supervision.

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Dr. H.N. Perera

Signatures of Supervisors: Date: 22^{nd} August 2022

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Abstract

Vehicle Routing Problem (VRP) is a well-studied area of operations research that has resulted in significant cost savings in global transportation. The primary goal of the VRP is to find the best route plan that minimizes the total distance traveled. The current study used VRP to solve the problem of fresh Agri products distribution in retail chains. With the advancement of computation power, researchers pay more attention to incorporating real-world characteristics when developing VRP, making it more practical for use in real-world applications. Existing literature identifies a research gap in richer problems that use real-world characteristics concurrently. This study created an integrated bi-objective VRP model that focused on resource optimization, order scheduling, and route optimization all at the same time. Two objectives aim to minimize distribution costs while ensuring product deliveries to retail outlets on time. To improve real-world applicability, the model incorporated multiple real-world characteristics simultaneously. All the algorithms were developed using an open-source optimization library called OR-tools.

This research compared several heuristics and metaheuristic methods respectively, to obtain the IBFS (Initial Basic Feasible Solutions) and iterative improvements. Thereafter, best performing heuristic method (savings algorithms) and metaheuristic method (guided local search) were hybridized to develop the proposed two-phase solution method. All the solution algorithms and the developed VRP model were tested using the data obtained from one of the largest retail chains in Sri Lanka. Numerical experiments show the efficiency of the proposed solution algorithm in solving a real-world VRP problem. Further, numerical experiments show that the proposed VRP model has achieved a 16% saving in daily distribution cost while ensuring on-time deliveries to 95% of the retail outlets. Further, on-time deliveries of fresh Agri products ensure the freshness conditions. The developed VRP model is efficient to use as an operational planning tool for planning distribution operations in retail chains.

Keywords:

Vehicle Routing Problem, Perishable goods distribution, Retail supply chain**,** Heuristic methods, Metaheuristic methods, Real-world application

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

COMVRP - Closed Open Mixed Vehicle Routing Problem

CVRP - Capacitated Vehicle Routing Problem

GLS - Guided Local Search

HFVRP - Heterogenous Fleet Vehicle Routing Problem

IBFS - Initial Basic Feasible Solutions

MDVRP - Multiple Depot Vehicle Routing Problem

MOVRP - Muti Objective Vehicle Routing Problem

OR - Operations Research

OSRM - Open-Source Routing Machine

SA - Simulated Annealing

SDVRP - Split Delivery Vehicle Routing Problem

TS - Tabu Search

VRP - Vehicle Routing Problem

VRPFPG - Vehicle Routing Problem for Perishable Goods

VRPTW - Vehicle Routing Problem with Time Windows

1. INTRODUCTION

1.1. Background and Motivation

Scholars have defined the term "optimization" in a variety of ways. Lockhart & Johnson (1996) explain the term optimization as the “process of finding the most effective favorable value or condition” (p. 610). In simple words, the term optimization could be defined as “doing the most with the least” (Gomez et al.,p.301, 2006). The goal of optimization is to find the best design or process subject to a set of constraints. Globally, many organizations have achieved a remarkable impact on increasing efficiency by applying the concept of optimization in their businesses (Hillier & Lieberman, 2001). As an example, world-famous personal computer manufacturer, Hewlett-Packard company gained $280 million more revenue through a production process optimization in 1998 (Hillier & Lieberman, 2001).

Operations Research (OR) applies analytical techniques to improve decision-making concerning optimization (Hillier & Lieberman, 2001). It is widely accepted that field of OR originated in the United Kingdom during World War II (Hillier & Lieberman, 2001). Just after the 2nd World War, scientists realized that this field of study is equally applicable for solving military problems as well as civilian problems (Hillier & Lieberman, 2001). Even though there is a misconception that OR is a set of mathematical techniques, it has a broader scope beyond that of OR being a systematic approach to solving multidisciplinary problems (Hillier & Lieberman, 2001). Operations research is useful for making better decisions in many areas including manufacturing, transportation, project management, supply chain management, etc (Hillier & Lieberman, 2001).

Vehicle Routing Problem (VRP) is a well-studied application of Operations Research in the field of supply chain management (Braekers et al., 2016; Thibbotuwawa et al., 2020). Dantzig & Ramser, (1959) introduced the VRP as a “truck dispatching problem”. The model attempted to find optimal routes for a homogeneous fleet of trucks from the central depot to gas stations. Later, VRP was generalized as a linear optimization problem (Clarke & Wright, 1964). Mathematically VRP is presented as a directed graph G (V, A), where V = {0,1,2, n} set of predefined vertexes, and A ={(i, j): i,j ∈ N} represents a set of arcs connecting any two vertexes (Clarke & Wright, 1964). The depot is represented by vertex i=0, and the other vertexes represent the customer locations (Clarke & Wright, 1964). The problem aims to serve its customers using vehicles to minimize travel distance or travel time. Optimization packages based on the Vehicle Routing Problem (VRP) have achieved substantial savings in global transportation (Utama et al., 2020).

Table 1-1: Different VRP extensions used in the research

VRP extension	Explanation
CVRP	Capacitated VRP applies to problems that are having vehicles with limited carrying capacity to pick up or deliver the products. (Thibbotuwawa et al., 2020)
VRPTW	VRP with time windows tackles problems where customers have requested specific periods to visit. (Thibbotuwawa et al., 2020)
MDVRP	Multi-depot VRP is important when geographically dispersed multiple distribution centers serve customers. (Fernando et al., 2022)
SDVRP	In some distribution channels, multiple vehicles serve one customer, and total service demand is split among vehicles. Split delivery VRP is applied for such occasions. (Thibbotuwawa et al., 2020)
COMVRP	Closed open mixed VRP tackles the applications where closed, and open routes exist simultaneously. (Fernando et al., 2022)
HFVRP	In real-world applications, a fleet consists of vehicles with different capacities. Heterogenous fleet VRP tackles such applications. (Fernando et al., 2022)
MOVRP	Muti-objective VRP tackles the instance where multiple criteria need to be concerned simultaneously. (Thibbotuwawa et al., 2020)

The problem is simplified as the well-known Travelling Salesman Problem (TSP) when the fleet consists of one vehicle. Therefore, VRP could be introduced as a more generalized version of the TSP. Both VRP and the TSP are known as NP-hard (non-deterministic polynomial-time hardness) problems (Thibbotuwawa et al., 2020;

Braekers et al., 2016). With the improvements in the computation power, researchers found effective solution algorithms and strategies to tackle many VRP extensions (Montoya-torres et al., 2015; Braekers et al., 2016). Therefore, an extensive number of scientific papers published on different extensions of VRP (Montoya-torres et al., 2015; Braekers et al., 2016). Those solve a set of specific routing problems with identical assumptions and constraints. The VRP extensions that have been incorporated in the current research are explained above in Table 1-1.

Different VRP extensions were applied to solve interesting applications like unmanned aerial vehicle routing (Thibbotuwawa et al., 2020), electric vehicle routing (Çalık et al., 2021), green vehicle routing with the emission factor (Moghdani et al., 2021), etc. The current research intends to apply VRP for perishable goods distribution (VRPFPG). Perishable products, including fresh Agri products, dairy, meat, and pharmaceutical products, need to be delivered before degrading their quality. Therefore, VRPFPG is different from traditional VRP, and operational complexities need to be addressed simultaneously with route optimization (Utama, Dewi, Wahid, & Santoso, 2020).

We apply VRP to optimize the processes of fresh Agri product collection and distribution. Food security is cited as one of the most serious threats to achieving the SDGs (Sustainable Development Goals) (Krishnan et al., 2020). Despite this, 33% of the global agricultural production is wasted as post-harvest waste (PHW) (Surucu-Balci & Tuna, 2021). In Sri Lanka, approximately 30%-40% of total agricultural production is wasted, and from that, around 48% is wasted due to inefficient transport and distribution processes (Weerasinghe and Priyadarshan, 2017). Further, Sri Lankan agricultural economy lost approximately three billion rupees due to inadequate transport and distribution systems (Weerasinghe and Priyadarshan, 2017). Therefore, it is critical to optimize the transport and distribution processes in the agricultural supply chains.

Specifically, the research applied VRP to optimize the distribution of vegetables in retail chains. With the growth of the global population, demand for commodities has increased drastically (He & Haasis, 2019). It has resulted in a significant increment in urban freight flows in retail chains (He & Haasis, 2019). It is estimated that the number of delivery vehicles will be increased by 36% over the next decade (Gutierrez-Franco et al., 2021). These trends are causes for the numerous challenges in managing urban traffic, thereby creating a massive threat to the smooth flow of urban distribution systems (Gutierrez-Franco et al., 2021). Especially fresh Agri products have a short shelf life and must be delivered before degrading the quality (Zulvia et al., 2020). Moreover, retail shops cannot keep extra stocks for fresh Agri products due to the perishability and need to be delivered frequently to meet the customer expectations (Zulvia et al., 2020).

1.2. Significance of the Research

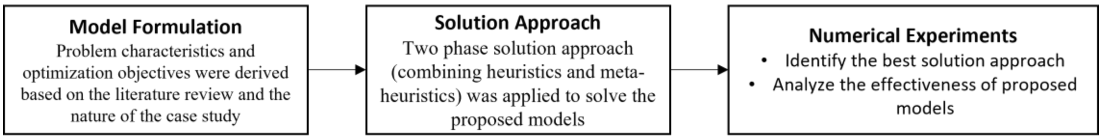

Figure 1-1:Research design

Researchers pay more attention to incorporating real-life characteristics when developing VRP, making it more practical for use in real-world applications (c; Braekers et al., 2016). Existing literature identifies a research gap in richer problems that use real-life characteristics concurrently (Montoya-torres et al.; Braekers et al., 2016). This research attempts to fill this research gap by incorporating real-world characteristics unique to retail chains and perishable goods distribution. Further, the majority of VRP research is aimed at pure investigation and not at applications (Utama, Dewi, Wahid, Utama, et al., 2020). The current research is more focused on real-world implications. The research is significant because it addresses several research gaps in the VRP domain while also solving a real-world industry problem. Figure 1-1 depicts a task flowchart that sequences the three major steps in the proposed research design. The research design was inspired by recently published research in high-ranking journals in a similar context (Zulvia et al., 2020; Hasani Goodarzi et al., 2020).

1.3. Structure of the Thesis

This thesis consists of five individual chapters. Chapter two (Literature Review) presents an extensive analysis of the existing VRP models and the solution approaches. At the end of chapter two thesis highlights the research objective development based on the research gaps identified through the literature analysis. Chapter three (Methodology) consists of the mathematical formulation of proposed models, assumptions, and details about the solution approach employed in this research. Furthermore, the results of the numerical experiments, including the comparison of different solution approaches and the performance of the proposed models, are presented in chapter four. In the final chapter, concluding remarks and future research are highlighted.

2. LITERATURE REVIEW

The literature review was carried out in two phases. The first phase of the literature review focused on analyzing scientific papers related to Vehicle Routing Problem for Perishable Goods (VRPFPG) distribution. The aim was to identify gaps between theoretical models and real-world word applications. Phase 1 focused on investigating the nature of the objective of existing VRPFPG models, problem characteristics, and solution approaches. Moreover, the second phase of the literature review focused on scientific papers published on Close-Open Mixed Vehicle Routing Problem (COMVRP). The findings highlight that COMVRP extension to VRPFPG has not been reported adequately in the literature.

2.1. Nature of the Objectives of VRPFPG Models

Among the reviewed VRPFPG papers, 67% (30 papers) focused on developing single objective models. Only 33% (15 papers) focused on multiple objective models. Moreover, very few researchers incorporated more than two objectives (Navazi et al., 2019; Zulvia et al., 2020). As a percentage, it was 4% (2 papers) of all the reviewed papers in literature review phase 1.

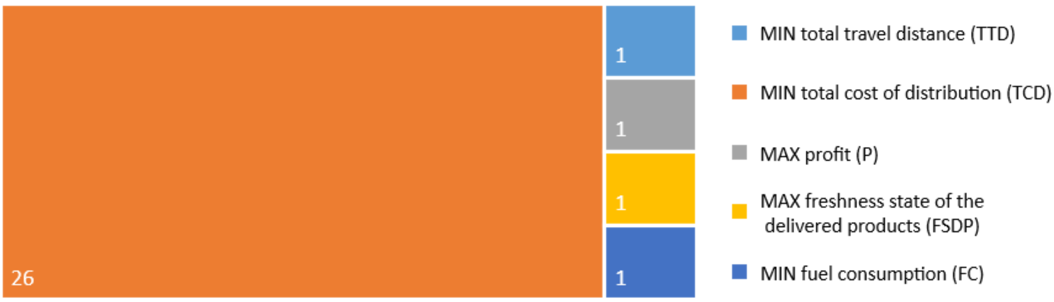

Figure 2-1: Nature of objective of single objective VRPFPG models

As shown in Figure 2-1, the most common objective used in existing single objective VRPFPG models is to minimize the cost of distribution (Utama, Dewi, Wahid, & Santoso, 2020). Depending on the focus of the studies, various cost components were considered. The majority of studies included transportation costs as a component of distribution costs (Tirkolaee et al., 2020; Yao et al., 2019). It comprised the fuel and fixed costs associated with the vehicles (Meneghetti et al., 2019). Furthermore, several types of penalty costs, such as the penalty for violating time windows and freshness conditions, were taken into account in a few studies (Taylor et al., 2013; Agustina et al., 2014).

Temperature-controlled vehicles transport perishable goods such as pharmaceuticals, meat, and dairy products. As a result, the cost of refrigeration was regarded as a component of distribution cost (Meneghetti et al., 2019). Additionally, some researchers included production and order scheduling costs as a component of distribution costs since the VRP models integrate production or order scheduling sub-models (Seyedhosseini & Ghoreyshi, 2014; Lacomme et al., 2018). Among single objective research reviewed in this study, very few (4 papers-13%) considered different objectives other than minimizing the total cost of distribution (Tirkolaee et al., 2020; Meneghetti et al., 2019).

Many logistics problems are multi-objective since there are various factors to consider simultaneously (Montoya-torres et al., 2015). Most of the time, those multiple factors conflict with one another (Montoya-torres et al., 2015). Therefore, considering those factors simultaneously is helpful to minimize the difference between theoretical models and real-world applications (Montoya-torres et al., 2015).

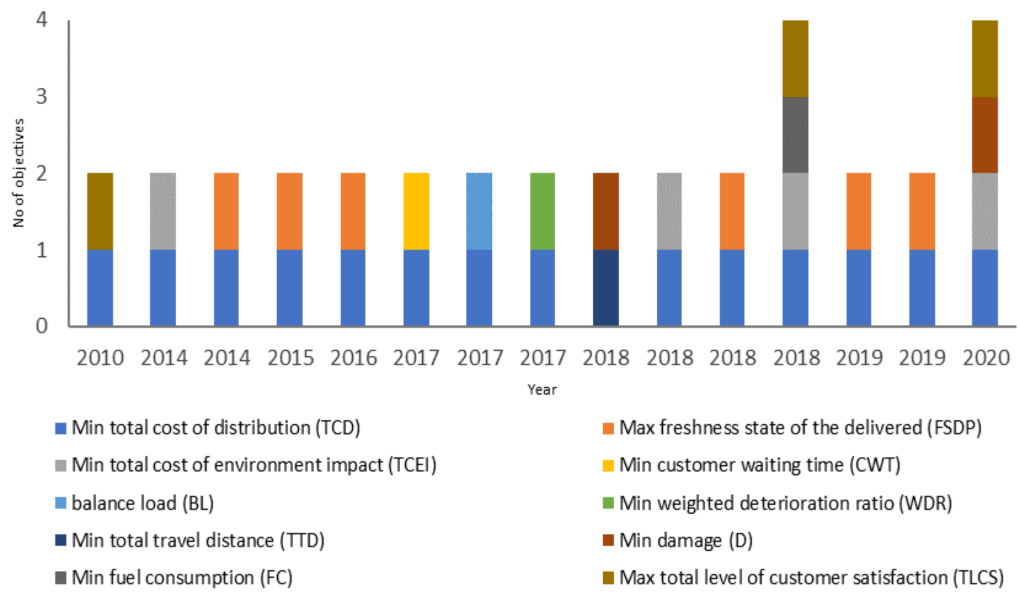

Figure 2-2: Nature of objective of multiple objective VRPFPG models

As illustrated in Figure 2-2 among the reviewed multiple objective models, 40% (6 papers) of the models focused on optimizing the distribution cost and the freshness of the products (Amorim & Almada-Lobo, 2014; Khalili-Damghani et al., 2015; Wang et al., 2016; Rahbari et al., 2019; Fatemi Ghomi & Asgarian, 2019). Amorim & Almada-Lobo, (2014) studied the trade-off between different distribution scenarios and the cost associated with the freshness states.

Several multiple objective models focused on incorporating environmental costs incurred during the distribution process. The environmental cost includes the cost of carbon and greenhouse gas emissions (Govindan et al., 2014; Sahraeian & Esmaeili, 2018). Moreover, findings highlight that environmental costs have been considered in all two papers that have used more than two objectives (Navazi et al., 2019; Zulvia et al., 2020). Other factors that have been considered in multiple objective models are minimizing travel distance (Buelvas et al., 2018), fuel consumption (Navazi et al., 2019), customer waiting time (Esmaili & Sahraeian, 2017), damage cost (Lu & Wang, 2018; Buelvas et al., 2018; Zulvia et al., 2020) as well as maximizing customer satisfaction (Gong & Fu, 2010; Navazi et al., 2019; Zulvia et al., 2020) and balancing the load (Kuo & Nugroho, 2017).

2.2. Problem Characteristics

This section intends to provide an analysis of the problem characteristics incorporated in the reviewed papers. The majority of the papers reviewed concentrated on single depot models with close-VRP. Only a few developed models considered intermediate depots (Nadhori & Ahsan, 2019; Tirkolaee et al., 2019). Only a few of these studies took into account fleets of vehicles with different capacity and the majority assumed

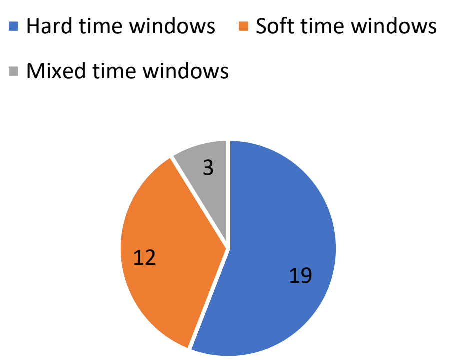

Figure 2-3:Nature of time window structure

identical vehicle capacities (Nadhori & Ahsan, 2019; Tirkolaee et al., 2019). Moreover, very few considered multi-compartment vehicles and multiple products (Chen & Shi, 2019).

interestingly, time windows were incorporated in 75% (34 of a total 45) of the reviewed VRPFPG papers. There were three types of time window structures included as hard (Nadhori & Ahsan, 2019), soft (Zulvia et al., 2020), and mixed (Rashidi Komijan & Delavari, 2017). Figure 2-3 highlights those existing models have incorporated different time window structures. Service providers must meet the hard time windows and if the service provider fails to meet this requirement they must drop that customer to keep the solutions feasible (Patidar et al., 2019). Amorim & Almada-Lobo, (2014) compared two distribution scenarios with narrow and wide hard time structures. It is highlighted that distribution cost is high for the narrow hard time window structure. In a soft time window structure, it is flexible to violate the time window with a penalty cost (Zulvia et al., 2020). Mixed time windows are a combination of soft and hard time windows. All the time windows included in reviewed papers had been imposed by the customers. Among the reviewed papers in the study, no one has considered the time windows imposed by the distribution center due to the limitations of the loading bays. Moreover, all the studies that incorporate time windows tend to use onsite service time (loading/ unloading time) as an input in their models.

Most of the VRPFPG studies developed optimization models as deterministic models. In deterministic models, all the data inputs are static values. Only a few researchers focused on developing stochastic models, including stochastic travel times and service demands (Li et al., 2013; Rong & Sha, 2014; Zulvia et al., 2020). Moreover, no reviewed article in the study used real-time data. Usually, travel times are varied based on the time of the day due to congestion (Zulvia et al., 2020). Hence considering time-dependent travel times guarantee real-world applicability of VRP models (Zulvia et al., 2020). Time-dependent travel time can be obtained using the average speeds of a considered road network based on varying congestion levels (Zulvia et al., 2020).

Problem characteristics such as pick up and delivery and multiple product delivery were rarely explored in existing literature (Abraham et al., 2012; Galarcio Noguera et al., 2018). Moreover, the findings highlight that most reviewed papers used synthetic data to test the models and rarely focused on using real-world case studies. Further, the Solomon benchmark dataset (Solomon, 1987) is popular among VRPFPG researchers. Most of the research using synthetic data employed this dataset (Buelvas et al., 2018; Galarcio Noguera et al., 2018). There is an urgent need to integrate VRPFPG models with production (Tirkolaee et al., 2017), order scheduling (Ma et al., 2017), and inventory routing sub-models (Seyedhosseini and Ghoreyshi, 2014).

2.3. Solution Approaches

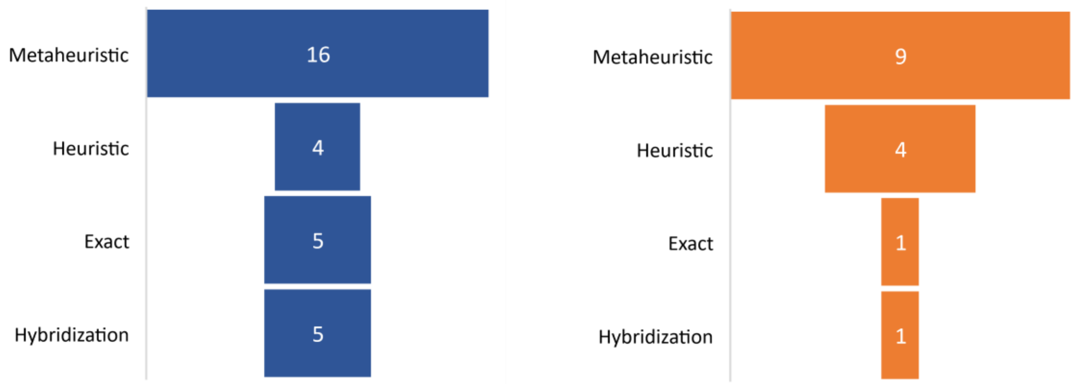

Figure 2-4: Solution approaches used to solve single and multiple objective VRPFPG models respectively

Different solution approaches are used to solve various extensions of VRP (Thibbotuwawa et al., 2020; Braekers et al., 2016). Those methods are highlighted as an exact, heuristic, metaheuristic, and hybrid methods (Thibbotuwawa et al., 2020; Braekers et al., 2016). As indicated in Figure 2-4 metaheuristic is the most widely used solution approach among the reviewed VRPFPG papers. Compared to metaheuristic algorithms, heuristic algorithms are problem-specific, and therefore, applicability is limited (Montoya-torres et al., 2015; Braekers et al., 2016). Exact methods can find optimal solutions if the problems are not NP-hard (non-deterministic polynomial-time hardness) (Thibbotuwawa et al., 2020; Braekers et al., 2016). Thereby a minimal number of VRPFPG researchers applied exact methods to solve the problems (Utama, Dewi, Wahid, & Santoso, 2020).

Under certain conditions, a single solution method for the VRP may be insufficient. Reasons cited include optimal solutions trapped in local minima, sub-optimal solutions, and impracticable computation time (Moghdani et al., 2021). To avoid limitations, two solution approaches are combined to introduce hybrid techniques. To achieve better results, researchers used combined metaheuristic-exact, metaheuristic-heuristic, and metaheuristic-metaheuristic methods (Moghdani et al., 2021). Additionally, hybrid solution methods are needed when the model consists of several sub-models.

Metaheuristic methods are well accepted among VRP researchers due to their applicability to solving a wide range of problems and achieving near-optimal solutions within a lower computation time (Braekers et al., 2016). A Genetic Algorithm (GA) is a Metaheuristic approach inspired by the natural selection process. Among the reviewed papers, the majority have used Genetic Algorithm to solve proposed VRPFPG models (Xu & Murata, 2010; Tunjongsirigul & Pongchairerks, 2010; Keskinturk & Yildirim, 2011; Abraham et al., 2012; Zhang & Chen, 2014; Rong & Sha, 2014; Salam et al., 2018).

Keskinturk & Yildirim (2011) showed that using the GA with a local search approach outperformed applying GA alone. Zheng, (2015) compared the performances of the improved GA with the traditional GA method. Results highlighted that the improved version had gained speed convergence (Zheng, 2015). Rabbani et al., (2016) compared the exact solver in GAMS software and the GA in solving multiple depots VRP. Results highlighted that GA outperformed better than the exact solver in terms of computation time and the quality of the solutions. Haerani et al., (2017) combined GA with Fuzzy Logic Controller (FLC) to avoid the solutions trap in a local minimum.

The research compared the Artificial Immune System (AIS) based metaheuristic with GA and Simulated Annealing (SA) to solve a real-world case study of the VRPFPG problem (Shukla & Jharkharia, 2013). Computational experiments showed that the AIS-based solution approach outperformed SA (Shukla & Jharkharia, 2013). Chen & Shi, (2019) compared traditional Particle Swarm Optimization (PSO) and hybrid PSO with SA in solving the multi-compartment VRP. Chen & Shi (2019) highlighted that hybrid PSO is efficient when the problem size is increasing. Kuo & Nugroho, (2017) used Gradient Evolution (GE) algorithms to solve the fuzzy objective VRPFPG model.

Computational experiments show that the proposed GE algorithm outperformed compared to GA. Sahraeian & Esmaeili, (2018) used the Multi-Objective Particle Swarm Optimization (MOPSO) method to solve a two-echelon vehicle routing problem with three objectives. Zulvia et al., (2020) proposed a many-objective gradient evolution (MOGE) algorithm to solve the green vehicle routing problem to optimize four model objectives simultaneously.

Except when the problem size is very small, the exact method does not help find optimal solutions for NP-hard problems (Utama, Dewi, Wahid, & Santoso, 2020). For small VRP problem instances, a Mixed-Integer Programming (MIP) solver in CPLEX is more feasible (Agustina et al., 2014). Nevertheless, when strategies to reduce the solution space are used, the MIP solver in CPLEX is efficient for medium and large-size problems (Agustina et al., 2014). In order to solve VRPFPG models, researchers compared the Exact solvers in CPLEX and GAMS software (A.Goli, M.Bakshi, 2017; Meneghetti et al., 2019; Tirkolaee et al., 2020).

Several VRPFPG researchers employed hybrid solution approaches to solve integrated routing models with production and order scheduling sub-models. Researchers emphasized the importance of integrating production and distribution planning (Seyedhosseini & Ghoreyshi, 2014). Seyedhosseini & Ghoreyshi, (2014) used LINGO commercial optimizer to solve the production sub-model and particle swarm optimization (PSO), and the distribution sub-model. Ma et al., (2017) used hybrid Ant Colony optimization to solve integrated order scheduling and vehicle routing models. Lacomme et al., (2018) used a Greedy Randomized Adaptive Search and a Local Evolutionary Search to solve a production and transport scheduling problem.

Wang et al., (2016) proposed a two-phase heuristic method by integrating Pareto Optimization and Genetic Algorithm to solve a multi-objective vehicle routing problem. Moreover, numerical experiments show that the proposed two-phase heuristic approach has significantly improved the quality of the solutions and the computation time. Galarcio Noguera et al., (2018) compared Genetic Algorithms and Hybrid Particle Swarm Optimization in solving a vehicle routing problem to deliver multiple perishable goods. Results highlighted that the hybrid solution approach had gained significant improvement compared to GA. Tabu Search and the Genetic

Algorithm were combined to solve an urban distribution problem by integrating sustainable aspects (Lin et al., 2019).

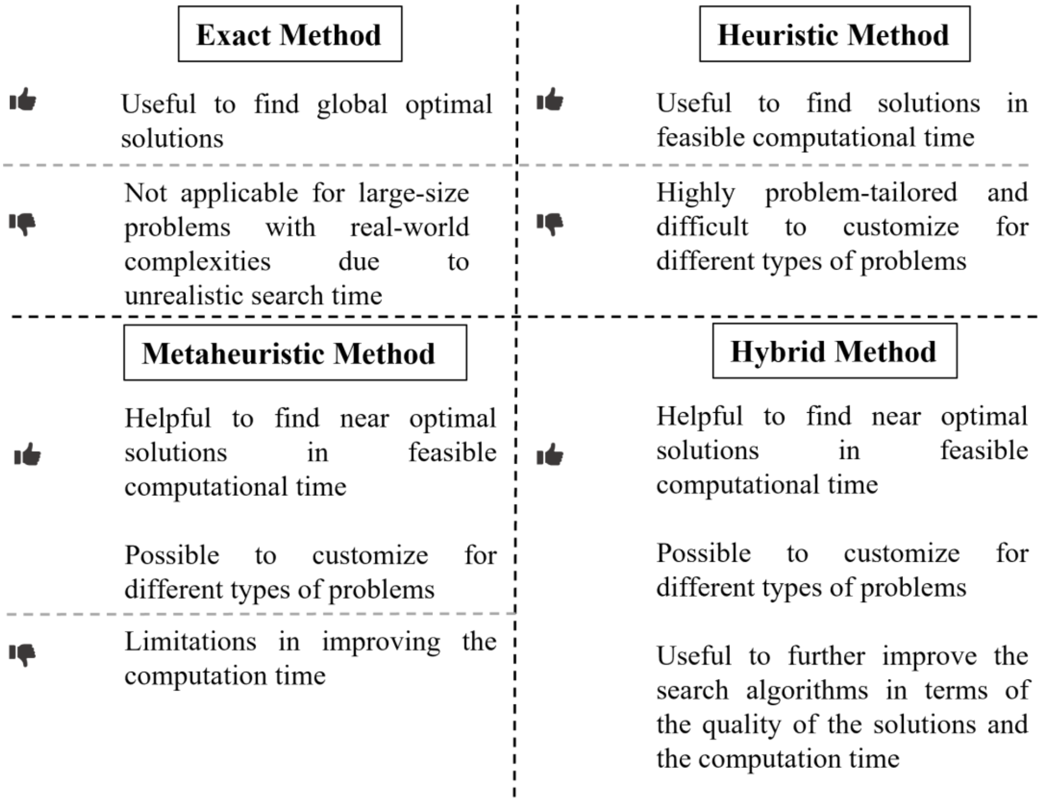

Figure 2-5: Comparison of different categories of solution approaches

The above comparison (Figure 2-5) was carried out based on the literature review for solution approaches. The comparison highlights the pros and cons of different solution categories identified in this literature review. According to the comparison, exact methods are not appropriate for large-scale, real-world problems due to unrealistic computation time. This literature review indicates that metaheuristic methods are the most popular among VRP researchers. Even though hybrid methods have more advantages, researchers haven’t explored these methods as the literature review of the current study reveal.

2.4. Close-Open Mixed Vehicle Routing Problem

Classical VRP is also called a close-VRP since vehicles start from the central distribution centers and return to the same-origin point after completing the designated tasks (Dantzig & Ramser, 1959). Open-VRPs consider the instances where vehicles do not return to the same origin point. All the reviewed VRPFPG models in this literature analysis focused on close-RP. But there are instances where close and open routes exist simultaneously. Liu & Jiang, (2012) introduced the Close-Open Mixed Vehicle Routing Problem (COMVRP), which takes both close-VRP and open-VRP into account. COMVRP's practical application is to address situations in which both internal and hired fleets are used in operation.

Seifbarghy & Mojhgan, (2016) developed a COMVRP model with semi-soft time windows and constraints for waiting time. The model attempted to minimize the transport cost and the study employed a genetic algorithm and tabu search in solving the proposed model (Seifbarghy & Mojhgan, 2016). Further, the study showed that genetic algorithms perform better (Seifbarghy & Mojhgan, 2016). Rabbani, Farrokhi-Asl, et al., (2016) suggested a COMVRP model in solving waste collection case-study with multi-compartment heterogeneous fleets. Moreover, the study used a hybrid genetic algorithm to solve the problem and benchmarked the results against the MIP solver in CPLEX (Rabbani, Farrokhi-Asl, et al., 2016).

Azadeh & Farrokhi-Asl, (2019) proposed a COMVRP model with multiple distribution centers by considering both internal and outsourced fleets. Further, the study developed a hybrid solution approach combining the genetic algorithm and the analytical hierarchy process (Azadeh & Farrokhi-Asl, 2019). The study showed that the proposed solution approach performs better than the conventional genetic algorithm and the MIP solver in CPLEX (Azadeh & Farrokhi-Asl, 2019). Rahmani, (2021) applied the COMVRP model to solve a cross-docking problem. Integrating COMVRP and cross-docking is helpful to solve many real-world logistics problems (Rahmani, 2021). Further, the study incorporates stochastic travel times between the retailer nodes (Rahmani, 2021). The study employed a hybrid solution approach to solve the proposed model combining robust optimization and a genetic algorithm (Rahmani, 2021).

Lu Zhen, Roberto Baldacci, Zheyi Tan, and Shuaian Wang, (2021) used the COMVRP model to solve a logistic problem of an e-commerce retailer case study that uses both internal and hired fleets. Moreover, the study employed MIP and a column generation-based solution approach to solve the proposed problem. Computational experiments showed the efficiency of the solution approach in solving the case study.

2.5. Research Objectives Development

Several research gaps were identified through the literature review to be addressed in this current research. The study developed the research objectives to align with those identified research gaps. Those research gaps could be listed as follows.

- The literature review of this study highlights that only 33% (15 of a total 45) of the papers have focused on multi-objective VRPs. It is emphasized that many logistics problems are multi-objective by nature and need to consider multiple factors simultaneously. Therefore, further research is required to consider numerous case-sensitive objectives in this study area of VRPFPG (Montoya-torres et al., 2015).
- The majority of existing VRPFPG models incorporated real-life characteristics individually or with a limited number of other factors. The literature review identified that several real-world characteristics such as multiple distribution centers, heterogeneous vehicle fleet, multiple product delivery, real-world driving distances, and closed-open mixed routes have been incorporated rarely in the existing VRPFPG literature. Further, very little attention has been paid to developing integrated VRP models. With the improvement of the computational power, researchers simultaneously attempt to incorporate several real-life complexities as the recent trend in this study area (Utama et al., 2020).
- Many researchers highly applied problem-tailored solution methods to solve the VRP models. Those methods are not directly applicable to other problem variants. Future research is needed to conduct a comprehensive investigation to compare the performance of different metaheuristic algorithms in solving the various extensions of VRP (Braekers et al., 2016). According to the literature review, hybrid solution approaches have been underutilized and it was 13% (6 of a total

45) of the reviewed papers. Further, the findings reveal that researchers have paid very little attention to combining heuristic and meta-heuristic approaches.

This study has planned to address the following research objectives to fulfill above mentioned research gaps.

RO1: *Formulates a bi-objective VRPFPG model, including more realistic assumptions and more industrial relevant constraints (Montoya-torres et al., 2015).*

***RO2**: Investigate the effectiveness of the different solution methods in solving the proposed model (Braekers et al., 2016).*

RO3: *Analyze the proposed VRPFPG model's applicability in real-world applications (Utama et al., 2020).*

3. METHODOLOGY

This chapter aims to provide information about the model formulation, including an overview of the model, notations, assumptions, and the mathematical model. This chapter also contains details about the case study that we used to test the proposed model. The model implementation includes the steps taken to create the computer application for the proposed model. Finally, the chapter discusses the two-phase solution method proposed through this research to solve the problem.

3.1. Model Formulation

3.1.1. Overview

The research identified the decision variables, objective functions, and constraints specific to the application of delivering fresh Agri products in a retail chain. Both literature review and the unstructured interviews conducted with industry experts were used to define the problem and to get a clear understanding of the goal that needs to be optimized. The proposed model is a combination of CVRP (Capacitated VRP) (Fernando et al., 2022), VRPTW (VRP with time windows – i.e. soft time windows with upper bound) (Ma et al., 2017), MDVRP (Multi-depot VRP) (A.Goli, M.Bakshi, 2017), HFVRP (Heterogenous fleet VRP) (Fernando et al., 2022), and MOVRP (Multi-objective VRP) (Zulvia et al., 2020).

Figure 3-1 depicts a high-level overview of the model's inputs, objectives, constraints, and outputs. The current research's literature review highlighted a research gap in application-oriented VRP models that address multiple real-world complexities (Braekers et al., 2016). As a result, all the input parameters were defined using data from a real-world case study. As the model inputs, location data, distance matrix, demand data, fleet data, and operation data need to be fed into the model. The model's overall goal is to reduce the costs associated with retail chain distribution. Since fresh Agri products are delivered very frequently in retail chains, it is critical to keep operating costs to a minimum (Zulvia et al., 2020). Furthermore, the model attempts to reduce stockout situations caused by late deliveries.

The constraints were defined as closely as possible based on real-world assumptions and classified into three categories as resource constraints, service constraints, and operational constraints. Further, the model guides industry practitioners under several aspects as highlighted in Figure 3-1. The first model output assists to allocate distribution centers to retail outlets and the heterogeneous fleet to loading bays. Secondly, the model can plan multiple product types and effectively allocate the retail outlets' order quantities to maximize truck capacity utilization. Finally, the model determines the optimal route plan for the retail chain network to minimize total distribution costs

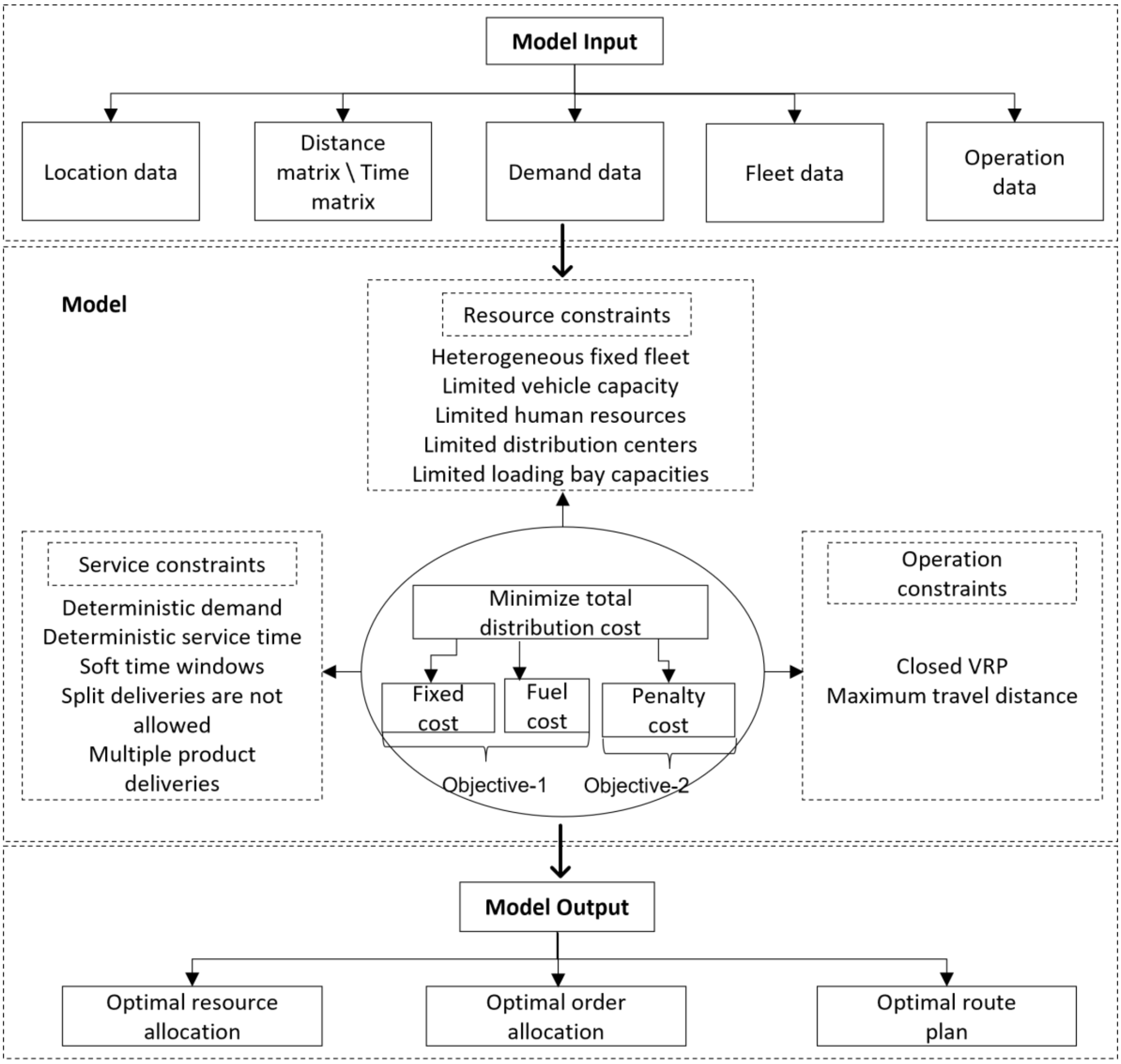

Figure 3-1: Model overview

3.1.2. Notations

Table3-1:Notations used for the model

Sets	Descriptions
D	$\{d \| d = 1, 2, \ldots, n\}$; Set of distribution centres
R	$\{r \| r = 1, 2, \ldots, n\}$; Set of retail outlets
N	$N \in D \cup R$; Set of nodes
K	$\{k \| k = 1, 2, \ldots, n\}$; Set of truck fleet
P	$\{p \| p = 1, 2, \ldots, n\}$; Set of Products
A	$\{(i, j): i, j \in N\}$; Set of arcs
Parameters	**Descriptions**
n_d	Number of depots
n_k	Number of vehicles
n_c	Number of retail outlets
d_{ij}	Driving distance of arc *(i,j)* ∈ A
t_{ij}^k	Driving time of k^{th} truck for an arc *(i,j)* ∈ A
v_{ij}	The traffic flow speed of *(i,j)* ∈ A
q_j^p	Quantity delivered to retail outlet *j* from product *p* in kilos
r^p	Number of kilos per vegetable crate from product p
$\tilde{q}_j^p$	Quantity delivered to retail outlet *j* from product *p* in crates
q_j	Total quantity delivered to retail outlet *j* (no of crates)
Q_k	The capacity (no of crates) of truck *k*
U_j^k	Cumulative quantity delivered by k^{th} truck at retail outlet *j*
ST_i	Average service time at retail outlet *i*
t_j^k	Time k^{th} truck visit retail outlet j
t_i^k	Time k^{th} truck visit retail outlet i
e_j	Upper bound of soft time windows
p	Penalty cost
F^k	Fixed cost
c_k	Fuel cost per km
$P_j(t_j^k)$	Penalty cost for violating time windows
d_{max}	Maximum trip length
Y_t^d	Number of trucks can be loaded in distribution center *d* at a given time *t*
c^d	Loading-bay capacity in distribution center *d*
φ	Large number
Decision variables	
$x_{ij}^k = \begin{cases} 1, & \text{If } k^{th} \text{ truck is used for arc } (i,j) \\ 0, & \text{Otherwise} \end{cases}$	

Table3-1 presents the notations for the sets, parameters, and decision variables used in the model.

3.1.3. Assumptions

The proposed optimization model was developed using the assumptions listed below. When defining the assumptions, ensuring the model's real-world applicability was afforded special prominence while the ability to solve a large-scale problem was also given a high weight.

- Each truck begins its deliveries at a central distribution center and returns to its origin point after providing services to designated retail outlets (close-route VRP).
- Before dispatching trucks, the product-wise demand and the delivery time window at each retail outlet is known.
- Split deliveries are not permitted, and each outlet is served by a single truck.
- Truck capacities are deterministic and heterogeneous, measured in terms of vegetable crates.
- Each route is assigned one truck, and the total quantity does not exceed the truck's capacity.
- Truck speeds between retail chain network nodes are deterministic and do not vary with time of day.

3.1.4. Mathematical Model

Objective 1

$$Minimize \sum_{k \epsilon k} F^k + \sum_{(i,j) \in A} \sum_{k \in k} c_k \, x_{ij}^k d_{ij} \tag{1}$$

The first objective of the model attempts to minimize the total transportation cost incurred during retail chain distribution. The first term of objective 1 represents the fixed cost of dispatching the trucks including the labor cost and the maintenance cost of trucks. Therefore, the model attempt to minimize the number of trucks associated with the distribution process and therefore maximize truck capacity utilization. This ensures that trucks can provide services to an optimal number of retail outlets. The second term of objective 1 is related to the fuel cost. It attempts to minimize the fuel consumption associated with retail chain distribution. Therefore, the proposed model finds a more economical route plan.

Objective 2

$$Minimize \sum_{j \in R} P_j(t_j^k) \tag{2}$$

The second objective of the proposed model attempts to minimize the stockout situations that occur due to late deliveries of products. In retail chains, fresh Agri products are delivered daily. Also, limited stocks are kept in retail outlets to avoid wastage happened due to perishability. Therefore, it is important to deliver fresh Agri products to the retail outlets before the requested time window. This objective has defined a penalty for late deliveries. The model attempts to meet the requested time schedules as much as possible to minimize this penalty. This penalty is related to the soft time windows constraint and details have been provided later (refer to constraint (8)) in this chapter.

Subject to the constraints 1-11.

$$\sum_{k \in K} \sum_{i \in N\ j \neq i} x_{ij}^k = 1\ for\ \ \forall j\ \in R \tag{1}$$

Constraint 1 ensures that each retail outlet should be served by exactly one truck. On the other hand, this is ensured to avoid split deliveries. In split deliveries, the total quantity can be delivered by several trucks.

$$\sum_{k \in K} \sum_{i \in D\ \ j \neq i} x_{ij}^k = \sum_{k \in K} \sum_{i \in D\ j \neq i} x_{ji}^k\ for\ \ \forall j\ \in R \tag{2}$$

Constraint 2 ensures that each truck should start from a distribution center. Further, all the trucks should return to the same distribution center after providing services to designated retail outlets. This constraint is related to the closed-route VRP.

$$\tilde{q}_j^p = q_j^p / r^p \; for \; \forall \, p \in P \tag{3}$$

Originally, vegetable quantities supplied to each retail outlet were measured in kilograms. However, each product is transported using vegetable crates. Therefore, it is more convenient to use vegetable crates as the unit of measurement. Equation 3 ensures this unit conversion. Here, the parameter (r^p) was used for this purpose.

$$q_j = \sum_{p \epsilon P} \tilde{q}_j^p \; for \; \forall \, j \in R \tag{4}$$

Constraint 4 ensures that the total quantity delivered to each retail outlet should equal the aggregate of individual products. Further, total quantity is measured using vegetable crates in this context.

$$U_i^k + q_j = U_j^k \; for \; \forall \, x_{ij}^k = 1 \;\&\; i, j \in R \;\&\; k \in K \tag{5}$$

Constraint 5 ensures that the total supply quantity up to the j^th outlet is the aggregate quantity supplied up to the previous retail outlet and the quantity supplied to the j^th outlet.

$$U_j^k \leq Q^k \tag{6}$$

Constraint 6 ensures that the total quantity supplied using the k^th truck shall not exceed the capacity of that truck. Since the proposed model incorporates a truck fleet with heterogenous capacities, this constraint considers each truck capacity individually.

$$t_j^k = t_i^k + ST_i + t_{ij}^k \; for \; \forall \, x_{ij}^k = 1 \;\&\; i, j \in R \tag{7}$$

Constraint 7 elaborates how the arrival time for the j^th retail outlet is calculated. It is calculated by adding the travel time (t_{ij}^k) to the departure time of the i^th outlet ($t_i^k + ST_i$).

$$P_j(t_j^k) = \begin{cases} 0;\ t_j^k \ \leq \ e_j \\ \\ p * \left(t_j^k - e_j\right) \end{cases} \tag{8}$$

Constraint 8 ensures to deliver the products to retail outlets before the requested time. The model applies the soft time window with a penalty cost. Here, $P_j(t_j^k)$ represents the penalty cost if truck *k* does not meet the time window imposed by the retail outlet *j*. Specifically, the model needs to minimize the stockout situations due to late deliveries. Therefore, the model has applied soft time windows with an upper bound to determine the penalty cost that was incurred due to late deliveries. The upper bound is represented by e_j in this case, and the products must be delivered before that time to avoid the penalty cost. This constraint is linked to objective 2, and it attempts to reduce late deliveries.

$$t_j^k \geq t_i^k - \varphi\left(1 - x_{ij}\right) for \ \ \forall\, x_{ij}^k = 1 \,\&\, i, j \ \in R \tag{9}$$

Constraint 9 is introduced to eliminate sub-tours in the routing plan for the retail distribution chain. In other words, this constraint doesn't allow a visit to a retail outlet more than once by all the trucks.

$$\sum_{(i,j)\in A} x_{ij}^k\, d_{ij} \leq \ d_{max}\, for \ \ \forall\, x_{ij} = 1 \,\&\, k \ \in K \,\&\, d \ \in D \tag{10}$$

Constraint 10 imposed a maximum trip length for each truck. Trucks can thus provide services to a limited number of retail outlets while adhering to the maximum trip length (d max). Furthermore, this constraint eliminates impractical trip lengths and manages driver working shifts.

$$Y_t^d = c_d \ \ \forall\, d \in D \tag{11}$$

Constraint 11 represents the limited number of loading bays in distribution centers. According to this, only a limited number of trucks can be loaded in distribution centers at any given time.

3.2. Data Collection

The research has obtained data from one of the largest retail chains in Sri Lanka. The data consist of location data, demand data, fleet data, and operation data. Location data includes locations of retail outlets and distribution centers. We employed data from 247 retail outlets and 2 distribution centers to test the proposed model. The main input for the proposed model is the distance matrix that was estimated using the location data. The research used real-driving distances between nodes of the retail chain network to estimate the distance matrix. The real driving distance is calculated using the OSRM (Open-Source Routing Machine) API and is defined as the shortest driving distance between two geographical locations. Additionally, the distance matrix and the traffic speeds were used to derive the time matrix.

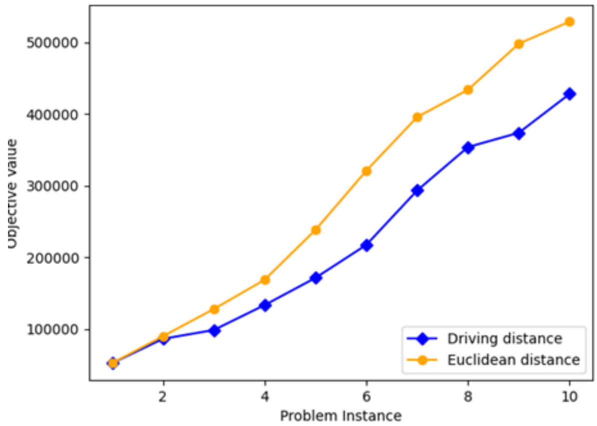

Figure 3-2: Comparing Euclidean distance and real-driving distance

During the preliminary analysis, the research identified that using Euclidean distance (straight line distance) instead of the real-driving distance is not appropriate for real-world applications. In that analysis Euclidean distances were measured using the "haversine" package in Python. Thereafter, the same routing model was tested for the two types of distance matrices measured using the OSRM API and the "haversine" package. Results highlighted that OSRM API outperforms in this regard (refer to Figure 3-2) (Fernando et al., 2022).

The proposed model incorporates multiple product deliveries in the retail chain distribution network. Therefore, it was required to collect the average quantities per delivery for different products (demand) requested by retail outlets. The research collected demand data for 32 types of vegetable products. Demand data was collected for all 247 retail outlets and measured in kilograms at first. In this case study, fresh Agri products are transported using vegetable crates to minimize wastage. Therefore, demands were estimated in terms of the number of crates since it is convenient to apply to the model. In this case parameter r^p (number of kilos per vegetable crate from product p) was defined and estimated for all product types using an unstructured expert interview as indicated in Figure 3-3. This parameter was used to do the required unit changes.

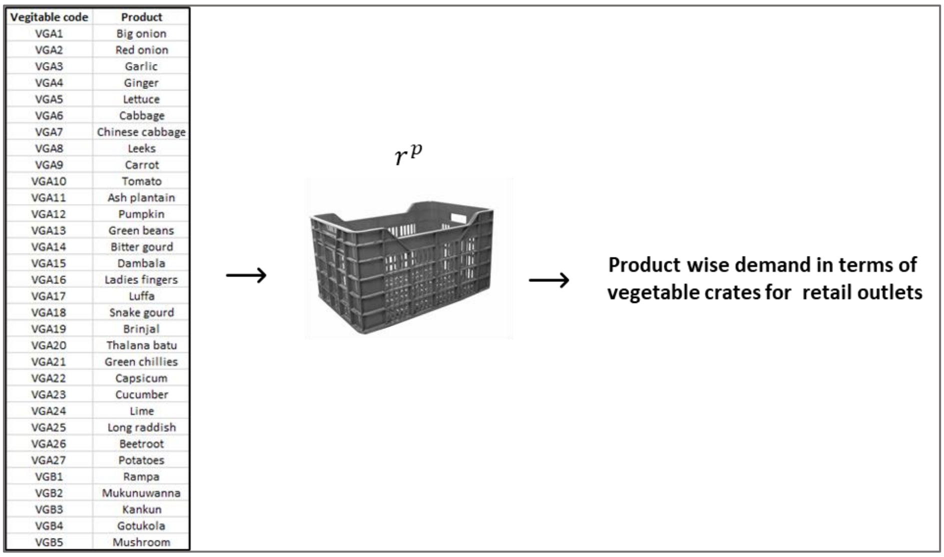

Figure 3-3: Estimate product-wise demand in terms of vegetable crates

Fleet data include information about 55 trucks used in the chosen retail chain. The carrying capacities of each truck were measured in terms of the number of vegetable crates that each truck can transport. In addition, the costs associated with the truck fleet were obtained through unstructured interviews with experts. Additionally, operation data such as loading bay capacities, the average time taken for loading at distribution centers, requested time windows, and service times at retail outlets were collected.

3.3. Model Implementation

The purpose of this subsection is to provide details about the systematic process of programming the proposed model. There are several open-source optimization software and software libraries available for academic use. During the literature review, we discovered that VRP researchers frequently used non-open-source software such as CPLEX (Rahbari et al., 2019), GAMS (Esmaili & Sahraeian, 2017), and LINGO (Seyedhosseini & Ghoreyshi, 2014). It is mentioned that pyomo and scipy are two examples of open-source python packages for developing optimization models. The current study made use of an optimization library called OR-Tools, which was created by Google developers (Furnon, 2019). This library can be used to solve combinatorial optimization problems. The main reason for choosing this was that it is open source and allows you to code in your preferred language (i.e., C++, Python, C#, or Java). Furthermore, it is an award-winning optimization library at the International Constraint Optimization Competition.

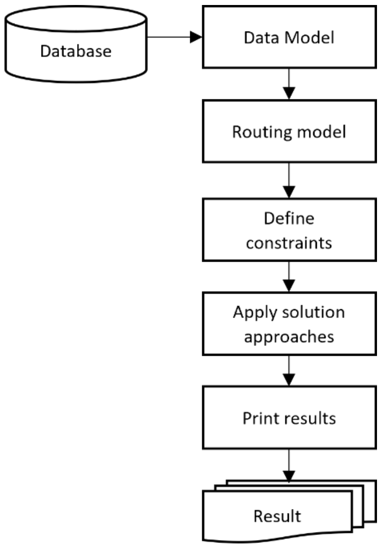

Figure 3-4: Process followed to develop computer application for the proposed model

Figure 3-4 depicts the main steps involved in implementing the proposed VRP model using OR tools. The procedure begins with reading data from the database. We previously provided a detailed explanation of the data requirement. The database contains CSV files, which are retrieved using the Pandas package's "read CSV" function. The data model must be created as the next step. The step converts data into proper data structures so that it is compatible with the model's input. The data model contains the following types of data, which are highlighted in Table 3-2.

Table 3-2: Details about the data model

Data Type	**Data Structure**	**Unit**
Distance matrix	Nested list	Kilometers
Travel time matrix	Nested list	Hours
Service time	Integer	Minutes
Demand data	Nested list	No of crates
Fuel cost	Integer	Fuel cost per Kilometer (LKR)
Fixed cost	Integer	The fixed cost associated with trucks (LKR)
Penalty cost	Integer	LKR
Traffic speed	Integer	Km/h
Number of vehicles	Integer	-
Vehicle capacities	List	No of crates
Time windows	List	In time format (HH: MM)
Number of Distribution Centers (DC)	Integer	- Note: Index of DCs in the Distance matrix
Number of loading bays available at DCs	List	-

The next step after defining the data model is to create the routing model. It begins by defining the scale of the routing problem, as shown below in Figure 3-5, by using the size of the distance matrix, truck fleet size, and the number of distribution centers. Thereafter, we must define the distance callback and time callback for the routing solver's internal reference. This is where the proposed model's objective 1 (minimize transportation costs including fuel costs and fixed costs) was defined. According to the proposed VRP model, an arc cost evaluator was defined, which combines the distance callbacks and the fuel cost, so that the solver can find the routes that minimize the fuel cost. Furthermore, fixed costs for all trucks were linked to the solver, allowing the solver to optimize the use of available trucks.

```
# Create the routing index manager.
manager = pywrapcp.RoutingIndexManager(len(data['distance_matrix']),
                                       data['num_vehicles'], data['depot'])
```

Figure 3-5: Defining the scale of the routing model

After defining the routing model, the next step was to define the constraints. Here all the constraints belonging to the three categories including resource constraints, service constraints, and operation constraints were linked to the routing solver. In this step, special attention was paid to defining soft time windows since minimizing the penalty for the time window violation defines the second objective of the proposed VRP model. After coding all the attributes of the proposed model in computer applications, the next step was to create a solution method to solve the model. Details about the different solution strategies used in this research have been provided in the next sub-section.

3.4. Apply Solution Approaches

Researchers used several categories of solution approaches to solve the VRP models. Those categories could be highlighted as Exact methods (Tirkolaee et al., 2020), Heuristic methods (Yao et al., 2019), Metaheuristic (Yao et al., 2019), and Hybrid methods (Lacomme et al., 2018). Figure 2-5 (LITERATURE REVIEW) presents a comparison of those categories of solution approaches. Further, this comparison was employed to find a suitable approach to solving the proposed VRP model in this research. By considering the pros and cons of each solution category, a Hybrid solution approach was selected. Usually, researchers used to hybridize exact-metaheuristic, heuristic-metaheuristic, and metaheuristic-metaheuristic to get better results (Moghdani et al., 2021). This research employed a two-phase solution approach by combining heuristic-metaheuristic methods. Here, the heuristic approach was used to obtain the initial feasible solutions for the proposed model. Thenceforth, the metaheuristic approach was applied to improve the solution until we get near-optimal.

3.4.1. Initial Solution Approaches

As mentioned earlier two heuristic approaches were applied to obtain Initial Basic Feasible Solutions (IBFS). Using heuristic approaches for obtaining IBFS is important (Amaliah et al., 2020). Thereby the number of iterations can be reduced in the improvement process of IBFS (Amaliah et al., 2020). Two employed heuristic approaches could be identified as the savings algorithm (Clarke & Wright, 1964), and the greedy algorithm (Gutin et al., 2002).

3.4.2. Metaheuristics

Figure 3-6: Continuous improvement process in neighborhood search method

Metaheuristics are widely used by VRP researchers since these methods are useful to obtain better solutions in less computation time. The current research used three metaheuristic approaches to improve the IBFS obtained using heuristic approaches. Three employed heuristic approaches are Guided Local Search (GLS), Simulated Annealing (SA), and Tabu Search (TS). Those metaheuristic approaches improve IBFS using a fundamental iterative improvement process called "neighborhood search" which has been highlighted in Figure 3-6 (Fernando et al., 2022). Local search methods examine the candidate solutions by applying changes continuously to the previous solution. The research applied one neighborhood structure operating within the route (two-opt procedure) and three neighborhood structures operating between the routes (relocate, exchange, and cross procedures) (Kilby et al., 2002). The algorithm terminates once it reaches the optimal solution, or when the defined stopping condition is met. The three approaches used in this research use different strategies to do the local search and have been discussed in a detailed manner below.

(a) Guided Local Search (GLS)

Guided Local Search (GLS) is a memory-based metaheuristic that applies a penalty-based augmented cost function shown below to proceed with the local search.

$$g(x) = f(x) + \lambda \sum_{i} (I_i\,(x) * p_i) \tag{1}$$

Here $\boldsymbol{g}(\boldsymbol{x})$ indicates the augmented cost function and $\boldsymbol{f}(\boldsymbol{x})$ indicates the original objective function of the proposed optimization model. The fundamental logic of this method is to penalize the features of the previously found local minimum. Thereby, the method searches for a better solution than before. In the above formula, $\boldsymbol{I_i}\,(\boldsymbol{x})$ indicates a decision variable that can be either zero or one. The value of $\boldsymbol{I_i}\,(\boldsymbol{x})$ becomes one when the current solution has similarities to previously found solutions. Further, $\boldsymbol{p_i}$ represent the penalty associated with those similarities. In this method, the penalty factor **($\boldsymbol{\lambda}$)** tunes the search procedure. For example, for a large value of **λ**, this method does a more diverse search and for a small value, it does a more intensive search. However, the entire penalty term repeatedly updates until we get a near-optimal solution (Kilby et al., 2002).

(b) Simulated Annealing (SA)

Simulated Annealing (SA) is a metaheuristic that applies a probabilistic approach to obtain the near-optimal solution in the process of local search. The SA algorithms' basic concept is to determine whether a given neighbor $\boldsymbol{x_{test}}$ (candidate solution) in the neighborhood $\boldsymbol{N_x}$ should be accepted or not. The acceptance probability $\boldsymbol{P}$ evolves and becomes lower and lower so that at the start of the algorithm, a large portion of the search space can be reached, and the probability gradually but steadily converges toward zero. Thereby, the algorithm reaches the final neighborhood. Here, the system is said to be moving toward lower energy states (Arostegui et al., 2006).

(c) Tabu Search (TS)

The Tabu Search is a memory-based metaheuristic that evaluates neighboring solutions until they reach the global optimal. This technique uses memory structures to store recently evaluated candidate solutions. The candidates stored in these structures are not eligible for further candidate generation and are thus considered "Tabu" by the algorithm. By utilizing these memory structures, the technique trades space for time, thereby speeding up the search for the best solution (Glover, 1986).

3.5. The Proposed Two-Phase Solution Method

The literature review of the current study has shown that only 13% (6 papers of a total of 45) of the reviewed papers used hybrid solution approaches in solving the proposed models. Further, research showed the effectiveness of hybrid methods compared to single solution approaches (Lacomme et al., 2018). Additionally, we have highlighted a research gap in comparing the performances of different metaheuristic approaches in solving the VRP (Utama, Dewi, Wahid, & Santoso, 2020). Considering those aspects this research proposes a two-phase solution approach combining the heuristic-metaheuristic methods.

Algorithm 1: Two-phase solution method

Input – Initial solutions obtained using j^{th} heuristical approaches (I); I = {x_o^j; j= savings algorithm, greedy algorithm}
    Meta-heuristic methods (M); M={GLS, TS, SA}
    Stop criteria; accepted neighbors = n
Output – Near-optimal solution (x_{best})
For j in I do
    For k in M **do**
        x ← x_o
        while stop criteria are not violated do
            1. Find neighborhood (N_x)
            2. Find "best" solution in Nx; x_{best}
            3. x ← x_{best}
        end while
    end For
end For

This research combined two heuristic approaches and three metaheuristics approaches in solving the proposed integrated VRP. As explained earlier, each heuristic approach was used to obtain IBFS, and metaheuristics were used to improve them. Since each heuristic method was tested with each meta-heuristic method. The pseudocode of the proposed two-phase solution approach is highlighted in Algorithm 1. It indicates the input, intended outcomes, and the fundamental logic behind the two-phase solution method. Additionally, it is needed to specify the stopping criteria to terminate the local search procedure of the meta-heuristic methods. This research has used “number of accepted neighbors” as the stopping criteria.

4. RESULTS AND DISCUSSION

This chapter presents the results of the numerical experiments we conducted. All numerical experiments were designed to be consistent with the ***RO2***, and ***RO3***. As stated in Chapter two, ***RO2*** attempts to investigate the effectiveness of various solution methods in solving the proposed VRP model, while ***RO3*** aims to investigate the applicability of the proposed model in real-world applications.

4.1. Conceptual Framework

This research carried out two types of numerical experiments that have been highlighted in Figure 4-1. In the first type of numerical experiment, we investigated various solution techniques for solving the proposed VRP model. Under the second type, the VRP proposed model was benchmarked concerning various model outputs. All numerical experiments were performed on a computer equipped with a Core i5, 5200U processor running at 2.40 GHz - 2.42 GHz, and 8 GB RAM in Windows 10 Home 64 bit. OR-Tools version 7.2 (Furnon, 2019) and Python version 3.9.6 in Visual Studio Code version 1.60 were used to develop the algorithms.

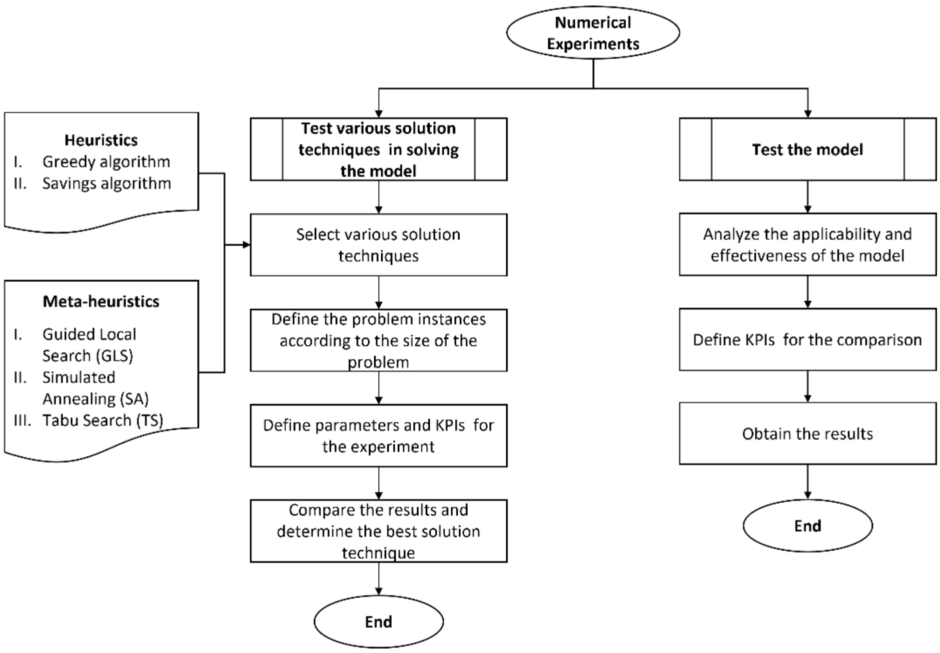

Figure 4-1:Conceptual framework for the numerical experiments

4.2. Comparison of Solution Techniques

As shown in Figure 4-1, we first compared the Greedy and Savings algorithms used to obtain Initial Basic Feasible Solutions (IBFS). Following that, three meta-heuristic methods, GLS, SA, and TS, were compared in terms of improving the IBFS. Finally, we put the proposed two-phase solution method to the test. We defined ten problem instances for these numerical experiments. Zulvia et al., (2020) defined problem instances, with the number of customers served changing for each problem instance. For the current research also problem instances were defined based on the size of the problem. The number of retail outlets and the number of trucks were used to define problem sizes. Further, objective value (cumulative route length) and computation time were selected as KPIs to compare the selected solution techniques.

4.2.1. Heuristic Methods

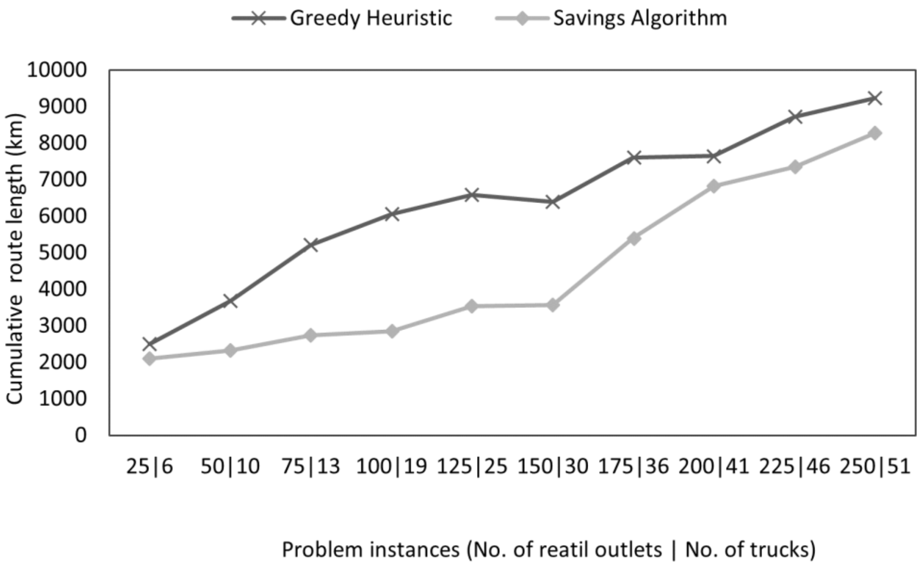

Figure 4-2: Heuristic methods comparison for obtaining IBFS

Figure 4-2 highlights the results obtained using two heuristic methods in obtaining an Initial Basic Feasible Solution (IBFS) for the proposed VRP model. According to the results, the savings algorithm outperformed in obtaining IBFS for the proposed model in terms of the objective value. Compared to the greedy heuristic, the savings algorithm obtained IBFS with a 31% of average reduction in cumulative route length. Because the savings algorithm is a heuristic method, it cannot guarantee an optimal solution to the problem (Clarke & Wright, 1964). However, the method frequently produces a reasonably good solution and deviates only slightly from the optimal solution (Clarke & Wright, 1964). Rabbani et al., (2016) also compared the random generation method and Clarke and Wright's savings method in solving an MDVRP model. Results highlighted the effectiveness of Clarke and Wright's savings method in solving that model (Rabbani, Farrokhi-Asl, et al., 2016). Current research also shows the effectiveness of the savings algorithm as an IBFS method compared to the greedy heuristic in solving the selected real-world case study.

4.2.2. Metaheuristic Methods

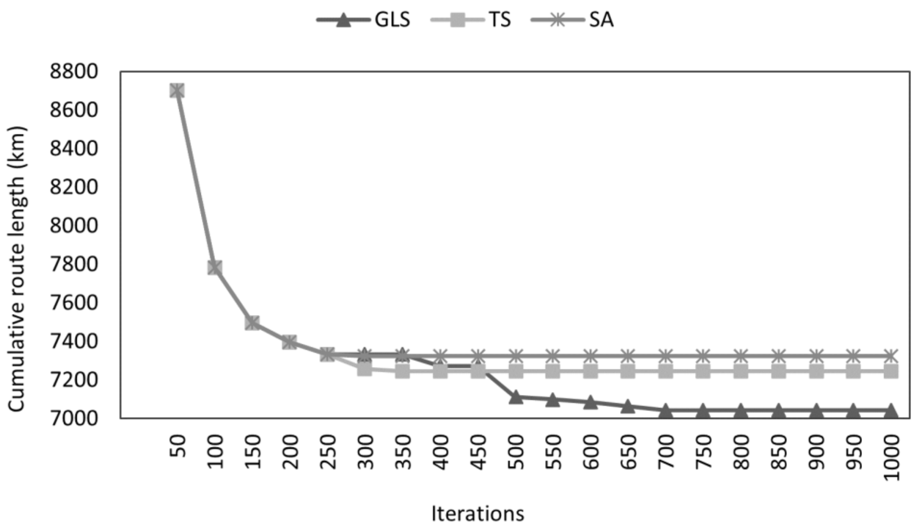

Figure 4-3: Comparison of meta-heuristic methods in terms of objective value

Figure 4-3 depicts the results of the proposed VRP model's solution using three metaheuristics. The goal of this experiment is to see how three metaheuristics perform when the number of iterations is changed. Further, this experiment was carried out using the largest problem instance of the selected case study (250|51). It is noted that IBFS were generated randomly for this experiment without using any heuristic method. Until 250 iterations, all three methods performed nearly equally, according to the results. Furthermore, until 250 iterations, we can see a significant improvement in IFBS. When the number of iterations exceeds 250, the objective values of the SA method tend to stay constant.

Furthermore, the results show that GLS outperforms the SA and TS in solving the proposed VRP model. In comparison to the SA and TS, GLS improve the solutions by 4% and 2.3%, respectively. Further, GLS improved IFBS by 19% when solving the model for the selected case study. Kilby et al., (2002) also showed that GLS outperforms compared to the TS in solving Solomon's instances which are not real. Current research shows the performance of GLS in solving a real-world case study.

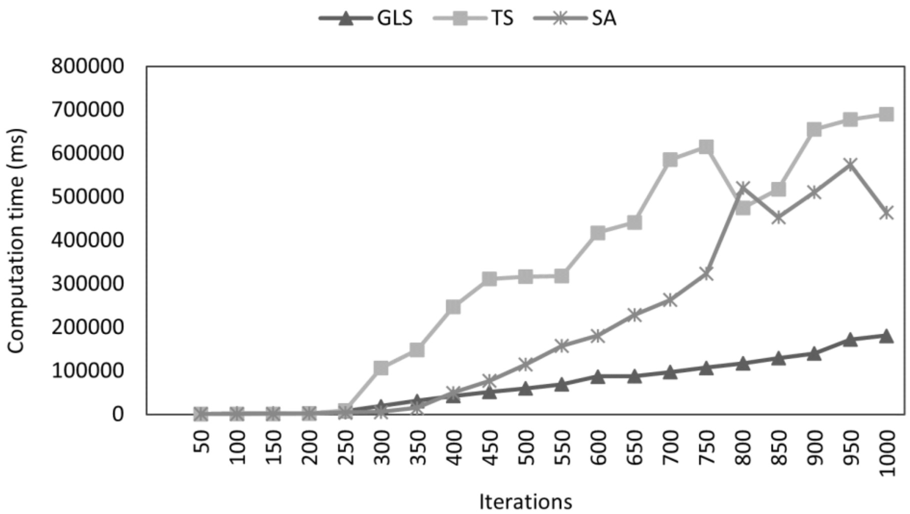

Figure 4-4: Comparison of meta-heuristic methods in terms of computation time

Figure 4-4 depicts a comparison of the computation time for the three meta-heuristic methods. It shows that GLS finds near-optimal solutions in less computation time than the other two methods. In comparison to the SA and TS, GLS saves computation time by 60% and 73.7% respectively when solving the proposed model for the selected case study. According to the results, GLS significantly reduces computation time when compared to the other two meta-heuristic methods, which is very effective when solving real-world problems with many nodes.

As we presented earlier, current research compared three metaheuristics: GLS, SA, and TS in terms of the objective value and the computation time. According to the summary, GLS outperformed the other two metaheuristics by a small margin (2 -4%). Nevertheless, GLS achieved a significant reduction in computation time (60-74%) when solving the proposed model. The results demonstrate the efficiency of GLS in improving the IFBS as a meta-heuristic method concerning the proposed model and the case study.

4.2.3. Benchmark Results of Proposed Two-Phase Solution Method

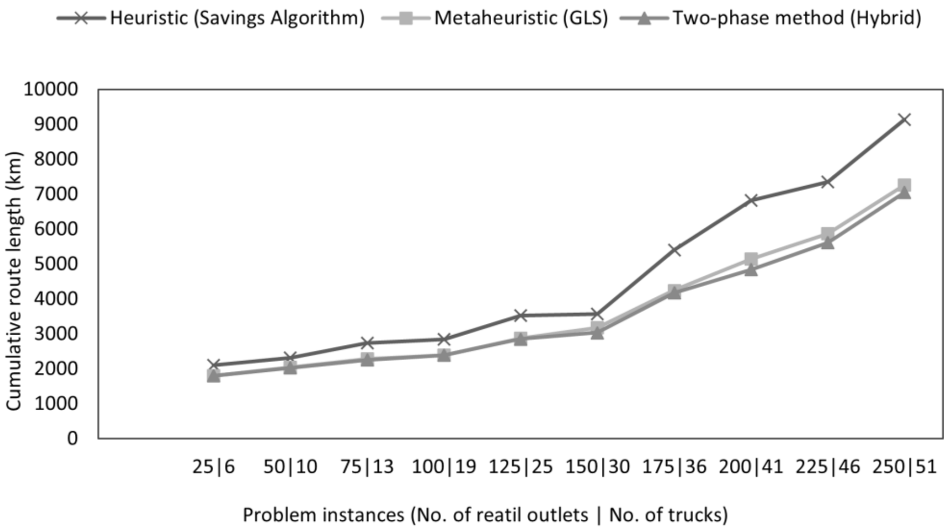

Figure 4-5: Benchmark results for two-phase solution method in terms of objective value

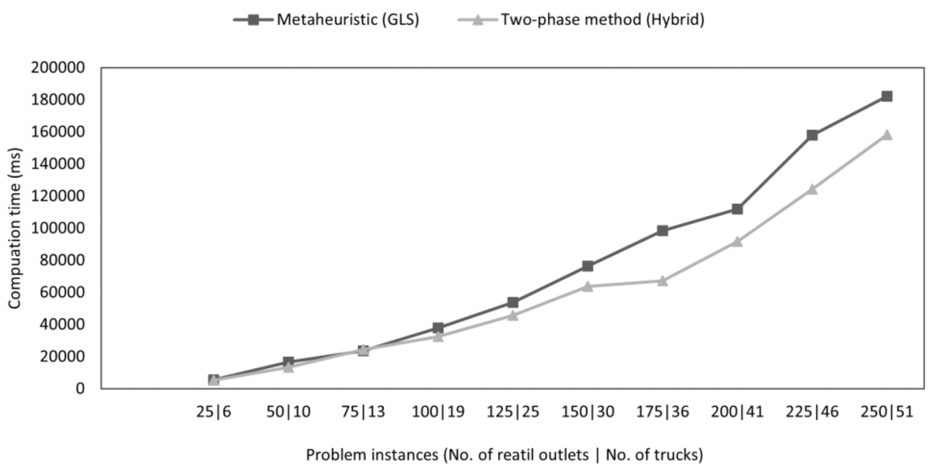

Figure 4-6: Benchmark results for two-phase solution method in terms of computation time

Usually, researchers used to hybridize exact-metaheuristic, heuristic-metaheuristic, and metaheuristic-metaheuristic to get better results (Moghdani et al., 2021). Researchers applied hybrid approaches to improve the quality of solutions while minimizing the computation time (Moghdani et al., 2021). This research used a two-phase solution method by combining heuristic-metaheuristic methods. Here heuristic technique was used to obtain IBFS for the proposed model. Thereafter meta-heuristic method was applied to improve the solution until we get near-optimal.

The purpose of this numerical experiment is to benchmark the developed two-phase solution method compared to the heuristic and meta-heuristic methods. As previously determined, the savings algorithm outperforms the IFBS method. In addition, the GLS meta-heuristic outperforms in terms of improving IFBS and obtaining near-optimal solutions. Therefore, to develop the proposed two-phase solution method, this study combined the savings algorithm and the GLS meta-heuristic.

We compared the proposed two-phase solution method against the savings algorithm (heuristic method) and the GLS (meta-heuristic method). Figure 4-5 highlights the computation results obtained based on the objective value for all three methods. Results depict that the suggested solution method has not achieved significant improvement in terms of objective value compared to the GLS. Since both GLS and the two-phase solution method perform almost equally, thereafter we compared the computation time of GLS and the two-phase solution method. As highlighted in Figure 4-6 computation times of the two methods are almost equal for small problem instances. Nevertheless, the proposed two-phase method outperformed GLS when the problem size is increasing. For the largest problem instance (250|51) the suggested method saves 13% of computation time compared to GLS. Therefore, the two-phase solution method is efficient to solve large problems, and thereby it is very applicable to solving real-world problems due to the less computation time. Existing literature also provides evidence for computation time-saving in two-phase solution methods (Wang et al., 2016). Here onwards all the computation results were obtained using the two-phase solution method combining the savings algorithm and GLS.

4.3. Test the Model

This section is intended to test the proposed VRP model's real-world applicability. To put the model to the test, all the input data were estimated using the real-world case study highlighted in Table 4-1. Using real-world data, all model outputs were tested to determine the model's effectiveness. The three numerical experiments conducted under this section are as follows:

i. Effectiveness of allocating retail outlets to distribution centers
ii. Effectiveness of retail outlets' order allocation

iii. Optimal route plan

Table 4-1: Input data for numerical experiments

Parameters	Value
n_d	2
n_k	55
n_c	247
d_{ij}	Appendix-B: Distance Matrix
t_{ij}^k	Appendix-C: Time Matrix
v_{ij}	30 km\h
Q_k	[30,35]
p	2500 LKR
F^k	5000 LKR
c_k	100 LKR\km
ST_i	30 min
e_j	4:00 PM
d_{max}	650 km
Y_t^d	[2,1]
c^d	[2,1]

4.3.1. Effectiveness of Allocating Retail Outlets to Distribution Centers

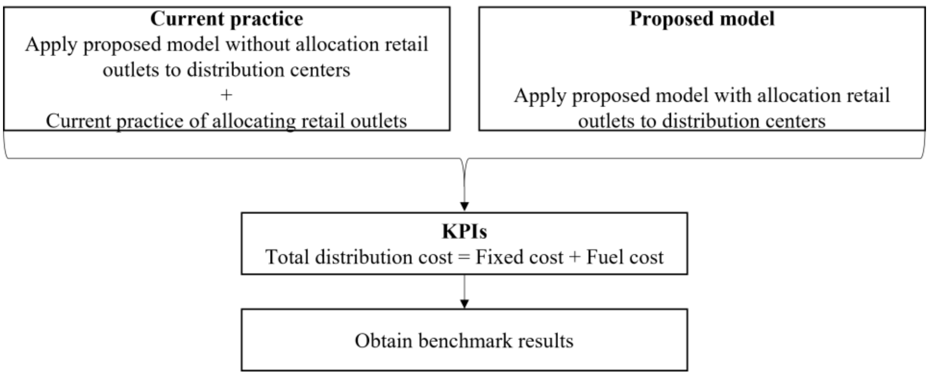

Figure 4-7: Comparing the current practice and the proposed model in allocating distribution centers

This numerical experiment is supposed to assess the effectiveness of allocating retail outlets to distribution centers using the VRP proposed model. The model is allocating retail outlets to multiple distribution centers to minimize the total distribution cost incurred in the retail chain distribution process. Therefore, this numerical experiment was planned to compare the proposed model output with the current practice of allocating retail outlets to the distribution centers (This data was collected as an operating practice of the selected retail chain) as highlighted in Figure 4-7. Hence, all the problem instances were solved using the current practice and the proposed model.

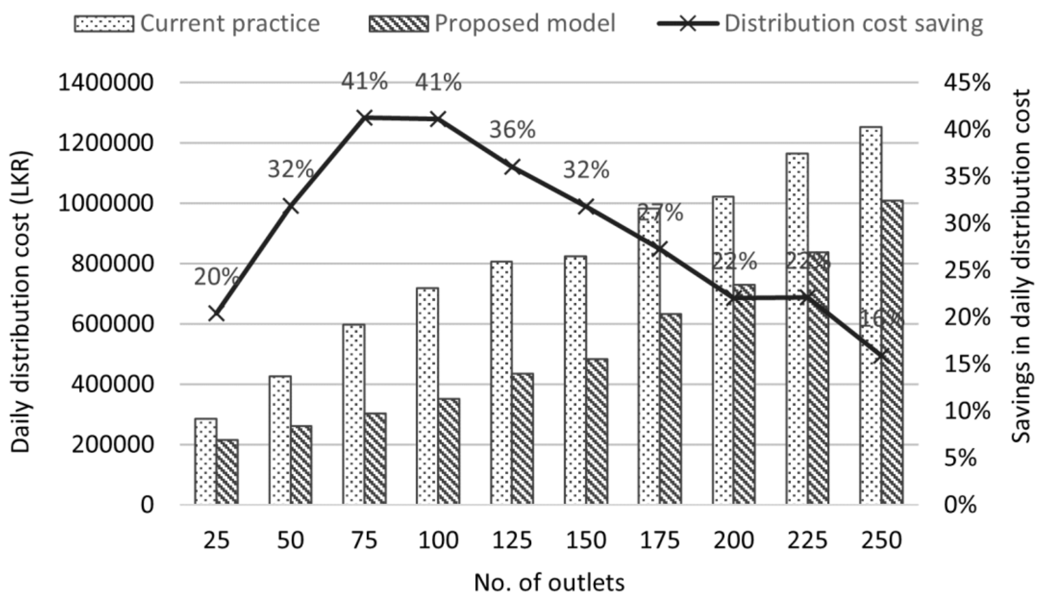

Figure 4-8: Distribution cost saving realized through the proposed model

As highlighted in Figure 4-7 total distribution cost was used as the KPI to carry out this comparison. The comparison results obtained through this experiment showed in the above Figure 4-8. As per the results, the proposed model has gained significant cost savings against the current practice of allocating retail outlets to multiple distribution centers. For the largest problem instance, (250 outlets) model achieved a 16% saving of daily distribution cost. Hence, we can prove that the proposed model is effective in the allocation of retail outlets into multiple distribution centers. Furthermore, this experiment was carried out in a real-world case study and thereby model can assist industry practitioners to optimize real-world multiple depot networks.

Table 4-2: Fuel cost and fixed cost savings realized through the proposed model

No of outlets	**Fixed cost component of daily distribution cost (LKR)**			**Fuel cost component of daily distribution cost (LKR)**		
	Current practice	**Proposed model**	**Cost-saving**	**Current practice**	**Proposed model**	**Cost-saving**
25	36000	36000	0%	249750	180400	28%
50	60000	60000	0%	367420	202510	45%
75	78000	78000	0%	521390	225860	57%
100	114000	114000	0%	605340	239090	61%
125	150000	150000	0%	657630	285030	57%
150	186000	180000	3%	639450	303200	53%
175	222000	216000	3%	761050	417290	45%
200	258000	246000	5%	764360	483390	37%
225	294000	276000	6%	871840	561630	36%
250	330000	306000	7%	923070	704290	24%

Table 4-2 shows the fuel cost and fixed savings realized because of the proper allocation of retail outlets to distribution centers. According to the results, the proposed model achieved significant fuel cost savings. By properly assigning retail outlets to distribution centers, it is possible to supply via more cost-effective routes, resulting in significant cost savings. When it comes to fixed cost savings, the results demonstrate that for the first five problem instances, no fixed cost savings were achieved. However, the proposed model has achieved 7% of fixed cost savings for the largest problem instance. It demonstrates that properly assigning retail outlets to distribution centers can help to minimize truck usage as well.

4.3.2. Effectiveness of Retail Outlets' Order Allocation

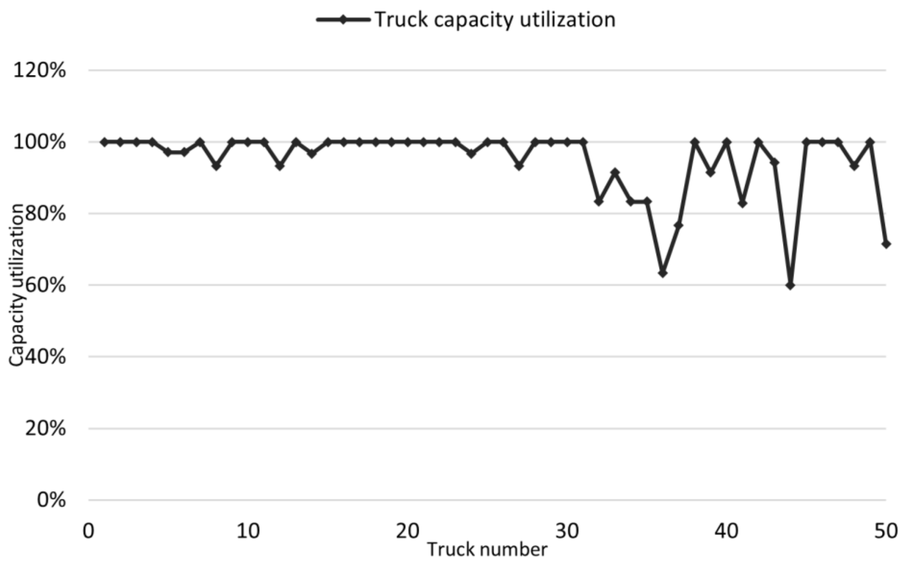

Figure 4-9: Truck capacity utilization realized through the proposed model

The VRP model proposed in this research can assist in retail outlets' order allocation with multiple products. This numerical experiment is planning to investigate the effectiveness of allocating multiple products to heterogeneous truck fleets. As explained in Chapter-3 (Data Collection) selected case study distributes vegetable products using the plastic crates in this retail chain. Therefore, the carrying capacity of trucks has been measured using the number of crates. Figure 4-9 highlights the truck capacity utilization achieved using the proposed model in retail outlet order allocation. According to the results, the model has achieved 100% of capacity utilization for 62% of trucks (31 of 50 trucks). Further, the average truck capacity utilization is 95% and it exceeds the current average truck capacity utilization (83%) for the selected retail chain. Therefore, the results provide evidence about the effectiveness of retail outlet order allocation of the proposed model while ensuring the standards of transporting the fresh Agri products. The results of this numerical experiment prove that the proposed VRP model is effective for the retail outlet order allocation and thereby can optimally utilize the truck fleet.

4.3.3. Optimal Route Plan

Table 4-3: Model output

Truck no	Distribution center & loading bay	Route plan	No of retail outlets	Truck load (No of crates)	Distance (Km)	Truck dispatch time	Expected arrival time to last outlet
1	Wattala-LB1	0, 241, 240, 246, 169, 226, 225, 0	6	35	448.2	5:00 AM	5:41 PM
2	Wattala-LB2	0, 185, 223, 224, 221, 222, 0	5	35	359.4	5:00 AM	2:16 PM
3	Wattala-LB1	0, 117, 118, 116, 119, 115, 178, 179, 0	7	35	276	5:20 AM	3:54 PM
4	Wattala-LB2	0, 243, 244, 245, 242, 18, 141, 0	6	35	184.2	5:20 AM	2:17 PM
5	Wattala-LB1	0, 126, 238, 233, 237, 236, 234, 0	6	34	148	5:40 AM	11:58 AM
6	Wattala-LB2	0, 184, 180, 189, 183, 177, 45, 0	6	34	143.8	5:40 AM	12:49 PM
7	Wattala-LB1	0, 19, 29, 175, 174, 20, 159, 0	6	35	106.8	6:00 AM	12:18 PM
8	Wattala-LB2	0, 187, 190, 182, 176, 0	4	28	106	6:00 AM	10:22 AM
9	Wattala-LB1	0, 148, 122, 120, 123, 147, 0	5	30	71.8	6:20 AM	10:14 AM
10	Wattala-LB2	0, 49, 58, 181, 188, 52, 33, 0	6	30	71.8	6:20 AM	11:04 AM
11	Wattala-LB1	0, 34, 42, 23, 153, 0	4	30	71	6:40 AM	9:55 AM
12	Wattala-LB2	0, 27, 55, 25, 24, 26, 76, 0	6	28	63.4	6:40 AM	11:05 AM
13	Wattala-LB1	0, 162, 128, 124, 135, 133, 129, 0	6	35	59.6	7:00 AM	11:38 AM
14	Wattala-LB2	0, 22, 21, 60, 64, 61, 88, 0	6	29	58.4	7:00 AM	11:32 AM
15	Wattala-LB1	0, 62, 54, 56, 53, 80, 0	5	30	57.4	7:20 AM	11:31 AM
16	Wattala-LB2	0, 44, 59, 57, 30, 0	4	30	56.9	7:20 AM	10:35 AM
17	Wattala-LB1	0, 130, 41, 156, 144, 0	4	35	50.5	7:40 AM	10:32 AM
18	Wattala-LB2	0, 28, 72, 63, 71, 0	4	30	48.7	8:00 AM	11:00 AM
19	Wattala-LB1	0, 125, 132, 154, 131, 0	4	35	48.4	8:00 AM	10:56 AM
20	Wattala-LB2	0, 36, 111, 106, 165, 166, 146, 0	6	35	47.7	8:20 AM	12:20 PM
21	Wattala-LB1	0, 151, 142, 152, 149, 155, 0	5	35	46.5	8:20 AM	11:53 AM
22	Wattala-LB2	0, 96, 95, 113, 98, 0	4	30	41.7	8:40 AM	11:26 AM
23	Wattala-LB1	0, 67, 51, 46, 90, 101, 0	5	30	40.2	8:40 AM	12:28 PM
24	Wattala-LB2	0, 83, 84, 82, 99, 39, 32, 43, 97, 0	8	29	36.8	9:00 AM	1:47 PM
25	Wattala-LB1	0, 70, 77, 40, 68, 66, 75, 0	6	30	36.1	9:00 AM	12:41 PM
26	Wattala-LB2	0, 65, 47, 114, 48, 0	4	30	35	9:20 AM	12:02 PM
27	Wattala-LB1	0, 74, 73, 69, 31, 0	4	28	31.7	9:20 AM	11:54 PM
28	Wattala-LB2	0, 108, 35, 107, 38, 79, 0	5	30	31	9:40 AM	12:55 PM
29	Wattala-LB1	0, 186, 91, 100, 87, 92, 105, 0	6	30	30.6	9:40 AM	1:24 PM
30	Wattala-LB2	0, 85, 109, 94, 93, 89, 0	5	30	26.7	10:00 AM	12:30 PM
31	Wattala-LB1	0, 102, 104, 50, 103, 78, 86, 0	6	30	26.6	10:00 AM	1:41 PM
32	Wattala-LB2	0, 37, 112, 110, 0	3	25	25.3	10:20 AM	12:21 PM
33	Wattala-LB1	0, 163, 164, 127, 134, 158, 0	5	32	23.5	10:20 AM	1:26 PM
34	Wattala-LB2	0, 150, 143, 145, 0	3	25	20.7	10:40 AM	12:30 PM
35	Wattala-LB1	0, 138, 137, 139, 0	3	25	17.7	10:40 AM	12:34 PM
36	Wattala-LB2	0, 160, 81, 161, 0	3	19	11.5	11:00 AM	12:43 PM
37	Wattala-LB1	0, 140, 157, 136, 0	3	23	11.3	11:00 AM	12:44 PM
38	Kurunagala-LB1	1, 15, 16, 4, 5, 12, 1	5	35	608.8	5:00 AM	10:44 PM
39	Kurunagala-LB1	1, 207, 173, 172, 171, 248, 9, 7, 1	7	32	630.7	5:20 AM	2:00 AM
40	Kurunagala-LB1	1, 10, 3, 6, 2, 227, 228, 1	6	35	570.9	5:40 AM	9:22 PM
41	Kurunagala-LB1	1, 218, 8, 247, 17, 232, 231, 1	6	29	532	6:00 AM	10:32 PM
42	Kurunagala-LB1	1, 11, 170, 167, 168, 1	4	35	529.8	6:20 AM	6:16 PM
43	Kurunagala-LB1	1, 229, 14, 13, 230, 201, 200, 1	6	33	333.6	6:40 AM	7:12 PM
44	Kurunagala-LB1	1, 239, 212, 1	2	18	178.7	7:00 AM	2:11 PM
45	Kurunagala-LB1	1, 194, 216, 217, 220, 219, 1	5	35	162.5	7:20 AM	1:49 PM
46	Kurunagala-LB1	1, 203, 121, 235, 211, 213, 1	5	30	157.9	7:40 AM	2:40 PM
47	Kurunagala-LB1	1, 197, 195, 193, 199, 204, 1	5	30	123	8:00 AM	1:24 PM
48	Kurunagala-LB1	1, 214, 210, 215, 209, 208, 1	5	28	90.1	8:20 AM	1:42 PM
49	Kurunagala-LB1	1, 198, 191, 192, 196, 1	4	30	80.4	8:40 AM	12:12 PM
50	Kurunagala-LB1	1, 205, 202, 206, 1	3	25	73.6	9:00 AM	1:39 PM

Table 4-3 provides the details about the Optimal route plan obtained using the VRP proposed model. It includes details about the allocation of distribution centers and loading bays, route plan (sequence of retail outlets served in each route), the number of outlets supplied by each truck, truckload, the distance of the route, truck dispatching time, and the expected arrival time to last retail outlet. These results show how the model effectively allocates trucks to limited loading bays (LB) according to their route length. The model dispatched the trucks that served long-distance delivery routes first. Therefore, the model effectively schedules the limited number of loading bays.

The second objective of the proposed model assists to serve retail outlets before the requested service time. As a practice, the selected retail chain targets to supply vegetable products before 4 pm to retail outlets to meet the customer demand. Therefore, the model tracks the expected arrival time to the last retail outlet to identify the delivery routes with late deliveries. As highlighted in Table 4-4, there are seven delivery routes with late deliveries (truck numbers 1, 38, 39, 40, 41, 42, 43). The results highlight that 86% of delivery routes (43 of 50) served their retail outlets before the requested time. Thereafter, we further investigated the delivery routes with late deliveries.

Table 4-4: Routes with late deliveries

Truck number	**Distribution center & loading bay**	**Route plan** Outlets with late deliveries	**Expected arrival times of late deliver outlets**	**Penalty cost (LKR)**
1	Wattala-LB1	0, 241, 240, 246, 169, 226, 225, 0	4:10 PM, 5:40 PM	10000
38	Kurunagala-LB1	1, 15, 16, 4, 5, 12, 1	5:00 PM, 10:44 PM	35000
39	Kurunagala-LB1	1, 207, 173, 172, 171, 248, 9, 7, 1	4:00 PM, 4:45 PM, 5:30 PM, 10:40PM, 1:55 AM, 2:00 AM	97500
40	Kurunagala-LB1	1, 10, 3, 6, 2, 227, 228, 1	9:20 PM	15000
41	Kurunagala-LB1	1, 218, 8, 247, 17, 232, 231, 1	7:10 PM, 10:30 PM	27500
42	Kurunagala-LB1	1, 11, 170, 167, 168, 1	4:25 PM, 5:55 PM, 6:16 PM	17500
43	Kurunagala-LB1	1, 229, 14, 13, 230, 201, 200, 1	5:05 PM, 6:40 PM, 7:12 PM	25000

Table 4-4 provides more details about the delivery routes with late deliveries. As highlighted in above Table 4-4, only 5% (13 of 247) of the retail outlets receive their orders after the requested time. Therefore, results prove that 95% of retail outlets receive their order on time, and thereby model has successfully achieved the second objective of the proposed model. Delivering the fresh Agri products on time helps to ensure the freshness conditions (Utama, Dewi, Wahid, & Santoso, 2020). Moreover, it caused to minimize the stockout costs of retail outlets (Utama, Dewi, Wahid, & Santoso, 2020). According to the results, 39^{th} trucks incur the highest penalty cost for the late deliveries. Moreover, the 39th truck supplies products for six retail (6 of 7) outlets after the requested time. Since this delivery has the highest number of late deliveries, we separately focused on that. This delivery route provides services to retail outlets located in the northern province of Sri Lanka and thereby, it is difficult to further optimize this delivery route with the current conditions.

The results obtained using the proposed VRP routing model ensure that the model is effective for optimal resource allocation, optimal order allocation, and optimal route planning as intended. Furthermore, all model outputs were tested with data obtained from the real-world case study, ensuring the model's real-world applicability. Industry practitioners will be able to reduce distribution costs while ensuring on-time delivery of fresh Agri products in retail chains by using the proposed VRP model. Furthermore, this model can be used to develop strategies and identify future improvements for the retail chain network. As an example, all most all the late delivery routes are served from the Kurunagala distribution center, and it has only one loading bay for Agri products loading. Therefore, an additional loading bay can be operated and loading operations can start before 5:00 AM to minimize the impact of the late deliveries. Further, retail outlets can plan inventory management strategies accordingly to minimize the negative impact of late deliveries.

4.4. Model Extension

The developed VRP model assumes that each truck begins its deliveries at a central distribution center and returns to its origin point after providing services to designated retail outlets (close-route VRP). For the selected case study this assumption is applicable. However, vehicles do not always return to the same starting point (close-route VRP). Moreover, there are instances where close and open routes exist simultaneously. Close-Open Mixed Vehicle Routing Problem (COMVRP), which takes both close-VRP and open-VRP into account (Liu & Jiang, 2012). COMVRP's practical application is to address situations in which both internal and hired fleets are used in operation (Liu & Jiang, 2012). We extend the model concerning this limitation and the developed model was tested using a separate case study. The extended model and the application were published as a conference proceeding (Fernando et al., 2022).

5. CONCLUSION

Many published VRP research focused on investigating algorithms and little attention was paid to the practical implication. This research attempted to fill this gap by incorporating several real-world characteristics concerning fresh Agri product distribution in retail chains. The proposed VRP model can be successfully used in the industry, for integrated planning (i.e., loading bay allocation, order allocation) and route optimization. Numerical experiments show that our model realized significant savings in daily distribution costs while ensuring the timely delivery of fresh Agri products to retail outlets.

5.1. Research Contributions

Table 5-1 highlights the research contributions of current research concerning the research objectives.

Table 5-1: Research contributions

Research Objectives	Contributions
RO1: Formulates a bi-objective VRPFPG model, including more realistic assumptions and more industrial relevant constraints (Montoya-torres et al., 2015).	• Our research presents a comprehensive analysis of the published VRPFPG models including their objectives and problem characteristics. • The preliminary analysis found that Euclidean distances are not adequate to formulate real-world applications of VRP models, even though most VRP researchers applied Euclidean distances. Therefore, current research employed real-driving distances, measured using the OSRM API to develop the routing model. • The proposed VRP model incorporated real-world characteristics such as a heterogeneous truck fleet, multiple distribution centers, multiple products, a limited number of loading bays, real-world road networks, etc., that have rarely been considered simultaneously in existing research.

RO2: Investigate the effectiveness of the different solution methods in solving the proposed model (Braekers et al., 2016).	• The current research presents a comprehensive analysis and comparison of different solution algorithms employed to solve published VRP models. • Two heuristic methods (the savings algorithm, and the greedy algorithm) were compared in obtaining IBFS. Numerical experiments showed that the savings algorithm outperformed the greedy algorithm with 10% of better IBFS for the largest problem instance. • The Research compared three metaheuristic methods (GLS, SA, and TS) in obtaining near-optimal solutions for the proposed optimization model. The numerical experiment showed that GLS outperformed the other two metaheuristic methods in terms of the quality of the solutions and the computation time. • This research proposed a two-phase solution approach by combining the savings algorithm and GLS. The proposed two-phase solution approach was benchmarked against GLS. Numerical experiments showed that the proposed solution approach has not achieved significant improvement against GLS in terms of the quality of the solution. However, it showed that the proposed solution method is more efficient than GLS when solving the large problem instances with a 13% computation time-saving.
RO3: Analyze the proposed VRPFPG model's applicability in real-world applications (Utama et al., 2020).	• Test the developed VRP model by employing the data, obtained from one of the largest retail chains in Sri Lanka. • The proposed model saves 16 % of daily distribution costs due to the effective allocation of retail outlets to distribution centers and route optimization. Furthermore, it

	represents a 24% reduction in fuel costs and a 7% reduction in fixed costs. • The proposed model is efficient in retail outlet order allocation concerning the multiple types of vegetable products. The model has achieved 95% of truck capacity utilization through effective allocation of orders. • The proposed model is efficient in scheduling the dispatching of trucks with a limited number of loading bays ensuring the on-time delivery of products to the retail outlets. The model ensures 95% of on-time deliveries to retail outlets. Moreover, 86% of delivery routes serve retail outlets without a single delay. Therefore, our model helps to ensure the freshness conditions of fresh Agri products through on-time deliveries. Moreover, it helps to minimize the stockout cost in retail outlets

5.2. Practical Implication

This research applied the developed VRP model to optimize a fresh Agri product distribution in a retail chain. Retail chains distribute fresh Agri products frequently (most of the time daily basis) to keep them fresh. Therefore, planning this daily distribution operation manually is time-consuming and difficult to obtain the optimal distribution plan. The proposed VRP model is efficient as an operational planning tool since it consumes less time to obtain the optimal distribution plan. Also, it achieves significant savings in daily distribution costs while ensuring the timely delivery of products to the retail outlets. Our research only focused to develop a real-world VRP model concerning the application and suggest an efficient solution algorithm. Nevertheless, when we apply the proposed VRP model to the corporate sector, it is required to develop as an operational planning tool. Figure 5-1 depicts the sample user interface for further developing the model as an operational planning tool.

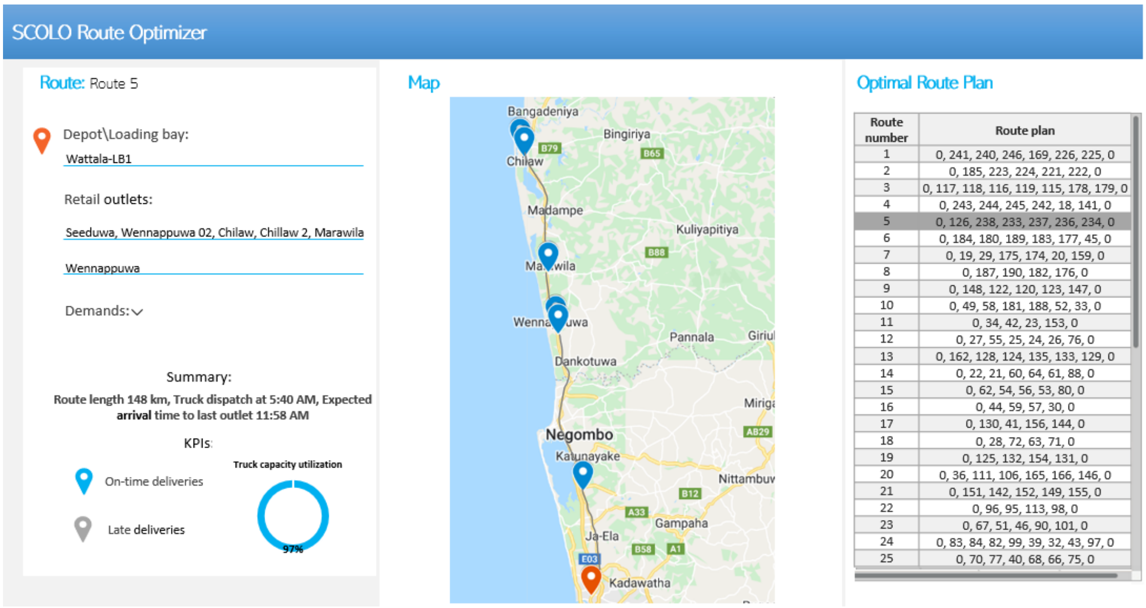

Figure 5-1: Sample user interface

5.3. Research Limitations and Future Directions

The current research incorporated a real-road network to develop the proposed routing model. We measured the travel time between the nodes based on the real-road network. However, this research did not consider the dynamic travel times which are changed according to the congestion of the day. Therefore, future research could extend our model with dynamic travel times, improving its real-world applicability even further. The proposed VRP model is concerned with distributing fresh Agri products in retail chains. The second objective of the proposed optimization model addresses the timely delivery of products and thereby it ensured the freshness of products through the on-time delivery. Further, the research could include the perishability factor of the fresh Agri products thereby, the model can further minimize and track the post-harvest wastage that happened in the distribution process.

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LIST OF APPENDICES

Appendix-A: Location Data of Retail Chain

Index	Outlet Name	Latitude	Longitude
0	Wattala DC	6.98723	79.8886
1	Kurunagala DC	7.473447	80.39139
2	Fc Ampara	7.2914	81.6753
3	Fc Kalmunei	7.41379	81.82724
4	Fc Akkaraipaththu	7.23127	81.85096
5	Fc Pothuvil	6.87543	81.82994
6	Fc Samanthurai	7.36248	81.80375
7	Fc Anuradhapura	8.33164	80.4091
8	Fc Ipalogama	8.07191	80.54647
9	Fc Anuradhapura 2	8.34012	80.41147
10	Fc Mahiyanganaya	7.34107	80.99358
11	Fc Bandarawela	6.8298	80.99411
12	Fc Badulla	6.9881	81.06028
13	Fc Welimada	6.90351	80.9128
14	Fc Bandarawela 2	6.831	80.98856
15	Fc Batticaloa	7.72582	81.68989
16	Fc Batticaloa 2	7.71419	81.69475
17	Fc Eravur	7.77755	81.60272
18	Fc Avissawella	6.95036	80.21374
19	Fc Hanwella	6.90786	80.07759
20	Fc Bandaragama 2	6.71258	79.98658
21	Fc Bokundara	6.81841	79.91805
22	Fc Boralesgamuwa	6.84039	79.90084
23	Fc Godagama	6.85324	80.03235
24	Fc Homagama	6.84133	80.00513
25	Fc Homagama 2	6.822	79.99816
26	Fc Homagama 3	6.85185	80.00393
27	Fc Kottawa	6.84239	79.96251
28	Fc Kottawa 2	6.84071	79.967
29	Fc Meepe	6.85859	80.09093
30	Fc Werahera	6.83293	79.90674
31	Fc Pitakotte	6.88271	79.90153
32	Fc Malabe	6.904	79.95411
33	Fc Kohuwala	6.86682	79.88379
34	Fc Athurugiriya	6.87922	79.98672
35	Fc Battaramulla	6.90182	79.91777
36	Fc Malabe 2	6.91468	79.97206
37	Fc Ethulkotte	6.90122	79.90581
38	Fc Kalapaluwawa	6.91405	79.91011
39	Fc Thalahena	6.90728	79.94574
40	Fc Udahamulla	6.86234	79.91339
41	Fc Millennium City	7.12155	79.91017
42	Fc Athurugiriya 2	6.87644	79.99172
43	Fc Malabe 03	6.90156	79.95666
44	Fc Rawathawatta	6.7911	79.88657
45	Fc Dehiwala	6.83295	79.86725
46	Fc Mount Lavinia Stc	6.83722	79.86729
47	Fc Karagampitiya	6.84999	79.87316
48	Fc Kohuwala 2	6.87025	79.87745
49	Fc Ratmalana	6.81871	79.87432
50	Fc Marine drive	6.90777	79.84944
51	FC Kawdana	6.84343	79.87548
52	Fc Borupana	6.81332	79.88891
53	Fc Piliyandala	6.8061	79.92132
54	Fc Kesbewa	6.79654	79.93953
55	Fc Mattegoda	6.81919	79.97015
56	Fc Kolamunna	6.79342	79.92498
57	Fc Moratumulla	6.78896	79.89861

58	Fc Moratuwa	6.76753	79.88344
59	Fc Moratuwa	6.77501	79.88389
60	Fc Moratumulla 1	6.788	79.89548
61	Fc Arawwala	6.83042	79.93488
62	Fc Polgasowita	6.78786	79.95958
63	Fc Maharagama	6.84531	79.92657
64	Fc Piliyandala 2	6.79965	79.91877
65	Fc Nugegoda	6.87558	79.88087
66	Fc Delkanda	6.86461	79.89723
67	Fc Attidiya	6.83912	79.88468
68	Fc Wijerama	6.85714	79.91007
69	Fc Mirihana	6.87496	79.90086
70	Fc Nugegoda 2	6.87252	79.89036
71	Fc Maharagama 2	6.84985	79.92283
72	Fc Pannipitiya	6.84669	79.95111
73	Fc Stanly Tmw	6.87473	79.89625
74	Fc Pagoda	6.87844	79.89397
75	Fc Wijerama 2	6.86481	79.89693
76	Fc Hokandara	6.87791	79.95922
77	Fc Kattiya Junction	6.86889	79.89845
78	Fc Kotahena	6.94877	79.85927
79	Fc Kolonnawa	6.93257	79.89195
80	Fc Dematagoda	6.92925	79.87757
81	Fc Mutuwal	6.9712	79.87445
82	Fc Kotikawatta	6.93463	79.91646
83	Fc Wellampitiya	6.9368	79.90439
84	Fc Kotikawatta 02	6.93849	79.91587
85	Fc Maradana	6.92576	79.8671
86	Fc Grandpass	6.94434	79.86707
87	Fc Majestic City	6.89407	79.85461
88	Fc Nawala	6.888	79.88758
89	Fc Park Road	6.88781	79.87299
90	Fc Wellawatte	6.87112	79.86187
91	Fc Dickmans Road	6.88674	79.85887
92	Fc Duplication	6.9024	79.85453
93	Fc Jawatta	6.89499	79.8667
94	Fc Ward Place	6.91603	79.87011
95	Fc Thalawathugoda	6.8735	79.93796
96	Fc Pelawatta 2	6.88832	79.93055
97	Fc Himbutana	6.92641	79.93391
98	Fc Thalapathpitiya	6.86601	79.92752
99	Fc Koswatte 2	6.90708	79.93
100	Fc Jaya Road	6.88652	79.85492
101	Fc Wattala 02	6.97695	79.88828
102	Fc Staples Street	6.92019	79.85583
103	Fc Kollupitiya 02	6.90974	79.85043
104	Fc Colombo City Center	6.91733	79.85543
105	Fc Fort	6.93577	79.84463
106	Fc Kaduwela	6.9369	79.97996
107	Fc Koswatte	6.90958	79.90585
108	Fc Rajagiriya 2	6.90853	79.89951
109	Fc Norris Canal	6.92239	79.86599
110	Fc Cota Road	6.91138	79.88666
111	Fc Kaduwela 02	6.93773	79.97758
112	Fc Rajagiriya	6.9101	79.89426
113	Fc Depanama	6.85881	79.94415
114	Fc Pepiliyana	6.85243	79.88302
115	Fc Ambalangoda	6.23789	80.0543
116	Fc Galle	6.03333	80.21541
117	Fc Karapitiya	6.06802	80.22808
118	Fc Galle 2	6.03521	80.21716
119	Fc Ambalangoda 2	6.23477	80.05419
120	Fc Nittambuwa	7.14141	80.09394

121	Fc Mirigama	7.24954	80.13055
122	Fc Thihariya	7.12901	80.07335
123	Fc Nittambuwa 2	7.14435	80.0928
124	Fc Negombo	7.21672	79.84566
125	Fc Jaela	7.08262	79.89093
126	Fc Seeduwa	7.12723	79.87679
127	Fc Ragama	7.02758	79.92353
128	Fc Negombo 2	7.20632	79.85059
129	Fc Jaela 2	7.07386	79.8926
130	Fc Ekala	7.10221	79.91015
131	Fc Raddolugama	7.13762	79.89972
132	Fc Seeduwa 2	7.14335	79.87385
133	Fc Kurana	7.1913	79.85805
134	Fc Ragama 2	7.0286	79.91578
135	Fc Negombo 03	7.21294	79.84414
136	Fc Kelaniya	6.96696	79.90673
137	Fc Dalugama	6.97259	79.91731
138	Fc Pethiyagoda	6.952	79.90527
139	Fc Kiribathgoda 02	6.97693	79.93174
140	Fc Kelaniya 2	6.96667	79.91503
141	Fc Kiribathgoda	6.98223	79.93117
142	Fc Gampaha	7.08963	80.00437
143	Fc Kadawatha	7.00035	79.94823
144	Fc Minuwangoda02	7.17066	79.95034
145	Fc Kadawatha 2	7.0032	79.95602
146	Fc Delgoda	6.98657	80.01302
147	Fc Weliweriya	7.03436	80.02685
148	Fc Yakkala	7.08672	80.03374
149	Fc Ganemulla	7.0674	79.95933
150	Fc Enderamulla	6.99493	79.91519
151	Fc Kadawatha 3	7.00357	79.95084
152	Fc Gampaha 3	7.09137	79.99255
153	Fc Welipillawa	6.8818	80.03396
154	Fc Awariwatta	7.16345	79.88335
155	Fc Ganemulla 02	7.06554	79.96156
156	Fc Minuwangoda	7.16638	79.94673
157	Fc Peliyagoda	6.96683	79.90737
158	Fc Welisara	7.02426	79.90838
159	Fc Makola	6.9753	79.9482
160	Fc Elakanda	6.99416	79.87447
161	Fc Bloemendhal	6.96139	79.86785
162	Fc Welisara 2	7.01247	79.89762
163	Fc Wattala	6.99066	79.89317
164	Fc Kandana	7.04955	79.8962
165	Fc Bandarawatte	6.93911	79.98694
166	Fc Biyagama	6.95033	79.9928
167	Fc Hambantota	6.12835	81.12586
168	Fc Ambalanthota	6.12216	81.01867
169	Fc Tangalle	6.02576	80.79463
170	Fc Thissamaharama	6.27858	81.28553
171	Fc Jaffna	9.66522	80.01372
172	Fc Manippay	9.72322	79.99736
173	Fc Chunnakam	9.74346	80.02742
174	Fc Horana	6.71751	80.05969
175	Fc Horana 2	6.7144	80.06349
176	Fc Panadura	6.70872	79.90797
177	Fc Aluthgama	6.43333	79.99779
178	Fc Beruwela	6.47466	79.98337
179	Fc Kalutara	6.58042	79.96167
180	Fc Katukurunda	6.56172	79.9815
181	Fc Panadura 2	6.70879	79.90803
182	Fc Kalutara North	6.59994	79.95653
183	Fc Dharga Town	6.44131	80.01397

184	Fc Wadduwa	6.66588	79.9297
185	Fc Mathugama	6.52244	80.11212
186	Fc Keselwatte	6.93352	79.85978
187	Fc Wadduwa 2	6.66075	79.93267
188	Fc Pallimulla	6.74178	79.90247
189	Fc Aluthgama 2	6.44154	80.01711
190	Fc Katukurunda 02	6.56159	79.96907
191	Fc Kandy	7.29287	80.6371
192	Fc Katugastota	7.31431	80.63155
193	Fc Pilimatalawa	7.26517	80.55788
194	Fc Akurana	7.36932	80.61716
195	Fc Kundasale	7.28029	80.67405
196	FC Katugastota 2	7.32126	80.6275
197	Fc Pallekele	7.28289	80.7197
198	Fc Gatambe	7.27072	80.60491
199	Fc Pilimathalawa 2	7.2642	80.5497
200	Fc Gampola	7.16062	80.56518
201	Fc Nawalapitiya	7.0558	80.53454
202	Fc Kegalle	7.24812	80.35136
203	Fc Warakapola	7.22853	80.2004
204	Fc Mawanella	7.25286	80.44903
205	Fc Kegalle 2	7.25142	80.34198
206	Fc Rambukkana	7.32159	80.39008
207	Fc Kilinochchi	9.38028	80.37699
208	Fc Kurunegala	7.49264	80.36636
209	Fc Kurunegala 2	7.48845	80.36082
210	Fc Kuliyapitiya	7.4687	80.03414
211	Fc Pannala	7.32904	80.02459
212	Fc Wariyapola	7.61802	80.24789
213	Fc Narammala	7.42725	80.21407
214	Fc Kurunegala 3	7.4785	80.35744
215	Fc Kuliyapitiya 02	7.47287	80.04439
216	Fc Matale	7.46746	80.62341
217	Fc Matale 2	7.47426	80.62252
218	Fc Dambulla	7.87822	80.65033
219	Fc Galewela	7.75934	80.57098
220	Fc Dambulla 2	7.87108	80.6487
221	Fc Matara	5.94941	80.54472
222	Fc Akuressa	6.09682	80.47705
223	Fc Weligama	5.97325	80.43223
224	Fc Matara 2	5.94309	80.55439
225	Fc Mirissa	5.94738	80.45813
226	Fc Dickwella	5.96469	80.69577
227	Fc Moneragala	6.87129	81.35009
228	Fc Wellawaya	6.73129	81.10201
229	Fc Nuwara Eliya	6.97608	80.76578
230	Fc Hatton	6.89279	80.59728
231	Fc Kaduruwella	7.94251	81.01224
232	Fc Polonnaruwa	7.92818	81.03409
233	Fc Chilaw	7.57868	79.79393
234	Fc Wennappuwa	7.34513	79.84057
235	Fc Dankotuwa	7.29813	79.88216
236	Fc Marawila	7.41573	79.83047
237	Fc Chillaw 2	7.5687	79.79919
238	Fc Wennappuwa 02	7.33378	79.84407
239	FC PUTTALAM	8.02734	79.83775
240	Fc Balangoda	6.64783	6.64783
241	Fc Palmadulla	6.62561	80.53875
242	Fc Ratnapura	6.67911	80.40207
243	Fc Eheliyagoda	6.85415	80.26101
244	Fc Ratnapura 03	6.69877	80.39105
245	Fc Rathnapura 2	6.68266	80.40476
246	Fc Embilipitiya	6.33146	80.85673

247	Fc Trincomalee	8.57756	81.22808
248	Fc Vavuniya	8.75232	80.49781

Appendix-B: Distance Matrix

https://drive.google.com/file/d/1UBpbO2JdYbshiJa-LM_Ti8JNjG51tj-5/view?usp=sharing

Appendix-C: Time Matrix

https://drive.google.com/file/d/17HrTy_x0FMiFbKIQ1YjQUxER5Omf1kmj/view?usp=sharing

Note: Demand data were not attached to protect the confidentiality of the data