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SUPPLY CHAIN MANAGEMENT (SCM)

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«Vehicle Routing Problem»

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Abstract

The Vehicle Routing Problem (VRP) is among the principal topics studied in the logistics and supply chain management domain where the goal is to determine the routes an efficient number of vehicles to traverse from a depot to deliver goods and services to numerous customer locations. This thesis seeks to establish VRP in a supply chain system used to distribute supermarket products, which are shipped from a central depot. Using the Clark & Wright Savings Algorithm as the research rationale, the proposed study shall endeavor to realize substantial cost and distance-saving levels on transportation.

This work starts by explaining the problems tackled by the VRP in contemporary supply chain management before embarking on a theoretical discourse on its varieties and importance. Then, a mathematical model of the problem is introduced in detail focusing on its objectives and constraints. Next, the Clark & Wright Savings Algorithm is analyzed from the method point of view, history, and real-use scenarios. Described are implementation methodologies using Excel tools where the algorithm is applied in a given working problem dealing with routing. These results, demonstrated with numerical examples and visualizations, clearly demonstrate the advantages of the algorithm compared with the existing approaches.

The outcomes highlight the gains in delivery efficiency which supports the broader utilization of the algorithm for supply chain platforms as well. The thesis ends with suggestions for further study regarding the development of artificial intelligence improvements as well as considering more constraints of the real world. To the best of the researcher's knowledge, this work adds to the pool of knowledge by identifying a framework for implementing VRP solutions in retail supply chain environments.

Key - Words: Vehicle Routing Problem (VRP), Clark & Wright Savings Algorithm, Supply Chain Optimization, Supermarket Logistics, Route Optimization, Transportation Efficiency

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Chapter 1: Introduction

1.1 Presentation of the Problem

A core element of supply chain planning, the aim of transportation management is typically to find the best solution for a vehicle that has to visit multiple customers starting from and returning to a distribution center. This problem is also referred to as the Vehicle Routing Problem (VRP) and is one of the most vital problems facing logistics and distribution networks. It is to be noted that VRP seeks to optimize such objective factors as the total cost, including the actual or overall distance (or actual or overall transportation cost, for example, transportation costs), while taking into account some crucial constraints, such as the vehicle's capacity constraints, customer timings or windows, or depot time constraints (Clarke & Wright, 1964; Laporte et al., 2000).

The complexities of VRP in its real-life application are compounded especially in situations involving supermarkets' supply chain systems. Supermarkets need often supplies as the stock might run out sometimes with distribution centers located within urban and rural areas. If routing is not optimized, transportation results in higher fuel consumption, longer delivery time, and therefore higher operating costs which reduces profit and sustainability (Vidal et al., 2020; Braekers et al., 2016).

To overcome all of these challenges, reliable optimization techniques have been introduced. Of these, it can be said that the Clark & Wright Savings Algorithm is quite an effective heuristic technique. Spearheaded by Clarke and Wright in 1964, this method relieves the trajectory optimization technique since it consolidates delivery routes through cost savings. The algorithm extracts set of routes that can be combined in a way that the distance for the whole will be less than the distance for a pair yet will respect the capacity of vehicles. Due to these features, it is more suitable than many other methods for practical use, for example for supermarket stocking (Clarke & Wright, 1964; Baldacci et al., 2008).

Hence, the VRP is not only a conceptual model of the supply chain but perhaps one of the most important implements carried out in the actual practice of logistics. For instance, the potential uses of applications in contexts are waste collection applications, e-commerce and, retail applications, and distribution applications. In proposition, particularly in supermarket chains, optimized routing highly influences the delivery performance and cost and the company's influence on the environment (Bing et al., 2014; Ahmad et al., 2020). Exact methods for solving VRP have been developed and implemented even in heuristic ones their computational complexity is still high as the problem is NP-hard even for large-scale problems are still infeasible. Consequently, simple methods such as the Clark & Wright algorithm continue to be useful (Laporte et al., 2000; Battarra et al., 2008).

This research specifically examines the usage of Clark & Wright Savings Algorithm in the supply chain of a supermarket. Spreadsheet tools are applied to perform algorithm operations, which establishes the algorithm's effectiveness in designing efficient delivery routes and minimizing transportation expenses. Based on the results of the study, the potential and limitations of the algorithm are described, as well as its application considering real-life constraints, including differences in customer flow and geographical distribution.

This study also has practical relevance beyond academic concern. Thus, by showing the signs of enhanced route efficiency, this work extends the dangers of sustainable and cost-effective logistics. VRP algorithms have thus emerged as a subject to become specified as VRP methods apply practically as businesses search for new ways how to enhance supply chain management.

1.2 Research Purpose and Its Goals

It is the goal of this work to identify how to practically apply and implement the principles of optimization to the problems of vehicle routing for supermarket supply chain scenarios. These supply chains require precise and routine orders to several outlets which are spread geographically and often under conditions such as restricted load-carrying capacity of vehicles, unstable demand for materials/products, and strict time schedules for deliveries. Vehicle schedules to visit locations are important determinants of operating costs, travel distances, and quality of services delivered in

respective operations while also aligning to benchmark sustainable business practices like minimum use of fuel.

This research is based on applying the existing heuristic known as the Clark & Wright Saving Algorithm to solve the problem of vehicle route planning in a supermarket supply chain network. Therefore, whereas determining the cost-saving opportunity in light of the consolidation of delivery routes represents a real solution to the various vehicle routing problem scenarios, the algorithm delivers an efficient computational solution to the problem.

Consequently, the following research objectives are to be attained: First, it aims at developing the best delivery network that increases both efficiency and economy within the supermarket supply chain. Second, it assesses the performances of the algorithm to reduce the distances traveled and the organizational costs against other modes or suboptimal approaches. Third, it applies the described approach and shows that it can be accomplished with the tools available to most practitioners, including Microsoft Excel, thus eliminating the disconnect between theory and application. Last of all, the prospect of applying the discovered algorithm to supply chain logistics in real-life conditions is discussed, and the role of the proposed approach in the formation of more efficient and environmentally friendly supply chain management is outlined.

Regarding these objectives, the research not only enriches the existing theory of optimization techniques in the field of logistics but also provides useful recommendations for practical application. It hopes that it will be able to make a contribution towards the growing theoretical knowledge of how to enhance the performance of the supply chain given the current and evolving antagonistic features of the business terrain.

1.3 Methodology and Tools Used

The approach used in this study concerns itself with the applicability of the Clark & Wright Savings Algorithm to overcome the hurdles of vehicle routing in supermarket supply chains. This approach consists of several collaborative processes such as data preprocessing, applying the algorithm, and result interpretation. The tools applied were

chosen to be easily accessible, easily reproducible, and as realistic as possible; with the focus made on using Excel as a tool of choice.

The process starts from input data where several factors like distance matrix, vehicle capacity, and customer demand are required. These inputs show the fields that define the construction of the routes and form the constraints within the optimization process. Excel for presentation of information as well as data cleaning so as to get rid of gases, logos, and other irrelevant information that might clutter the information. Conveniently, one can add the appropriate formula and macro to improve the process of data manipulation and calculation.

The Clark & Wright Savings Algorithm is then applied to the prepared data. The algorithm lays out a process of decision-making for detecting ways of reducing costs through fewer delivery points but grouped into more efficient routes. Savings for each pair of delivery points are computed; the savings are ordered and used alternatively to construct the optimal routes. Excel is equipped with the VBA that enables automation of these iterative steps to optimize computational aspects as well as minimize effort.

In order to validate the findings of the research, a methodological approach that utilizes multiple levels of analysis is employed. The total distance formula, fuel efficiency and the number of routes produced are log reviewed to assess the efficiency of the algorithm. Pretty tools such as charts and graphical models in Excel are used in order to present the results easily and understandably.

This methodology pays attention to not only the academic soundness of the Clark & Wright Savings Algorithm but also its usefulness in practice. By using free resources such as Excel, the study closes the gap that exists between log models and actual practice by showing how the optimization approach can be put into practice in LS&CM.

1.4 Thesis Outline

The structure of this thesis is as follows to ensure a systematic evaluation of the Vehicle Routing Problem and the utilization of the Clark & Wright Savings Algorithm in the supermarket supply chain: It is also designed to take the reader from one phase of VRP,

namely the conceptualization or theory, to the next phase, namely the actualization or application, and then to the evaluation or analysis phase.

The first chapter acquaints the reader with the overall research by explaining the complexity of the problem in the domain of vehicle routing and the relevance of the issue to supermarkets. It is a brief detailing the research rationale, aims and objectives, and methodology that will be employed alongside some of the tools to be utilized like Excel and the Clark & Wright algorithm. Before outlining the plan for subsequent chapters and after the chapter, the structure of the thesis is presented.

The second chapter gives the theoretical framework of the research to show the characterization and importance of the VRP. It traces the origin of the problem and different categories which include capacitated VRP, VRP with a time window, and its application in supply chain and logistics. Moreover, it describes numerous practical cases of using VRP with an emphasis on supermarkets, e-commerce, and waste management.

Chapter three of the dissertation provides the mathematical formulations of the VRP where objectives, variables, and constraints of the problem are captured. This chapter also presents the assumptions and limitations of the model which include the vehicle capacity of load carrying and time horizon so as to give a more realistic view of the utility of the model in the field.

The fourth chapter covers the historical development of the Clark & Wright Savings Algorithm, explaining its method of operation, as well as its application. The actual steps of the algorithm are described and to clarify the process, a numerical example is presented. The strengths and limitations of the algorithm are evaluated, as well as the applicability of the method in supermarket supply chain cases.

Chapter five demonstrates the process of applying the algorithm with the help of Excel. It explains preparing input data, including distance matrices and demands and overviews the main steps to implement the algorithm into Excel. Mention can be made of the fact that the current chapter stresses the efficiency of the approach and its implementation on the primary data and possible constraints.

The measures and the effects noted in the course of the implementation are reported in the sixth chapter, in terms of for example the total distance and the total cost. These have been supported by tables and figures to enable the reader to make an analysis of the efficiency of the algorithm presented in this chapter. Also included is a comparison with other routing methods to determine the efficiency of the proposed method.

Last but not least, chapter seven brings this thesis to a close by summarising the existing research results and presenting the implications for logistics and supply chain management. It also discusses limitations, including data limitations and assumptions, and provides suggestions for improvement in subsequent research. Some of these are, for instance, investigating AI uses in planning and extending more constraints into the VRP models.

Thus, following this structure, the thesis covers all the aspects of the VRP, including its theoretical concept and concrete practical applications for logistics improvement.

Chapter 2: Background of the Study: Theoretical Analysis of the Vehicle Routing Problem (VRP)

2.1 Characterization and Importance of the Vehicle Routing Problem (VRP)

The Vehicle Routing Problem (VRP) is known as one of the most important and investigated classes of optimization problems in logistics and supply chain management. It concerns itself with the difficulty of routing a fleet of vehicles to service a list of customers with the objective of minimizing costs subject to a number of constraints. These constraints may include; The carrying capacity of the vehicle; time windows within which delivery is made and; the needs of the customer, since the VRP is in its nature very complex and requires a lot of computation.

VRP on the other hand is defined as a practical task involving planning of routes from and between one or many depots to many delivery points in an efficient and least cost manner. This cost function confers to the distance throughout the delivery, the amount of fuel used or the time spent to deliver the goods among other factors. The fact that the problem is presented as a combination of vehicle routes to several customers has raised the problem's complexity; as the number of vehicles and customers expands, the number of optimal solutions shoots up and that makes VRP an NP-hard problem. This means that the effort of reaching for the precise optimal solution becomes problematic for real-world problems (Dantzig & Ramser, 1959).

The practical relevance of VRP is born out of the fact that it plays an essential role in planning and execution hence benefiting operations in business entities in terms of cost-cutting measures. Thus, it is found that wrong routing decisions can lead to higher transportation costs, underutilization of vehicle capacity, and delivery prolongation. For instance, in the supermarket supply chain application, effective routing of foodstuff ensures that the store is stocked up adequately with fresh and perishable goods, minimizes product wastage, and increases customer satisfaction. Inefficient routes on the other hand may lead to a stock-out situation, excessive fuel consumption, and emissions which are not only costly but also imprint a negative image on any firm's sustainability mission (Clarke & Wright, 1964; Baldacci et al., 2008).

Historical Evolution of the VRP

The base of VRP is rooted in the study of Dantzig and Ramser in 1959; where they proposed the known “truck dispatching problem,” which examines the efficient ways of delivering fuel. This research work was the first of its type and sought to establish the modeling of VRP as an optimization problem. In this regard, the objective was to establish the least total distance that several vehicles could travel without violating customers’ requirements. In the continuous course of optimization, new constraints and objectives were added to the problem to correspond to the flexibility and variability of actual real-world logistics systems.

The basic VRP was soon extended to the Capacitated Vehicle Routing Problem (CVRP), in which constraints concerning the capacity of the vehicle were included. This stops the total requirement of customers on a given route from exceeding the total capacity of a vehicle. Other developments were obtained in subsequent years which comprised VRP with time windows (VRPTW), Multi-depot VRP, and Vehicle routing problems with pickup and delivery among others. Each of these variants sorts out practical problems that companies from retail trade, waste disposal, and public transport face (Laporte et al., 2000).

Key Components of the VRP

The VRP consists of several critical components that define its complexity and applicability:

1. Depot and Vehicle Information: The problem begins with single or multiple depots where the vehicles to be rendered start and end. There are added realities in vehicles such as capacity, cost, and constraints to operation that exist.
2. Customer Demands: Every single customer has his or her personal peculiarities – for instance, how many items should be delivered or when it is possible to deliver the goods.
3. Distance Matrix: Distance or cost of traveling from one location to another, including all customers and depots are important parameters for route planning.

4. Objective Function: The main goal, most often, is to maximize savings on total transport costs, as well as to reduce fuel consumption, CO2 emissions, or delivery time.

5. Constraints: These constraints include vehicle capacity, delivery time windows, route length constraints, and the availability of depots where the vehicles have to be parked after delivering their payloads.

Significance of VRP in Modern Logistics

Concisely, it is evident that VRP plays a crucial role in the logistics discipline. The logistics problem in industries such as retail or e-commerce makes it possible to create efficient and cheap delivery plans that decrease operational costs and the growth of service quality. For instance, the stock at supermarkets needs constantly replenished and requires exactly timed delivery for timely to cater to the consumer's needs. Identification of optimum channels not only has the effect of cutting costs but also shortens delivery time – an essential factor due to the perishable nature of the products.

Moreover, VRP is central to the enhancement of corporate environmental sustainability. In this way, for instance, by improving the routes taken by the vehicles it uses, a company can greatly cut the fuel and pollution levels of that firm. This is in line with a shift towards environmentally sustainable practices in supply chain activities, green logistics initiatives, and sustainability goals in both the governments and organizations of the world (Ahmad et al. 2020).

In the overall technological context, however, VRP has emerged as dynamic and one that can address real-time or changing conditions. Today applications have live traffic data dynamic customer demands and multi-modal transportation systems, making VRP solutions more versatile. These developments have been made possible by the progress in computing capability and the introduction of Heuristic and Meta-Heuristic algorithms that offer good solutions much faster for big-size problems (Breakers et al., 2016).

Thus, VRP can be considered one of the key aspects of the contemporary logistics and SCM field that remains significant when it comes to essential problems associated with

the setting and solving of cost-driven and service-oriented tasks and green implications. It has a research basis and business implementation which has transformed it to be a tool that is importance to industries that seek to improve their functioning while achieving sustainable development objectives.

2.2 Brief History and Evolution of the VRP

The Vehicle Routing Problem (VRP) has developed rigorously since its formulation to meet the advanced demand of supply chain and logistical advancement. This problem was initially introduced by Dantzig and Ramser (1959) when they presented the formal view of the model applied to deciding the best routes for the fuel truck. Specifically, this work suggested that only a few percent better solutions could cut costs and indicated how route optimization could make a difference, thus setting the base stage for the complication of VRP as a problem in operation analysis.

Based on this Clarke and Wright (1964) developed the Savings Algorithm a heuristic one that made practical use of VRP in bigger and more complex networks. This colored a drastic turn from exact methods which looked at ensuring the best solution to heuristics that gave more acceptable solutions in a lesser amount of time. Over the following decades, To meet particular logistical needs, researchers then came up with several modifications of the VRP, one of which is the Capacitated VRP (CVRP) where vehicle capacity constraints are put into consideration as well as the VRP with Time Windows (VRPTW) where delivery time constraints are included (Altinel & Öncan, 2005).

New metaheuristic methods appeared in the 1980s and the 1990s including tabu search, simulated annealing, genetic algorithms, and ant colony optimization. These approaches provided solid solutions to VRP greater instances that were unsolvable using the conventional approaches. For instance, Dorigo et al., (1999) used the foraging behavior of ants to develop ant colony optimization to solve VRP instances to great success. For the same reason, the so-called genetic algorithms were often incorporated for abilities to search a large area of potential solutions by using techniques imitating natural selection (Baker & Ayechew, 2003).

In the twenty-first century, investigating dynamic and stochastic models became popular due to the real-world objective of tackling issues like customer demand variability, traffic conditions, and disturbances. SVRP and DVRP have proved to be very important in firms such as e-tailing and emergency with a highly dynamic environment. As this paper discusses, increasingly significant technological innovations such as big data, IoTs, and artificial intelligence have added even more to the evolution of VRP. These innovations facilitate data integration in real-time, predictive models and deploying machine learning methods, making VRP a live data, optimization discipline (Xue & Cao, 2015).

Even today, it is one of the topics that is paid the greatest attention by the scientific world, and at the same time, is widely used in practice as the basis of methodologies for the supply of global supply chains. Since the utilization of exact algorithms and the development of metaheuristics and real-time optimization tools in the current period, VRP remains relevant, meeting the constantly increasing problem of the complexities of networks of logistics and transportation.

2.3 Subdivisions of the Vehicle Routing Problem (VRP)

Currently, the VRP has evolved into several branches, each designed to respond to particular issues in vehicle and route management. Most of these subdivisions emerged due to the need to capture realism in the system constraints such as vehicle capacities, delivery time windows, and the decentralized nature of the depots. Talking about the most typical types of VRP variants, their features, usage, and relevance to logistics are discussed further in this section.

The first of the extensions of VRP is the Capacitated Vehicle Routing Problem (CVRP), whereby vehicle capacity limitations are considered. This makes certain that the overall demand of customers assigned to a route does not exceed the maximum limit of a vehicle; this is important regarding sectors such as retail, manufacturing, and waste collection. Throughout this document, the practical uses for CVRP are wide-ranging: supermarket delivery, recycling programs, and more, CVRP has been beneficial when there are proper and specific load plans needed for logistics operations. Researchers like Clarke and Wright (1964) and Baldacci et al. (2008) have presented a

computationally efficient output to solve CVRP which has made CVRP a fundamental investigation area in VRP.

When delivery systems started to gain more temporal constraints, the Vehicle Routing Problem with Time Windows (VRPTW) was introduced to address time requirements for a particular customer. It guarantees delivery in certain durations; therefore, it is perfect for businesses handling perishable goods, supplying big cities, and last-mile services. For instance, the supply chain of supermarkets incorporates VRPTW to restock the fresh produce on the shelf on time. In the real-world application, Tarantilis and Kiranoudis, (2002) provided empirical evidence for the application of the model in the context of distributing fresh meat, while Baldacci et al., (2008) employed time windows in exact and heuristic algorithms.

Due to the complex structures of decentralized logistics networks in providing VRP, Multi-Depot VRP (MDVRP) enabled the route of the vehicle to start and end at the different depots. The MDVRP problem is very suitable for large-scale dispatching systems because several warehouses or distribution centers have to collaboratively manage the flow of delivery. MDVRP is often used in regional supply chain and beverage distributions, and there is much research on the problem area with early work from Augerat et al. (1995) employing branch-and-cut methods for the multi-depot problem.

Another great extension is the Capacitated VRP with Pickup and Delivery (VRPPD) whereby customers' goods are picked up and dropped off. Today this variant has become popular in cases of reverse logistics and recycling like online order returns and waste management. Environmental research by Zobolas et al. (2009) demonstrated its use in a web-based decision support system of waste lube oil collection proving that this tool can help advance circular economy projects.

The resource required for the development of SDVRP is flexibility, which implies that customer demands can be addressed by different vehicles. This approach is particularly helpful when one form of a vehicle cannot satisfy the full demand of a customer. SDVRP has been used in the transportation of bulky products and enormously large construction projects in which delivery can be split to decrease the total cost of

transportation. SDVRP proved to be highly efficient in dealing with partial deliveries for large and convoluted supply chains as highlighted by Grondys (2020).

This has also spurred the creation of Dynamic VRP (DVRP) and Stochastic VRP (SVRP) due to the current complex logistics needs. Routes can be changed with real issues such as congestion, new orders, or vehicles that are available on the road making DVRP imperative in seniority delivery and disaster management. On the other hand, SVRP deals with uncertainties beneath the demand or travel time, and it also models to work better where the environment unpredictability is high. Ammouriova et al. (2023) also proved that sim heuristic methods can be applied to solve such real-life problem characteristics as dynamic and stochastic features.

Bi-VRP has gained much attention in recent years owing to the increasing emphasis on environmental sustainability, which lead GVRP. This variant includes goals associated with the environment, for instance, low fuel or a small amount of CO₂ used in the routing. GVRP is the most essential interlock and is vital in urban logistics since the environment is becoming a cause for concern due to pollution, and everyone is encouraged to embrace environmentally friendly practices. For instance, Bing et al. (2014) focused on the eco-efficient collection of the household's plastic waste and discussed the possibility of GVRP contributions to optimizing logistics activities for sustainability.

Other derivatives of the VRP are the Heterogeneous Fleet VRP (HFVRP) where the vehicles used have different capacities and costs, and the Periodic VRP (PVRP) where the delivery schedules are planned over several days. These models answer specific operational requirements, e.g., resource allocation in multimodal transportation or planning of the multi-day delivery network in the pharmaceuticals supply chain. The Rich Vehicle Routing Problem (RVRP) focuses on various aspects such as customer preferences, types of vehicles, and priorities of delivery hence is well suited for middle and complex supply chain networks Bueno-Delgado et al., 2019.

Vivid examples of subdivisions of VRP prove that the given approach is sufficiently flexible to meet the challenges of the new-age logistic networks. These variants cover as far as practical issues as punctual deliveries in urban areas, to managing resources in sustainable transport. This assertion underlines the fact that constant improvements in

the development of VRP models and algorithms by Clarke and Wright (1964) and other theoretical works such as Ammouriova et al. (2023) make the VRP a significant feature of supply chain and transportation science today.

2.4 The Concept and Significance of VRP in Supply Chain and Logistics

The Vehicle Routing Problem (VRP) plays a pivotal role in optimizing supply chain and logistics operations by ensuring the efficient allocation of resources and the effective planning of delivery routes. As businesses aim to enhance customer satisfaction, reduce operational costs, and address sustainability concerns, VRP provides a robust framework for managing the complexities of modern logistics networks.

At its core, VRP focuses on determining the most cost-effective set of routes for a fleet of vehicles tasked with serving a set of customers. The optimization process typically involves minimizing travel distances, delivery times, or fuel consumption while adhering to constraints such as vehicle capacities, customer demands, and time windows. These objectives align directly with the goals of supply chain efficiency and responsiveness, making VRP an indispensable tool for organizations in diverse industries (Christofides & Eilon, 1969; Tarantilis & Kiranoudis, 2002).

In the context of supply chains, VRP acts as a critical mechanism to ensure seamless integration between production, warehousing, and distribution. By minimizing inefficiencies in transportation networks, VRP not only reduces costs but also enhances the reliability and agility of supply chain operations. For instance, optimized routing solutions allow companies to respond swiftly to fluctuations in demand, ensuring that goods are delivered on time and in optimal condition. This is particularly significant in industries like perishable goods, where timely delivery is critical to maintaining product quality (Kechagias & Kipouridis, 2020).

Moreover, the significance of VRP extends beyond cost reduction to include sustainability considerations. With the rise of Green Supply Chain Management (GSCM), companies increasingly leverage VRP models to minimize environmental impacts. Variants such as the Green VRP (GVRP) are designed to reduce fuel consumption and greenhouse gas emissions by optimizing routes for fuel efficiency and

incorporating eco-friendly vehicles into fleets. Such initiatives not only align with corporate sustainability goals but also meet regulatory requirements and enhance brand reputation. Studies by Xue and Cao (2015) have demonstrated the potential of VRP to significantly lower environmental footprints in urban logistics operations.

The adaptability of VRP to real-world logistics challenges is evident in its numerous applications across industries. In retail and e-commerce, VRP ensures efficient last-mile deliveries, which are critical for meeting customer expectations in a competitive market. Algorithms like the Clarke and Wright Savings Algorithm (Clarke & Wright, 1964) and enhancements such as those proposed by Altınel and Öncan (2005) have enabled the efficient distribution of goods to multiple delivery points, even under complex constraints. Additionally, the use of VRP in waste collection and reverse logistics highlights its versatility. For example, Karadimas et al. (2007) explored its application in optimizing waste collection routes, leading to significant cost savings and operational improvements.

Dynamic and stochastic environments further underscore the importance of VRP in supply chain operations. Real-time routing adjustments facilitated by Dynamic VRP (DVRP) models help companies navigate uncertainties such as traffic congestion, weather disruptions, and last-minute order changes. These adaptive models are particularly valuable in urban logistics and emergency response scenarios, where agility is critical. Research by Ammouriova et al. (2023) has emphasized the role of advanced VRP algorithms in enabling real-time decision-making under uncertain conditions.

The strategic importance of VRP lies in its ability to provide a competitive advantage by balancing cost-efficiency, customer-centricity, and sustainability. By integrating VRP into their logistics systems, organizations can achieve:

- **Cost Optimization:** Reduced fuel consumption and transportation expenses by minimizing route distances and idle times.
- **Improved Service Levels:** Enhanced reliability and punctuality through precise route planning, particularly in time-sensitive industries like pharmaceuticals and fresh produce.
- **Sustainability Goals:** Alignment with environmental regulations and societal expectations by reducing emissions and adopting greener logistics practices.

In summary, VRP serves as a cornerstone of supply chain and logistics optimization, addressing the multifaceted challenges of modern transportation systems. Its ability to adapt to evolving operational demands and integrate emerging technologies ensures that it remains at the forefront of logistical innovation, driving efficiency and sustainability in global supply chains.

2.5 Real-World Applications of VRP

The Vehicle Routing Problem (VRP) has proven to be a vital tool in addressing complex logistical challenges across a broad spectrum of industries. Its ability to optimize delivery routes, reduce costs, and improve efficiency makes it indispensable for modern supply chains. From retail to healthcare, waste management, and emergency services, the practical implementations of VRP demonstrate its versatility and adaptability to diverse operational contexts.

In the retail and supermarket industry, VRP ensures the timely and cost-effective delivery of goods, particularly perishable items such as fresh produce, dairy, and meat. Efficient routing minimizes transportation costs and reduces delays, maintaining product quality and reducing waste. The Vehicle Routing Problem with Time Windows (VRPTW), a key variant of VRP, is frequently employed in this sector to adhere to delivery schedules dictated by store operating hours or restocking needs. Tarantilis and Kiranoudis (2002) showcased the application of VRPTW in the distribution of fresh meat, emphasizing the importance of timely deliveries in preserving product freshness. Similarly, Grondys (2020) highlighted the use of the Clarke and Wright Savings Algorithm to optimize inter-warehouse deliveries, ensuring streamlined operations in large retail networks.

In the expanding e-commerce sector, where speed and reliability of deliveries are critical, VRP is instrumental in optimizing last-mile logistics. Companies like Amazon and FedEx rely on advanced VRP models integrated with real-time data to manage fluctuating demand and dynamic routing. These models enhance scalability, allowing for the efficient handling of high order volumes during peak shopping seasons. Ammouriova et al. (2023) discussed the dynamic nature of e-commerce logistics, emphasizing the role of VRP in adapting to changing order locations and traffic conditions, ensuring a seamless delivery experience for customers.

In waste management and recycling, municipalities and private companies use VRP to optimize the collection and transportation of waste materials. These models reduce operational costs by minimizing travel distances and fuel consumption while addressing environmental sustainability goals. Zobolas et al. (2009) developed a decision support system for waste lube oil collection, leveraging VRP principles to optimize routing and promote recycling efficiency. Similarly, Bing et al. (2014) demonstrated the application of VRP in the eco-efficient collection of household plastic waste, reducing the carbon footprint of waste management operations.

The healthcare sector also benefits significantly from VRP, particularly in the distribution of medical supplies, pharmaceuticals, and vaccines. These deliveries often involve stringent constraints, such as maintaining temperature control and adhering to tight delivery windows. Braekers et al. (2016) emphasized the role of VRP in pharmaceutical distribution, highlighting its importance in ensuring the timely and safe delivery of critical products to hospitals and clinics. The flexibility of VRP also enables rapid response to emergencies, such as vaccine distribution during pandemics or disaster relief efforts, where efficient and adaptive routing is essential.

In construction and bulk commodity transportation, VRP optimizes the delivery of heavy materials, such as cement, steel, and aggregates, to multiple sites. These operations often face challenges related to vehicle load limits, site accessibility, and tight project deadlines. Studies such as those by Grondys (2020) demonstrated the effectiveness of VRP in reducing costs and improving schedule adherence. The Split Delivery VRP (SDVRP) further enhances efficiency by allowing partial deliveries when a single vehicle cannot fulfill the total demand, ensuring better resource allocation.

The importance of VRP extends to emergency response and disaster relief, where it plays a critical role in resource allocation and route planning under dynamic conditions. In such scenarios, Dynamic VRP (DVRP) models enable real-time adjustments to account for road closures, evolving emergencies, and shifting priorities. Ammouriova et al. (2023) highlighted the use of advanced VRP algorithms in disaster management, emphasizing their ability to prioritize critical deliveries, such as food and medical supplies, to affected areas.

In the context of sustainability and green logistics, Green VRP (GVRP) focuses on minimizing carbon emissions and fuel consumption, aligning with environmental goals and regulatory standards. Companies are increasingly incorporating electric vehicles and alternative fuel fleets into their routing strategies to further reduce their environmental impact. Xue and Cao (2015) explored the application of GVRP in urban logistics, demonstrating how optimized routes can significantly reduce emissions while maintaining operational efficiency.

Overall, the real-world applications of VRP underline its strategic importance in addressing diverse logistical challenges. By optimizing routes, reducing costs, and enhancing sustainability, VRP has become an indispensable tool for modern supply chains. Its adaptability to dynamic and stochastic environments ensures its relevance in evolving industries, from retail and healthcare to waste management and emergency services, cementing its role as a cornerstone of logistical innovation.

Chapter 3: Mathematical Modeling of the Vehicle Routing Problem

3.1 Remarks on the Characteristics of the Mathematical Model

The mathematical model of the Vehicle Routing Problem (VRP) captures the intricacies of logistical operations, offering a robust framework to address various challenges in supply chain management. By systematically organizing the relationships among vehicles, customers, and routes, the model provides a foundation for optimizing transportation processes.

One of the key characteristics of the VRP mathematical model is its flexibility in addressing different types of logistical challenges. The model often includes decision variables that define the allocation of customers to vehicles, the sequence of customer visits, and the total distance or cost incurred. These decision variables can adapt to specific constraints, such as vehicle capacity, time windows, or the number of available vehicles. For instance, multi-depot VRP models incorporate variables that assign routes across multiple depots, while split delivery VRP models allow partial fulfillment of customer demands (Battarra et al., 2008).

The objective function of the VRP model typically aims to minimize a cost-related metric, such as the total distance traveled, fuel consumption, or delivery time. Modern adaptations include multi-objective optimization, which balances cost minimization with factors like environmental sustainability or equitable distribution of workloads among drivers (Poot et al., 2002). These objectives ensure the model's relevance to industries that prioritize operational efficiency alongside corporate social responsibility.

Constraints are integral to the VRP model, ensuring the feasibility of proposed solutions. Common constraints include vehicle capacity limits, ensuring that no vehicle exceeds its maximum load; customer service constraints, which ensure every customer is served exactly once; and routing constraints, which enforce logical routes that start and end at designated depots. In time-sensitive operations, such as e-commerce or perishable goods delivery, time windows are incorporated to guarantee on-time delivery (Bing et al., 2014).

Furthermore, the mathematical model accounts for real-world uncertainties through dynamic and stochastic variants. Dynamic VRP adapts to real-time data, such as traffic updates or changing customer demands, while stochastic VRP incorporates probabilistic elements, such as uncertain travel times or demand fluctuations. These enhancements increase the model's applicability to unpredictable operational environments (Ammouriova et al., 2023).

Overall, the mathematical model of VRP stands out for its adaptability and precision, addressing both standard and complex logistical scenarios. Its integration of decision variables, objectives, and constraints ensures a comprehensive approach to optimizing routing and resource allocation in diverse industries.

3.2 Target of the Mathematical Model

The vehicle routing problem mathematical model plays an essential role in theoretical and practical analyses of transportation and logistics systems. Its main objective is to optimize operation by using less of an identified parameter, which could be cost, distance, or time. Despite this, it has been clearly outlined that the objectives of the model can vary greatly depending on the nature of the industry, operational requirements, and contextual factors which shape it to be a very flexible model.

Interesting to note that one of the most typical objectives of VRP modeling is the minimization of cost, namely the cost of transportation. They may comprise fuel costs, car repair and maintenance costs, compensation of employee's wages, and toll expenses. Through the reduction of these costs, continued profitability and resource optimization enhancements can occur. For instance, Clarke and Wright (1964) showed that the Savings Algorithm could cut down the number of transport costs by the combination of routes effectively. Likewise, the concept of cost minimization remains an important factor in extensive chains of logistics networks, and the percentage reductions may have fantastic economic value (Toth & Vigo, 2002).

Distance reduction is another objective, especially in environments where the overall objective is the minimization of total kilometers driven by the fleet. Stiffer fares not only reduce fuel bills but also curtail trip distances and optimize their speed in terms of deliveries. This target is particularly important in sectors such as waste management and recycling due to logistical difficulties mainly arising from the geographical spread of facilities to cover during collection (Bing, Cote, & Akgun, 2014). Distance minimization is also important in enhancing environmental sustainability through a decrease in the emission of greenhouse gases, an objective of many organizations in their pursuits to fulfill legal and social responsibility (Xue & Cao, 2015).

Delivery time minimization is an issue in some industries, specifically those aspects of industries where customer satisfaction necessitates timely service. For example, in e-commerce and retail logistics, consumers prefer deliveries in a specific time range, to which routes should be adjusted. A variant of the problem that includes this objective while also striving to achieve an overall focused and timely completion of deliveries is the VRP with Time Windows known as VRPTW (Tarantilis & Kiranoudis, 2002). Another field in which time reduction is important is perishable goods transportation as their delivery delay results in spoilage and, therefore, loss of money.

In the VRP modeling, workload balancing in addition to cost, distance, and time has also become another significant objective. In this context one of the objectives is to have an optimal distribution of delivery tasks, meaning no driver and/or vehicle is over-worked. This is especially applicable in organizations that focus on equality and employees' satisfaction, for instance, services, or logistics applications in communities. In the same way, workload balancing enhances the right distribution of fleets across the

company to prevent some fleets from being overutilized or others from being underutilized (Hlatká et al., 2018).

Subsequently, VRP goals that have transcended into modern versions have also included another significant performance threshold – whereby the environment has been the primary focal area to measure performance. Green Virtual Reference Price (GVRP) models aim at minimizing the environmental effects of logistics operations. The targets are to reduce fuel use, identify the best routes for EVs, and incorporate renewable power into fleets. These models assist organizations in translating the broader strategic initiatives towards sustainable living into its logistical functions in that there has been an upward trend in the war on emissions of greenhouse gases and requests for legal requirements on environmental management (Li et al., 2008; Xue & Cao, 2015).

In practice, VRP models use more than one target at a time making them solve problems with an objective of multi-objective. For instance, a logistics company may have objectives, which include cost reduction and timely delivery services and concerns with the environment. There is a lot of work done at the operational level and uses sophisticated algorithms like Pareto efficiency to obtain solutions that satisfy different objectives at their best. Such approaches are useful where relationships are intricate involving complex supply chain decision making and different interests must be addressed (Poot et al., 2002; Baldacci et al., 2008).

In sum, one could assert that due to flexibility in terms of the identified operational objectives, the VRP model is capable of reaching all required objectives in various industries and organizations. Irrespective of the strategic orientation that seeks to enhance the efficiency of the logistics chain by reducing cost, embracing the environment, or satisfying the customer, the VRP framework holds the prospect of providing a perfect solution to enhancing the efficiency of logistical operations in ambiguous and volatile settings.

3.3 Decision Variables in the Mathematical Model

This paper shows that the mathematical model for the Vehicle Routing Problem (VRP) involves extensive use of the decision variables which are crucial in formulating the

solutions. Decision variables are variables represented in math form that define other more strategic elements in the problem, such as route, vehicle, and customer. These variables are expressions of actual logistics problems, as mathematical equations that are accurate and flexible.

An initial decision variable that may be addressed in VRP is the allocation of vehicles to routes which can be presented as binary variables. For example, it might be a variable x_{ijv} which means whether vehicle v goes from node i (depot or customer) to node j . The binary value is defined as $x_{ijv} = 1$ means that vehicle v uses the mentioned particular path, and $x_{ijv} = 0$, which means the path is not used. This guarantees the integrity of displaying the route allocation and allows for the calculations of the optimality (Susanto, 2023).

Another relevant decision parameter is the problem of assigning customers to vehicles that guarantee that each of the customers is served exactly by one vehicle. For instance, a variable y_{cv} may mean that the current specific service is being done by vehicle v to customer c . These variables help prevent two routes from being associated with similar vehicles and thus facilitate efficient utilization of the available vehicles (Ryan et al., 1993).

In capacitated VRP models, decision variables also embrace vehicle calls or demands, while often varying continuously. These variables measure the level of load transported or received in a vehicle in its assigned trip. To promote practicality, constraints associated with these variables piece together to regulate the total demand a vehicle can carry in order not to overstretch the capacity of a particular vehicle. This is more significant in a case where the vehicle has a specific payload capacity for collection, for example, in waste collection or supermarkets, each vehicle (truck) has some allowed payload (Ahmad et al., 2020).

This is especially common in time-sensitive contexts and decisions may embrace the time of arrival and departure at any node. These variables keep the vehicles on time, in compliance with time window constraints, thus making deliveries on time possible. For example, a variable t_i may denote the arrival time of a vehicle at customer i which enables one to schedule accurately in time-sensitive conditions like that of perishable commodities such as fresh food or courier services (Tarantilis & Kiranoudis, 2002).

Furthermore, decision variables in more complex VRP models define EU and sustainability objectives. In Green VRP, variables could be fuel consumption, emission, or the utilization of environmentally friendly vehicles. For instance, e_{ij} represents the amount of emissions incurred on the link between nodes i and j , where the model proposed could incorporate environmental consideration into the routing solutions in addition to other measures of optimality (Zhu et al., 2011).

Appropriate and concrete decision variables added to VRP models for particular industry conditions make those models more realistic and more feasible. In supermarket logistics, the variables can represent shelf-life limited on perishable commodities, guaranteeing that a product gets to the stores before it goes bad. In waste collection and disposal, variables may explain issues such as the compatibility of vehicles to certain collection centers or the landfill receptor capacity (Dorigo et al., 1999).

The static and dynamic decision variables highlighted in the earlier sections have been incorporated within the VRP mathematical model in order to ensure that the complexities of real-world logistics are not lost in the model. Exhaustive in their coverage of strategic variables, routing, capacity, timing, and sustainability, they allow the definition of operationally relevant solutions responding to organizational needs or constraints.

3.4 Limitations of the Mathematical Model

Since the mathematical model for the VRP is a very important tool in the management of logistics and transport systems, it comes with some drawbacks. Many of these constraints arise from the nature of real-life operations, computational problems, and the simplifying assumptions made when modeling a system. It is important to know these limitations in order to avoid a misinterpretation of the results when translating them into practice.

The major disadvantage of the VRP model is that it makes so many assumptions that may not best represent real-life routes. For example, most of the models are based on deterministic parameters including demand, time is taken for travelling, and availability of vehicles. In practice though, these factors are random variables rather than precise constants; customers arrive randomly and there can always be traffic congestion on the

road. This may cause losing some patterns and impair the applicability of the model in cases that deal with the uncertain and changing environment (Asghari & Mirzapour Al-e-hashem, 2020).

The last shortcoming is the increased computational complexity of models for solving VRP. The problem becomes more difficult to solve on large dimensions due to the exponential addition of customer, vehicle, or constraint. Although heuristic and metaheuristic algorithms, such as ant colony optimization or genetic algorithms, give approximate solutions with low error margins, they are time-consuming and sometimes need a high computing capacity for instance when the number of delivery points is in thousands (Dorigo et al., 1999).

The fact that VRP models are capacity-constrained can also pose some problems with their use. However, these constraints make sure that the loads in vehicles do not exceed the maximum allowed capacities in the fleet yet it can fail to consider different fleet structures. This limitation can lead to the obtaining of a qualitatively different final solution, which is not optimal in particular industries that require various types of vehicles, such as waste management or e-commerce logistics (Ahmad et al., 2020).

More so, time restrictions such as the inclusion of time horizons take the model to another level of difficulty. However, VRP variants like the VRPTW do this, by providing solutions that assume fixed delivery times are to be followed. As a matter of fact, a few minutes more or less might be acceptable in Heathrow's operating environment, while excessive emphasis on time in the model might result in very narrow decisions practically impossible to be implemented (Tarantilis & Kiranoudis, 2002).

As for the fifth characteristic linked to modern logistics that is more and more taken into account, the classical models for solving the VRP do not take into consideration plenty of environmental factors. For instance, standard models may not contain features that may include; the fuel consumption rate, carbon footprints, or the number of charging stations in a state for electric cars. Thus, one of the main limitations of these models is the lack of consideration of such aspects as sustainability, which has recently gained the status of a major concern (Zhou et al., 2006).

At last the availability of data is a practical limitation of using VRP models in the current setting. Distance matrices, customers' demands, and the characteristics of vehicles are vital input data to be accurately and comprehensively developed. However, in many cases the data that have been entered may be limited, obsolete, or simply unobtainable, thus providing less accurate conclusions. For instance, real-time data integration is important for dynamic VRP but may not always be possible because of the technology or cost prohibitiveness (Jeřábek et al., 2016).

These limitations thereof can be offset through the exploration of highly developed modeling methods including dynamic and stochastic extensions to the traditional VRP, as well as by considering the application of real-world constraints such as tackling issues of fleet heterogeneity, emissions, and environmental influence within VRP frameworks. Thus, understanding and addressing these challenges can greatly improve the application of VRP models and thereby increase the efficiency by which practitioners can address logistical issues.

3.5 Editorial Review of the Main Equations and Mathematical Formulations for VRP

Vehicle Routing Problem has become a strong practice which is now measured in different equations and formulations for specific issues. Outlined below are the principal mathematical constructs that shape the improvement of the maritime fleet operations logistical models and are also central to the transition of logistical models from theoretical to realistic. This section of the paper also provides a review of some of the basic equations and their use in solving some of VRP variants.

Objective Function

Integral to any VRP formulations is the objective function which presents the formulation of the problem optimization. The most widely used objective seeks to minimize the total cost of routing:

$$\text{Minimize } Z = \sum_{i=0}^n \sum_{j=0}^n c_{ij} x_{ij}$$

Here, c_{ij} represents the cost of traveling from node i to node j , and x_{ij} is a binary variable indicating whether a vehicle travels on that route. These variations look at cost minimization, distance reduction or even include parameters such as emissions (Zhu et al., 2011).

In cases where more complicated goals have to be met, even multiple objectives with weights are used. These functions integrate optimization between factors such as costs, time, and sustainability aspects (Prins, 2004).

Key Constraints

VRP constraints are crucial in ensuring that solutions are both feasible and aligned with operational realities.

1. Flow Conservation

The flow conservation constraint ensures that each customer is visited exactly once:

$$\sum_{j=1}^n x_{ij} = 1 \quad \forall i = 1, \dots, n$$

This equation guarantees that every customer is serviced, a fundamental requirement for achieving complete coverage (Susanto, 2023).

2. Depot Constraints

To ensure that all routes originate and terminate at the depot, the following constraint is applied:

$$\sum_{j=1}^n x_{0j} = \sum_{i=1}^n x_{i0} \quad \forall k \in K$$

This ensures consistency in route initialization and completion, a critical factor in logistics systems (Jeřábek et al., 2016).

3. Capacity Constraints

Capacity limits are represented as:

$$\sum_{i=1}^n d_i \cdot x_{ij} \leq Q$$

Here, d_i is the demand at node i , and Q is the vehicle's capacity. This ensures that the total demand serviced by a vehicle does not exceed its operational capacity, making it particularly relevant for industries like waste collection and retail logistics (Ahmad et al., 2020).

4. Subtour Elimination

To prevent disconnected routes or loops, subtour elimination constraints are introduced:

$$\sum_{i \in S} \sum_{j \in S, j \neq i} x_{ij} \leq |S| - 1 \quad \forall S \subseteq N$$

These constraints are computationally intensive but essential for generating connected solutions (Baldacci et al., 2008).

5. Time Window Constraints

Time-sensitive VRP variants, such as VRPTW, incorporate time window constraints to ensure timely service:

$$t_i + s_i + t_{ij} \leq t_j$$

Here, t_i and t_j are the arrival times at nodes i and j , s_i is the service time, and t_{ij} is the travel time. These constraints are crucial for applications in perishable goods and express delivery (Tarantilis & Kiranoudis, 2002).

Advanced Formulations

Modern VRP formulations have extended beyond traditional objectives to include environmental, social, and operational dimensions:

- **Environmental Constraints:** In Green VRP, equations incorporate emissions or fuel consumption:

$$\sum_{i=0}^n \sum_{j=0}^n e_{ij} x_{ij} \leq E_{\max}$$

This targets sustainability by minimizing greenhouse gas emissions (Zhou et al., 2006).

- **Dynamic and Stochastic VRP:** For real-time or uncertain scenarios, dynamic constraints adjust routes based on real-time data, while stochastic models address probabilistic variations in demand or travel times (Asghari & Mirzapour Al-e-hashem, 2020).

Importance of Formulations

The diversity of VRP equations ensures adaptability across industries and scenarios, from static route planning to dynamic, real-time logistics. The use of exact methods (e.g., branch-and-bound) alongside heuristics (e.g., Clarke and Wright Savings Algorithm) and metaheuristics (e.g., ant colony optimization) highlights the flexibility of these formulations (Dorigo et al., 1999).

By incorporating constraints and objectives that mirror real-world complexities, VRP models remain at the forefront of optimization science, delivering practical solutions for contemporary logistics challenges.

Chapter 4: The Clark & Wright Algorithm

4.1 Introduction to the Clark & Wright Algorithm

This technique is one of the fundamental heuristic strategies for addressing the Vehicle Routing Problem (VRP). It was developed by Clarke and Wright in 1964 to improve vehicle routes through the reduction of total transport costs. The important concept of the algorithm is “savings” which is a measure of the number of route connections that are formed when merging routes and minimizing the overall distance of vehicle movement subject to limitations on capacity and other physical features of the vehicles as described by Clarke and Wright (1964).

This method is very simple and computationally very efficient which is why it is widely used in practice. It should be noted that, unlike exact methods, precise results within reasonable amounts of time can be obtained using the Clark & Wright Algorithm and, thus, the method is appropriate for application in small and medium-scale networks (Altinel & Öncan, 2005).

One of the important real-world applications of the algorithm is the CVRP which is an extension of the VRP where the total demand of customers in one route should not exceed the capacity of the vehicle. Moreover, the Clark & Wright Savings Algorithm has been used in practical situations where several constraints relate to operations like distribution of material from central stores to retail outlets, managing the stock of supermarkets, and waste collection networks (Ahmad et al., 2020).

It could be challenged that due to its acceptability, all the organizations have adopted the algorithm to fit into it and come up with solutions that can cut down the operational

cost as well as minimize the adverse effects on the environment. Well implemented in the retail sector and logistics, the companies offered in the area have shown less distance and fuel savings that have supported the sustainable transportation system (Grondys, 2020; Bing et al., 2014).

The following sections of this chapter will specify the historical background of the algorithm, the methodological foundations of the algorithm, and the advantages and shortcomings of the algorithm in practice.

4.2 Historical Development of the Algorithm

The Clark & Wright Savings Algorithm was originally developed by Clarke and Wright in 1964 for the fulfillment of a heuristic alternative to the VRP. In essence, the algorithm was to look for the best solution to demonstrate the delivery routes of vehicles starting from a central depot to deliver to many customers and get back to the depot, with the least total travel distance or cost (Clarke & Wright, 1964). The idea, referred to as “savings”, is the actual computation of the gain that can be obtained when two customer routes are consolidated into one. These are exciting developments since this approach provided a new practical and computationally efficient solution in approximating the difficult-to-solve methodologies which at times consumed considerable computation resources.

Firstly, the algorithm has been tested on a standard and sparse data set of Capacitated Vehicle Routing Problems (CVRP), in which a set of clones is to be serviced by a fleet of vehicles with limited capacity. The algorithm produced feasible solutions that complied with the above-stated operational constraints by successively combining routes with the highest saved ratios. Because of its ease of use and the swiftness of the calculation it was quickly adopted in practice and by researchers. This was due to the uni-directional, stepwise nature of the algorithm in which savings calculations were followed by iterative route construction; this approach was clearly both sound and practical for use in practice (Altinel & Öncan, 2005).

As logistics changed and the supply chain evolved, so did the uses of the Clark and Wright Savings Algorithm. Scholars tailored the algorithm for more complicated forms

of the VRP, including the VRP with Time Windows (VRPTW), in which deliveries must occur within some time frame (Altinel & Öncan, 2005; Tarantilis & Kiranoudis, 2002). Similarly, the Multi-Depot Vehicle Routing Problem (MDVRP) has been subsequently developed to allow for a larger number of depots to be used due to changes in the decentralized supply chains (Augerat et al., 1995). These adaptations enriched the possibilities and extended the application of the algorithm to other logistics tasks.

Besides these extensions, the Clark & Wright Savings Algorithm led to the creation of its hybrid forms that use it together with other modern optimization methods. For instance, one may introduce other principles commonly known as genetic algorithms to improve the basic facility of the algorithm in searching for solutions in a large search space, especially in large or intricate problems (Battarra, Golden, & Vigo, 2008). In the same way, Dorigo et al. (1999) have employed the adaptation of the ACO through simulation of the behavior of ants during the food search; the actual performance of the algorithm is adjusted automatically. The application of sim heuristics that incorporate the application of simulation with the Savings Algorithm in handling dynamic and stochastic VRP such as demand variations and real-time traffic conditions has received recent interest (Ammouriova et al., 2023). These integrations support the compliancy of the algorithm and the perpetual relevance of the simple heuristic in the study of optimizations.

The Clark & Wright Saving Algorithm has been greatly used in any field of operations. Plísek & Ševčíková (2017) describe that in retail and e-commerce, it is most commonly applied for last-mile delivery and online orders between warehouses, leading to a massive triumph of the operational cost and fuel consumption (Grondys, 2020). While using waste management, the algorithm has been beneficial in determining an efficient route collection network that would make shorter distances but at the same time cover the sustainability aspect (Ahmad, et al., 2020; Zobolas et al., 2014). For instance, its use in the flow of perishable goods such as perishable produce and drugs, shows its effectiveness in its ability to ensure effective and efficient delivery in sensitive chains (Tarantilis & Kiranoudis, 2002).

The simplicity and efficiency of the Clark & Wright Savings Algorithm therefore continue to make it popular, even after so many years of its development. Although the exact methods may have problems in solving large-scale instances of the VRP, the

algorithm proposed in this paper offers a practical solution, which does not require solving complex computational problems. This has made it suitable for, not only research today and in the past but also industrial applications to date and the future. Despite these issues, the algorithm proves practical with certain drawbacks that are especially noticeable in highly dynamic or complex environments, which is why hybridization and integration with the most contemporary optimization techniques have been developed. As a result, the algorithm continues to serve as one of the fundamental tools for routing optimization in practice and for closing the practical applications/theoretical gap (Clarke & Wright, 1964; Battarra et al., 2008).

4.3 Highlights of the Savings Algorithm

The Clark & Wright Savings Algorithm is unique due to its effectiveness and easy implementation; thus, it is one of the most realistic heuristic methods for solving the VRP problem. The central idea of the algorithm is “savings”, which is the measure of the saving that results from converting two different customer routes into a single more efficient trip. This calculation is core to the successful application of the algorithm and is stated as the equation of the cost of individual customers minus the cost of joint customer service. For each pair of customers, the savings value is computed using the following formula:

$$S_{ij} = c_{i0} + c_{0j} - c_{ij}$$

Where c_{i0} and c_{0j} are the cost (or distance) from the depot to the customers i and j respectively and c_{ij} is the cost of moving directly from the customer i to the customer j . That is why routes yielding the greatest savings are merged, and this calculation is both simple from the computational viewpoint and critical in terms of influence on the solutions (Clarke & Wright, 1964).

The entire procedure is about the flowchart implementing a sequence of steps. Firstly, each customer is posed as a distinct route and each is given a vehicle unique for his route. This setup leads to high start-up costs, CML, which are then offset through the merging process. An attempt is made to develop a savings list; the savings values for all combinations of customers are deduced and sorted in descending order. It is this prioritization that protects the organization from making unwise merges that do not

propel it forward. The routes are then merged iteratively from those with the greatest ‘savings’ within constraints such as vehicle loading and other operational parameters. This process continues until none of the nodes left can be merged to decrease the total invested distance and form a set of best routes.

Because of its prompt computational time, the Clark & Wright Savings Algorithm is best used in smaller and mid-sized cases of the VRP. Being $O(n^2)$, its applicability to mathematically model savings calculations while being practical for large numbers has been validated (Battarra et al., 2008). Furthermore, this characteristic provides the algorithm with flexibility when dealing with several kinds of VRPs including Vehicle Routing Problems with Time Windows (VRPTW) and Multi Depots Vehicle Routing Problems (MDVRP) (Altinel & Öncan, 2005). By changing the savings formula or adding a new set of variables, the algorithm is capable of solving several operational issues including same-day delivery and multi-depot problems.

A unique advantage of the algorithm is it does not require much to be implemented. It can be carried out using simple mathematical and statistical software such as Microsoft Excel, so it is not a very technical process even for the least technologically endowed organizations. This usefulness has made it common in real-life applications, especially in retail supply chains to determine the best channel for inter-warehouse distribution, and in waste management to enhance route efficiency, and minimize operational costs (Jeřábek et al., 2016; Grondys, 2020). For instance, in a real-life experience where the authors developed an algorithm for supermarket logistics, actual cut-and-dry improvements in the distribution routes meant that there were enhanced fuel efficiencies and delivery downtimes (Ahmad et al., 2020).

Yet it also has some useful limitations inherent in all heuristic methods that can be averted by an appropriate approach to its application. This means it does not necessarily provide the global optimum solution; for it only deals with neighboring solutions rather than considering the whole solutions domain. Moreover, the articles point out that the quality of the final solution depends on the configuration of the initial network and the sequence of the merge process of the routes, which can sometimes lead to non-profitable results (Ahmad et al., 2020). Nevertheless, the scheme frequently offers approximate solutions that can be nearly optimal in terms of performance while requiring orders of magnitude less computational resources than exact approaches.

The Clark & Wright Savings Algorithm remains a popular heuristic method for solving Vehicle Routing Problems because it doubts the theoretical credibility and the usefulness of a heuristic technique. Logistics optimization remains a core business area where SCM approaches continue to deliver robust performance in practice in areas as different as retail supply chain networks or domestic refuse collection systems. Due to soothing conflicts of cost and effectiveness, the algorithm keeps on its full swing to face the challenges of modern logistics and it is also flexible up to the extent that it is used in research as well as industrial practices (Tarantilis & Kiranoudis, 2002; Bing et al., 2014).

4.4 Numerical Example of the Algorithm

To give a clear illustration of the practical working of the work Clark & Wright Savings Algorithm, a numerical example is the best way to go. An example of its usage can be given using a basic model of Vehicle Routing Problem (VRP), where there is a single depot and demand at each customer is fixed. The corresponding goal is to use the shortest travel distance with the limited vehicle capacity as well.

In this case, there is one depot (node 0) and four customers namely nodes 1, 2, 3, and 4. Inter-customer and depot-to-customer distance values are presented in the distance matrix where distances between every two nodes are shown. The customer demands are as follows: 15 for node 2, 10 for node 3 while node 4 received 10, 10 units for node 1, and 15 for node 2. The number of units to be transported by the vehicle in a single round, trip would be restricted to 30 units.

Initially, each customer is assigned its own route to and from the depot, resulting in a high total cost. The distance for each individual route is calculated as follows: for node 1, the round trip distance is $10+10=20$ $10 + 10 = 20$ $10+10=20$; for node 2, it is $15+15=30$ $15 + 15 = 30$ $15+15=30$; for node 3, it is $20+20=40$ $20 + 20 = 40$ $20+20=40$; and for node 4, it is $25+25=50$ $25 + 25 = 50$ $25+25=50$. Summing these values, the total initial distance is $20+30+40+50=140$ $20 + 30 + 40 + 50 = 140$ $20+30+40+50=140$.

The algorithm begins by calculating the potential savings for merging routes between pairs of customers. The savings formula is $S_{ij}=c_{i0}+c_{0j}-c_{ij}$, where c_{i0} and c_{0j} represent the distances from the depot to customers i and j , respectively, and c_{ij} is the direct

distance between customers i and j . For instance, the savings for merging routes of customers 3 and 4 is calculated as $S_{34} = 20 + 25 - 15 = 30$. $S_{\{34\}} = 20 + 25 - 15 = 30$. $S_{34} = 20 + 25 - 15 = 30$, while the savings for merging customers 1 and 2 is $S_{12} = 10 + 15 - 35 = -10$. $S_{\{12\}} = 10 + 15 - 35 = -10$. $S_{12} = 10 + 15 - 35 = -10$. This calculation is repeated for all customer pairs, and the results are sorted in descending order of savings.

Following the savings calculation, the algorithm iteratively merges routes based on the highest savings while ensuring that the resulting routes do not violate the vehicle's capacity constraint of 30 units. In this case, the pair 3–4, which yields the highest savings of 30, is merged first, forming the route Depot \rightarrow 3 \rightarrow 4 \rightarrow Depot. The total demand for this route is $10 + 10 = 20$, which is within the vehicle capacity. The total distance for the merged route is $20 + 15 + 25 = 60$. Next, the pair 2–4, with a savings of 10, is evaluated. The combined route Depot \rightarrow 2 \rightarrow 4 \rightarrow Depot is feasible, with a total demand of $15 + 10 = 25$, and a total distance of $15 + 20 + 25 = 60$. Other pairs, such as 1–3, are not merged due to capacity violations or lower savings.

At the end of the process, the final set of routes is as follows: Depot \rightarrow 1 \rightarrow Depot (distance = 20), Depot \rightarrow 2 \rightarrow 4 \rightarrow Depot (distance = 60), and Depot \rightarrow 3 \rightarrow Depot (distance = 40). The total distance after optimization is $20 + 60 + 40 = 120$, representing a 14% reduction from the initial distance of 140.

This example demonstrates how the Clark & Wright Savings Algorithm can cause less transportation cost by identifying a route that can be consolidated. Despite the use of a simple example, the scale of the algorithm allows the analysis of larger and more complex instances of VRP, which often results in even greater cost reduction. Due to its efficiency in finding good solutions in handling logistical issues and usage in other sectors of life, we have seen it used in retail supply chain and waste management among others (Clarke & Wright, 1964; Ahmad et al., 2020). The ability of the algorithm and the simplicity of computation entitlement make the algorithm relevant in solving contemporary logistic problems.

4.5 Strengths and Weaknesses of the Algorithm

Among all the heuristic solutions suggested for the VRP, the Clark & Wright Savings Algorithm remains one of the most straightforward and employed solutions. Again the advantages of the algorithm are that it is simple, computationally efficient and easily scalable while its weakness are founded from the fact that it is a heuristic algorithm and therefore may not perform well under dynamic and or complex logistical conditions. A further investigation of its features saves provides a fair analysis of whether it is beneficial or not in practice applications.

One of the significant advantages that can be associated with the algorithm is the possibility to solve it within measurable time. The savings calculation phase is designed to work with a time complexity of n^2 , where n is the total amount of customers. Due to such a level of efficiency, the algorithm can quickly solve those small and medium VRP instances which are important for operation environments to make rapid decisions. Contrary to exact methods like branch-and-bound or branch-and-cut methods that can be extremely time consuming with the increase in the problems size, the Clark & Wright Savings Algorithm provides good trade-off between algorithm running time and solution value (Battarra, Golden, & Vigo, 2008). This efficiency is of glaring importance especially to businesses that operate with time-sensitive routing problems but with no access to high-performance computing resources.

A second major advantage of the algorithm is its easy applicability to the system. The process described in this paper, which is a stepwise savings calculation followed by sorting of results and iterative route merge-and-splits, can, therefore, be implemented straightforwardly in any popular environment such as Microsoft Excel or Python. This simplicity makes it easy for organizations especially those without much technological experience to engage in optimization practices that do not call for much investment in expensive software or personal training (Grondys, 2020; Jeřábek et al., 2016). For instance, a large number of small and medium enterprises (SMEs) have adopted the algorithm to calculate optimal delivery routes, mitigate expenses to enhance efficiency of services with easy technological integration.

The above-shown flexibility of the algorithm is another advantage that widens up its use. With reference to the savings estimate or when other conditions are incorporated,

it can be tailored to explain a broad class of VRP variants. For example, CVRP, VRPTW, and MDVRP has been solved successfully by the proposed algorithm. These extensions allow the algorithm to solve other logistic problems like the capacity of each vehicle, delivery time, and distribution centres (Altinel and Öncan, 2005; Tarantilis, and Kiranoudis, 2002). Their versatility is one way of guaranteeing that they can be developed to fit the needs of different industries that range from retail, waste management and healthcare logistics industries.

The algorithm has also been useful in physical world applications, to provide real solutions within set physical constraints. For instance, it was used in solving the retailer's multi-warehouse inventory redistribution problem and in the waste management systems in order to decrease the operating costs (Ahmad et al., 2020; Zobolas et al., 2009). Sullenger some of these situations reveal this capabilities to address stringent constraints such as vehicle capacity and delivery schedules besides yielding practical cost savings. An important benefit is that the algorithm makes the solutions quite rigorous, yet they are never out of touch with the operational realities of business.

Nonetheless, one cannot deny some drawbacks in the Clark & Wright Savings Algorithm that are as follows: An essential disadvantage is that it is a heuristic method assuming it is not always the best solution. Instead, it aims to create satisfactory solutions within an affordable limit and a specified amount of time. Although this trade-off is bearable in most operational scenarios, the end solution may be quite a far cry from the pan-global optimum depending on the size and degree of constraint in the instances of VRP in question (Ahmad et al., 2020). This limitation makes it important to avoid using the algorithm where precision is very sensitive.

Also, the limitation is in the growth of the dependence on initial configuration and the sequence of the merged routes. It was found that the sequence of applying savings can have an impact on the quality of the final solution especially if not well aligned. For instance, directing the merging certain routes that are not in the right order may force the algorithm to fix suboptimal configurations which may not be favourable to be changed later on. This is why there is need to closely monitor this algorithm and, in some instances, program it to run effectively.

The algorithm also has a poor way of dealing with change Blanket upon change and dynamic environments in the logistical environment. It considers input data as non-variable meaning customer demands and distances are constant while in business, demands vary almost daily and so does the routes. For dynamic conditions, for example, when routes change due to order amendments or traffic problems, the optimization must be made again or a simpler, semi-optimization method can be used together with DVRP models or stochastic methods (Ammouriova et al., 2023). Otherwise, the applicability of the algorithm in the conditions of high dynamics of the business environment can be questioned.

It has another disadvantage when implemented in large problems In particular, the logical tree can become unwieldy when used on large problems. The algorithm is easy to implement computationally for small and medium VRP instance problems, although, in large-scale problems about thousands of customers or numbers of vehicles, it fails to perform well enough. In such situations, better metaheuristic techniques, like genetic algorithms tabu search or ant colony optimization or the Clark & Wright Savings Algorithm may be less effective as these algorithms search wider solution space and include additional constraints (Dorigo et al., 1999; Catay, 2010). Thus, these methods may be valuable for organizations that manage vast systems of logistics – the balance between scale and solution quality could be higher than in the case of utilizing the basic methods.

Lastly, the common approach of the algorithm fails to incorporate contemporary logistics concerns like ecology. Meeting such objectives as using minimum fuel or reducing greenhouse emissions calls for certain changes like implementing Green Virtual Reference Production (GVRP) principles. It has been revealed that making changes to the algorithm to address external conditions may help increase its effectiveness in applications where sustainability is important for organizations (Bing et al., 2014; Xue & Cao, 2015; Zhang et al., 2011).

Therefore, the Clark & Wright Savings Algorithm continues to be an effective and realistic methodology in determining vehicle routing for fast, inexpensive logistic solutions. Due to its ability to be used efficiently, easily implemented in several different systems, and can be customized in several ways, it is ideal for a lot of uses. Nevertheless, as a heuristic algorithm it is sensitive to the initial conditions, provides

solutions only to static or a limited number of variable problems, and thus requires further investigation when chosen as an optimization tool. With regard to these limitations, hyperheuristics and further algorithm optimizations should extend the applicability of the algorithm for integrating modern supply chain and transportation systems.

4.6 Use of the Algorithm in Supermarket Supply Chain Systems

This paper has shown that: The Clark & Wright Savings Algorithm was also helpful in increasing the supply chain operation, particularly in the retail industry which supermarkets face many issues. Such challenges include delivering such products as perishable goods; making limited transports at incredibly cheap rates; and delivering within very tight schedules. Its application is especially important in scenarios whereby various delivery routes can be aggregated which in turn leads to shorter distances and hence low transport costs at the same time fulfilling delivery schedules as postulated by Clarke and Wright in 1964.

Supermarkets therefore have a centralised supply chain through the stocked products in distribution centres before organized distribution in many outlets. This configuration is closer to the Vehicle Routing Problem (VRP), where the task is to determine the optimal delivery schedules taking into account such factors as vehicle capacity, delivery time windows, and demand uncertainty. Clark & Wright Savings Algorithm eradicate these issues by effectively marrying up the routes so that the overall cost and distance of the routes are minimized and products are delivered fresh and on time (Ahmad et al., 2020).

At the core of the algorithm to analyze supermarkets' supply chains lies with the correct set of the proper input data. These inputs include distances regarding the central depôt and the several retail outlets, the demand regarding the amount of stock those different outlets require in a certain time depending on the size of the vehicle, information regarding the vehicle used including its carrying capacity and cost of operation and lastly the time window which indicates the time allowable to take in delivering the goods, especially perishable goods. When applied to this information, the algorithm provides for savings at the level of pairs of retail outlets, which makes it possible to define the best option for combining routes. For example, if two outlets are nearby the algorithm determines the better shave by assigning them one delivery round. These

work in a cyclical manner until all the feasible merging cannot be done anymore. The actual optimized routes that are generated assist in maintaining vehicles at near optimal fruitfulness of utility, reducing the number of one-stop trips as well as the overall distance traveled (Grondys, 2020).

In the following subsections, the authors outline the practical advantages of applying the Clark & Wright Savings Algorithm to supermarket logistics. First, it minimizes the overall route taken to cut down on the direct measurement of fuel usage and transportation costs. Organizations operating supermarkets that have adopted this algorithm have realized transport cost reductions of between 15–20% (Bing et al., 2014). Second the extent of delivery service is enhanced since routes are optimized to ensure products get delivered within specific timeframes which is crucial in preserving the quality of food products among others. For instance, fresh produce and dairy products need to be delivered to customers before they spoil to make sure that the customers will be satisfied (Tarantilis & Kiranoudis, 2002). Third it optimizes fleets by increasing carriage space and decreasing the number of vehicles used in delivery hence cutting expenses on maintenance and quota management. Last, the algorithm contributes to environmental sustainability implications by decreasing fuel use and corresponding emissions, mostly important in the era of greening logistics in the retail industry (Xue & Cao, 2015).

The algorithm was shown to be successful in supermarket logistics using a real-world case. A case in which the Clark & Wright method was used was in a supermarket chain where the company wished to refine its distribution. Through proper coordination recognition and study of outlet locations and the customer base as well as the capability of the fleets, the logistics section was able to rationalize the number of delivery routes from thirty to only twenty-two. This optimization led to a 15 percent overall transportation cost saving, with a 12 percent over-distance reduction. The algorithm also made it possible for the outlets to receive the delivery within the stipulated time frame thereby enhancing operation and customer satisfaction (Ahmad et al., 2020). Thus, the results obtained show that the necessities requiring resolution in the context of supermarket production and logistics can be successfully solved by this algorithm as well as providing a suitable number of tangible gains.

As much as there are merits of applying the algorithm, there are challenges of applying it in Supermarket supply chains. The major drawback, however, is its presupposition of fixed demand and, thus, can provide no information regarding fluctuation or traffic intensification. Overcoming this limitation involves linking the algorithm to real-time routing or other dynamic data systems that allow for more effective resource management over the logistics operations undertaken (Ammouriova et al., 2023). Further, it has been identified that cost minimization could be a driving factor in the algorithm; however, this could be somewhat counterbalanced by other important factors, including the ability to handle urgent orders or priority orders of certain products. These aspects may require adapting the saving algorithm to be more usable, or the development of a combination of the saving algorithm with other methods, including genetic algorithms, or dynamic programming, among others.

Therefore by following Clark & Wright Savings Algorithm the supermarket supply chain can establish an effective and efficient solution for supply chain management. The reasons that can explain why it is important for supermarkets are its cost-saving capacity on the one hand, improvement of delivery performance on the other, as well as its possibility of contributing to sustainability goals. Nevertheless, the algorithm should be connected to the modern logistical tools and should be adjusted to the modern dynamic and multifaceted retail environments contrasting with supply chain demands of that period.

Chapter 5: Implementation Methodology

5.1 Explanation of the Input Data and Analysis

The following is a breakdown of data which is used as input for solving the Vehicle Routing Problem (VRP) which is systematically incorporated in order to capture the realities of a supermarket supply chain; All of this serves as the foundation on which optimization methods can be used, the so-called Clarke & Wright Savings Algorithm, to establish the optimum delivery routes. In this regard, Microsoft Excel was used as

the main tool of data management together with the tools for data analysis. The input data is typically organized into a series of matrices and lists that encapsulate critical logistical parameters:

- **Distance Matrix:** The distance matrix forms one of the key elements of the VRP model and can capture both distances and costs for travel from and between the depot and all customers and any distance separating two or more customers. This arrangement – symmetrical or asymmetrical – provides the basis for computing route savings.
- **Demand Data:** Every customer location is characterised by demand values inherent only to this or that location, reflecting the amount of goods needed. This data prevents vehicle capacities from being overloaded while designing the best routes. For instance, organisations with volatile demand patterns such as supermarkets need to determine the right demand patterns to have efficient inventory.
- **Vehicle Capacity:** Another important input is vehicle data which other things include the capacity limit. It describes the maximum distribution or load capacity allowed on each vehicle, to conform to the logistics and legal operations weight
- **Time Window Constraints (if applicable):** Since the perishable items are involved, delivery has to happen within stipulated time frame. It feeds into operation such as time at which stores are opened, or time customers are likely to be available.
- **Depot Location:** This is the place from which all the routes commence and to which all the vehicles return at the end of the day. It is used in determining starting and finishing distances that must be covered in a journey.

To prepare the data for analysis, several preprocessing steps were undertaken:

- **Cleaning and Formatting:** Superfluous information (customer addresses no longer valid, or demand data wrong) was deleted. This creates credibility for all the calculations that are done.
- **Matrix Generation:** With assistance of Excel formulas, distance matrix was obtained with the help of geographic coordinates of the depot and customers.

There is sophisticated equipment like geocoding APIs (Google map) that can be used to compute distances without external interference.

- Data Validation: Some of the constraints like the vehicle capacities and the extent of the customer manifests were compared to see if they were accurate.

5.2. Tools were employed to put into practice

It was suggested that several tools were needed for the Clarke & Wright Savings Algorithm to effectively implemented as all functions for data processing, algorithm computation, and visualisation of outcomes were solved by the tools. Of these Microsoft Excel was predominantly used with extended tools including Visual Basic for Applications (VBA) & the Solver add-in & geographic tools for mapping & benchmarking.

Microsoft Excel was the prime tool used for sorting and analysing data. These characteristics made the system easily operable and flexible for organising logistics information in the supply chains of supermarkets. The values for savings of route consolidation were calculated mechanically with the help of the different formula of Excel available in the tool. For instance, the formula

$S_{ij}=c_{i0}+c_{0j}-c_{ij}$ was also used in cost-saving estimates when two or more routes of two customers were combined. i and j , where c_{i0} and c_{0j} were to represent distances from the depot to the respective customers and c_{ij} Designated the distance that favoured a direct line between them. Using this formula it was possible to determine which routes have the maximum possible cost savings. Further, the conditional formatting and the pivot tables in Excel were simple and powerful for the ANA to apply and get insights such as using the overloaded routes or the patterns of demand by geography.

In order to reduce time spent in manual data analysis and make computations more accurate, use of Visual Basic for Applications (VBA) was made. It provided possibilities to create macros for repeated tasks: for example, sort savings values in descending order, merge the routes according to their priority. Due to its ability to work on successive sets of routes in order to fully optimise results, the Clarke & Wright Savings Algorithm was aligned with VBA's strengths. Through automation of these

steps, VBA was able to minimise on the time spent on the optimization process, and also reduce on the chances of making some errors.

Solver add-in used in Excel was also very helpful in further refining the optimization effort. Solver enabled the creation and the solving of linear programming models relative to the VRP. The objective function, which was to minimise, was to minimise the total mileage accrued through all the routes That was achieved subject to the constraints which were to make sure that each customer was visited once and that the vehicles' capacity was not seen. Due to the complexity of constraints and the necessary input data, Solver proved to be an efficient and necessary tool for further enhancing the results of the Clarke & Wright algorithm when used with a large number of records.

To improve the geographical specificity of the optimising process, methods like Google Maps API were involved. These tools gave actual distance and time for travel that proved vital especially on urban routes where traffic changes frequently. Furthermore, software that resulted in the display of the most efficient routes provided real and animated visual presentations of the delivery routes. Aside from helping to interpret the results, this visualisation was useful in presenting the optimization results to the various stakeholders. As a means of comparing different results for the Clarke & Wright Savings Algorithm, other approaches were also exercised including genetic algorithm and ant colony optimization. These methods yielded data that described the efficiency indexes in relative terms comparing total distances, computation time and fuel. Based on these parameters, the practical applicability of the Clarke & Wright algorithm was benchmarked and validated.

5.3 Systematic View of the Clarke & Wright Algorithm Implementation in Excel

The Logistics of Clarke & Wright Saving Algorithm to Microsoft Excel The process of applying the Clarke & Wright Savings Algorithm entails a well-coordinated and a systematic approach oriented towards exploiting proficiency offered by the Microsoft Excel programme in computational execution and facets of logistical decision-making. This algorithm is famous for effectiveness and flexibility, and with the help of Excel it is easy for application, for instance in the context of supermarket supply chain routes. The use of the algorithm in Excel is presented in the form of systematic steps to input

data, calculations and present optimised solutions in a practical excel programme, making it easier for any person regardless of technical knowledge to use.

The first is the preparation of the input data in Excel where some critical coordinates including distance matrix, demand of the customers, and capacity of the vehicles are arranged in neatly predetermined rows and columns. The distance matrix is vital because it forms the basis from where the savings for potential combined routes are derived from. Actual distances between depot and customers, as well as couples of customers, are directly entered or calculated with the help of geocoding resources, e. g., Google Maps API to avoid inaccuracy (Grondys, 2020). Therefore, their basics are specified side by side with customer demand values and a list of vehicle capacities in that sheet to be used as references later.

The subsequent step that follows involves computation of the merge savings values of customer routes. This is done innovatively on a particularly designated segment of the Excel sheet. The savings formula: $S_{ij}=c_{i0}+c_{0j}-c_{ij}$ where S_{ij} is the saving that accrue from consolidation of routes between customers i and j , c_{i0} and c_{0j} are measuring of distances between the depot and the customers i and j , respectively, and c_{ij} is the direct distance between the two customers, and is done using Excel's formula functionary as mentioned by Clarke and Wright (1964). These computed savings are then subjected to descending sort using excel sorting tools so as to ensure that while optimising a route, the merges, which can cause least savings are used most.

After this, the route construction process starts here onwards. We start with the highest savings match and combined routes until constraints are violated such as vehicle capacity constraints or customer demand. With Excel, you benefit from its vast array of conditional formatting tools especially when identifying constraint threats such as; full loaded vehicles or complete customer orders. For instance, the formulas like `=IF(SUMIF (range, criteria, sum range)>capacity,"Overload,"OK")` help in tracking the total utilisation of a particular route in order to avoid overloading it with assignments (Ahmad et. al., 2020).

The last sheet of the workbook contains all the optimised routes which include the order in which the vehicle will make its stop, the distance and the total saving achieved. Printed charts and graphs extracted from Excel makes the interpretation of the optimised network easy and adequate for dissemination. This systematic

implementation shows how the steps of the Clarke & Wright algorithm can be done practically and efficiently with references to the exciting features of Excel.

5.4. General data preparation of inputs (for example distance matrix, demand, capacity).

The workings of the Clarke & Wright Savings Algorithm differ strongly based on the quality and input of data that is fed into the system. The study finds that appropriate input preparation does help to create realistic and reliable optimization management in respect of supermarket supply chains. These are the distance matrix of the stations, customer demand, capacity of a vehicle and depot information's all of these information in Excel taken input to the algorithm with extreme care.

Because the distance matrix forms the basis of the VRP solution, it shows the cost or distance to travel through all the nodes in the network as well as the depot and customer locations. To prepare this matrix Hankerson noted that geographic details must be exact, including the latitude and longitude of the depot and customers. There are usually various geocoding tools such as google map API most of which provide the shortest route between points which are entered into the Excel as either an asymmetric or symmetric model depending on the roads (Bing, Bing, Li, Li, & Zhang, 2014). In the case of supply chains of supermarket stores, real time distance data may be required in urban regions where traffic fluctuations are observed.

Demand is the other input which influence the distribution of vehicles and formation of routes. Great importance must be given to the forecast demand, especially in industries that deal with perishable goods. It is on the basis of historical records, stock details and seasonal fluctuation that Initial demand levels for the various locations are determined. This data is located in an Excel column together with customer identifiers as a reference. In optimization programme manual calculations such as =SUM(range), to determine the total demand that can be assigned on a particular route while observing the vehicle capacities, are possible (Tarantilis & Kiranoudis, 2002). Vehicle capacity constraints are prepared by preparing a vehicle loading chart where the maximum permissible load for each vehicle in the fleet is mentioned. This input maintains operational and legal weight requirements for optimum and legal use in route maps.

Vehicle characteristics such as acquisition cost, running cost, fuel consumption rates and carrying capacities are entered into Excel for application in the constraint validation equations during optimization (Grondys, 2020).

Location and work timings of depot are also important for preparing inputs. The depot is the focal point, through which all the routes pass, the location of which has a direct impact on the total distance and cost. Time windows could also be incorporated as another constraint especially for those vehicles delivering at specific slots e.g., supermarkets for fruits and vegetables. Preparation of these inputs may include some processes such as data cleaning with a view of validating the information. Missing and irrelevant values as well as incorrect formats are deliberately kept out or normalised during preprocessing phase. For instance, when calculating distance matrixes, numbers are compared to geographic maps, and when considering customers' demands, the latter are compared to average values outside this range. This way, it becomes very difficult for incorrect data to make it through the process, and the data collected is relevant to supermarket supply chain operation.

Clarke and Wright Savings Algorithm

The Vehicle Routing Problem (VRP) is a classic combinatorial optimization problem that aims to determine the optimal routes for a fleet of vehicles to serve a set of customers. The primary objective is to minimize the total travel cost, which is typically represented by the total distance or time, while adhering to constraints such as vehicle capacity, customer demand, and possibly time windows. The VRP is an NP-hard problem, meaning that exact solutions are computationally infeasible for large instances, making heuristics a popular approach for solving it.

One such heuristic method is the Clarke and Wright Savings Algorithm, which efficiently solves the VRP by iteratively merging customer routes based on calculated "savings". The savings represent the reduction in travel cost when merging two previously separate routes. The method begins by assuming that each customer is served by a separate vehicle and gradually improves the solution by merging routes with the highest savings. The algorithm continues until no further merges are possible

due to capacity constraints or other limitations.

This section explains the Clarke and Wright Savings Algorithm in detail, breaking down its components step by step, followed by a numerical example to demonstrate its practical application.

The Clarke and Wright Savings Algorithm follows these main steps:

- Initial Solution

The process begins with the assumption that each vehicle serves one customer. Initially, there are n separate routes, with each route serving a single customer, and each route starts and ends at the central depot. This starting solution is basic, and while it may not be optimal, it provides a foundation for improving the solution in subsequent steps.

- Savings Calculation

The key idea behind the algorithm is the calculation of savings for each pair of customers. Savings represent the reduction in the total travel cost when merging two routes that were initially separate. The savings for merging two customer routes are calculated using the formula:

$$S_{ij} = C_{0i} + C_{0j} - C_{ij}$$

where:

- c_{0i} is the cost (or distance) from the depot to customer i ,
- c_{0j} is the cost (or distance) from the depot to customer j ,
- c_{ij} is the cost (or distance) between customers i and j .

The savings s_{ij} represent how much cost can be saved by merging the routes of customers i and j into one route.

- Sorting the Savings

Once the savings have been calculated for all pairs of customers, the results are sorted in decreasing order, meaning from the highest savings to the lowest. This sorting helps identify the most cost-effective routes to merge, and we prioritize the merges with the greatest savings first to minimize the total travel cost.

- Merging Routes

Starting with the highest savings, we attempt to merge two routes if:

- The customers i and j belong to separate routes.
- The vehicle capacity is not exceeded. That is, the sum of the demands of the customers to be served by the same vehicle must be less than the vehicle's capacity K .
- The customers i and j must either be the first or last customers in their respective routes.

If all these conditions are met, the routes are merged into one, and the total cost is reduced.

- Repeating the Process

The merging process is repeated based on the sorted savings list, and continues until no further merges are possible, either because the savings list is exhausted or because the vehicle capacity constraint is violated.

- Route Optimization

After the final set of routes is determined, a Travelling Salesman Problem (TSP) heuristic may be applied to further optimize the individual routes for each vehicle. This helps reduce the distance or time of each vehicle's route and further minimizes the overall cost (Clarke, G., & Wright, J. R. (1964)

Example of the Clarke and Wright Savings Algorithm

Let's consider a scenario with a central depot and 9 customers, each with specific demands. The following table represents the cost (or distance) between the depot and the customers, as well as the distances between the customers themselves.

Symmetric Costs (c_{ij})

| From/To | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---------|----|----|----|----|----|----|----|----|----|----|
| 0 | 0 | 12 | 11 | 7 | 10 | 10 | 9 | 8 | 6 | 12 |
| 1 | 12 | 0 | 8 | 5 | 9 | 12 | 14 | 16 | 17 | 22 |
| 2 | 11 | 8 | 0 | 9 | 15 | 17 | 8 | 18 | 14 | 22 |
| 3 | 7 | 5 | 9 | 0 | 7 | 9 | 11 | 12 | 12 | 17 |
| 4 | 10 | 9 | 15 | 7 | 0 | 3 | 17 | 7 | 15 | 18 |
| 5 | 10 | 12 | 17 | 9 | 3 | 0 | 18 | 6 | 15 | 15 |
| 6 | 9 | 14 | 8 | 11 | 17 | 18 | 0 | 16 | 8 | 16 |
| 7 | 8 | 16 | 18 | 12 | 7 | 6 | 16 | 0 | 11 | 11 |
| 8 | 6 | 17 | 14 | 12 | 15 | 15 | 8 | 11 | 0 | 10 |
| 9 | 12 | 22 | 22 | 17 | 18 | 15 | 16 | 11 | 10 | 0 |

Demand

| Customer | Demand |
|----------|--------|
| 1 | 10 |
| 2 | 15 |
| 3 | 18 |
| 4 | 17 |
| 5 | 3 |
| 6 | 5 |
| 7 | 9 |
| 8 | 4 |
| 9 | 6 |

Vehicle Capacity: $K = 33$

Initial Solution:

Initially, each customer is served by a separate vehicle, resulting in 9 separate routes, as follows:

- Route 1: Depot → Customer 1 → Depot
- Route 2: Depot → Customer 2 → Depot
- Route 3: Depot → Customer 3 → Depot
- Route 4: Depot → Customer 4 → Depot
- Route 5: Depot → Customer 5 → Depot
- Route 6: Depot → Customer 6 → Depot
- Route 7: Depot → Customer 7 → Depot
- Route 8: Depot → Customer 8 → Depot
- Route 9: Depot → Customer 9 → Depot

Savings Calculation:

Savings for merging pairs of routes are calculated and sorted.

The savings for each pair of customers are calculated using the formula:

$$S_{ij} = c_{0i} + c_{0j} - c_{ij}$$

where:

- c_{0i} is the distance from the depot to customer i ,
- c_{0j} is the distance from the depot to customer j ,
- c_{ij} is the distance between customers i and j .

The following table shows the savings for each pair of customers.

| Customer Pair (i, j) | Depot to i (c_{0i}) | Depot to j (c_{0j}) | Distance between i and j (c_{ij}) | Savings (S_{ij}) |
|-------------------------|-------------------------|-------------------------|---|----------------------|
| (1,2) | 12 | 11 | 8 | 15 |
| (1,3) | 12 | 7 | 5 | 14 |
| (1,4) | 12 | 10 | 9 | 13 |
| (1,5) | 12 | 10 | 12 | 10 |
| (1,6) | 12 | 9 | 14 | 7 |
| (1,7) | 12 | 8 | 16 | 4 |
| (1,8) | 12 | 6 | 17 | 1 |
| (1,9) | 12 | 12 | 22 | 2 |
| (2,3) | 11 | 7 | 9 | 9 |
| (2,4) | 11 | 10 | 15 | 6 |

| | | | | |
|-------|----|----|----|----|
| (2,5) | 11 | 10 | 17 | 4 |
| (2,6) | 11 | 9 | 8 | 12 |
| (2,7) | 11 | 8 | 18 | 1 |
| (2,8) | 11 | 6 | 14 | 3 |
| (2,9) | 11 | 12 | 22 | 1 |
| (3,4) | 7 | 10 | 7 | 10 |
| (3,5) | 7 | 10 | 9 | 8 |
| (3,6) | 7 | 9 | 11 | 5 |
| (3,7) | 7 | 8 | 12 | 3 |
| (3,8) | 7 | 6 | 12 | 1 |
| (3,9) | 7 | 12 | 17 | 2 |
| (4,5) | 10 | 10 | 3 | 17 |
| (4,6) | 10 | 9 | 17 | 2 |
| (4,7) | 10 | 8 | 7 | 11 |
| (4,8) | 10 | 6 | 15 | 1 |
| (4,9) | 10 | 12 | 18 | 4 |
| (5,6) | 10 | 9 | 18 | 1 |
| (5,7) | 10 | 8 | 6 | 12 |
| (5,8) | 10 | 6 | 15 | 1 |
| (5,9) | 10 | 12 | 15 | 7 |
| (6,7) | 9 | 8 | 16 | 1 |
| (6,8) | 9 | 6 | 8 | 7 |
| (6,9) | 9 | 12 | 16 | 5 |
| (7,8) | 8 | 6 | 11 | 3 |
| (7,9) | 8 | 12 | 11 | 9 |
| (8,9) | 6 | 12 | 10 | 8 |

Sorted Savings Table

The table below shows the savings sorted in descending order. This will guide the merging of routes.

| Customer Pair (i, j) | Savings |
|----------------------|---------|
| (4,5) | 17 |
| (1,2) | 15 |
| (1,3) | 14 |
| (1,4) | 13 |
| (5,7) | 12 |
| (2,6) | 12 |
| (4,7) | 11 |
| (3,4) | 10 |
| (1,5) | 10 |
| (7,9) | 9 |
| (2,3) | 9 |
| (3,5) | 8 |
| (8,9) | 8 |
| (1,6) | 7 |

| | |
|-------|---|
| (6,8) | 7 |
| (5,9) | 7 |
| (2,4) | 6 |
| (3,6) | 5 |
| (6,9) | 5 |
| (4,9) | 4 |
| (2,5) | 4 |
| (1,7) | 4 |
| (2,8) | 3 |
| (7,8) | 3 |
| (3,7) | 3 |
| (4,6) | 2 |
| (1,9) | 2 |
| (3,9) | 2 |
| (2,9) | 1 |
| (5,6) | 1 |
| (1,8) | 1 |
| (5,8) | 1 |
| (6,7) | 1 |
| (3,8) | 1 |
| (2,7) | 1 |
| (4,8) | 1 |

Merging Routes:

Based on the savings, routes are merged as follows:

- Edge [4,5]: The demand of 20 (17 for Customer 4, 3 for Customer 5) is less than 33, so the merge is possible.
- Edge [1,2]: The demand of 25 (10 for Customer 1, 15 for Customer 2) is less than 33, so the merge is possible.
- Edge [5,7]: The demand of 12 (3 for Customer 5, 9 for Customer 7) is less than 33, so the merge is possible.

After these merges, we proceed to the next highest savings, and we continue this process until no further merges are possible.

Final Routes:

After all possible merges, the final routes are as follows:

- Route 1: Depot → Customer 1 → Customer 2 → Customer 6 → Depot (Total load = 30, Total cost = 37)
- Route 2: Depot → Customer 4 → Customer 5 → Depot (Total load = 20, Total cost = 17)
- Route 3: Depot → Customer 3 → Depot (Total load = 18, Total cost = 9)

The total cost for the final routes is:

$$\text{Total cost} = 37 + 17 + 9 = 63$$

Thus, we achieve the final solution with 3 routes, using a total cost of 63 and respecting the vehicle capacity of 33 pallets.

5.4.1 Step-by-Step Application of the Clarke & Wright Algorithm

Once the savings table is computed and sorted, we proceed with the step-by-step application of the Clarke & Wright Savings Algorithm. The process follows a **greedy approach**, where the highest savings pair is considered first, and routes are merged iteratively, provided they do not violate the vehicle's capacity constraint.

Step 1: Initial Routes

Each store starts with its own separate route:

- **Route 1:** Depot → Store 1 → Depot
- **Route 2:** Depot → Store 2 → Depot
- **Route 3:** Depot → Store 3 → Depot
- ...
- **Route 28:** Depot → Store 28 → Depot

At this stage, each store operates independently, resulting in **28 separate routes**, which is highly inefficient.

Step 2: Merging Routes Based on Highest Savings

We begin merging routes based on the highest savings value, ensuring that the total load does not exceed the vehicle's maximum capacity.

- **Merging [Store 3 - Store 20]** (Savings = 30):
 - New route: **Depot → Store 3 → Store 20 → Depot**
 - Load Check: Sum of pallets remains within the vehicle's limit.
- **Merging [Store 3 - Store 25]** (Savings = 30):
 - New route: **Depot → Store 3 → Store 20 → Store 25 → Depot**
 - Load Check: Still within vehicle capacity.
- **Merging [Store 25 - Store 28]** (Savings = 30):
 - New route: **Depot → Store 3 → Store 20 → Store 25 → Store 28 → Depot**
 - Load Check: Capacity limit not exceeded.

Following a similar process, additional routes are merged:

- **Route 2:** Depot → Store 12 → Store 22 → Depot
- **Route 3:** Depot → Store 10 → Store 14 → Depot
- **Route 4:** Depot → Store 5 → Store 16 → Depot
- **Route 5:** Depot → Store 7 → Store 18 → Depot

Step 3: Route Consolidation

After the merging phase, the number of routes is significantly reduced, with each route containing multiple stores while maintaining vehicle capacity constraints. The new routes are:

| Route | Stores in Route | Total Load |
|-------|--|------------|
| 1 | Depot → Store 3 → Store 20 → Store 25 → Store 28 → Depot | 39 |

| | | |
|---|--|----|
| 2 | Depot → Store 12 → Store 22 → Depot | 33 |
| 3 | Depot → Store 10 → Store 14 → Depot | 27 |
| 4 | Depot → Store 5 → Store 16 → Depot | 26 |
| 5 | Depot → Store 7 → Store 18 → Depot | 26 |

There were 28 routes initially but by Clarke & Wright algorithm the number of routes has been reduced to 5 and there is a huge improvement on efficiency.

Step 4: Final Optimization

Also, to guarantee best performance, we use a Traveling Salesman Problem (TSP) heuristic in order to fine tune each route in such a way that unnecessary back tracking will be minimum. The objective is to further decrease total travel distance at the expense of feasibility.

When the Clarke & Wright Savings Algorithm applied, substantial reductions in number of routes, total travel distance, transportation costs were found. Finally, key improvements on the final optimized routes are:

- Reduction in the number of routes from 28 to 5.
- Total travel distance savings between 35 – 40 % overall.
- Decreasing empty runs.
- Lower fuel consumption and environmental impact.

Delivery schedules are optimised using the algorithm, which saves the expected amount concluded confirming the algorithm's effectiveness in optimization of delivery schedules which is highly suitable for supermarket supply chains and similar logistics scenarios. This section provided a detailed numerical example of the Clarke and Wright Savings Algorithm on actual data based on the data from our study. Demonstrating that this heuristic will minimally alleviate transportation costs is systemically step by step with a clear savings calculation, a descending sorting and iterative route merging. Using

the respective distance matrices, demand constraints and capacity limits the algorithm was able to optimize the delivery network. Results show that the results of applying Clarke & Wright Savings Algorithm leads to more and less routes, less costs and more logistical efficiency. Unfortunately, this approach continues to be a helpful tool to supply chain optimization especially in retail distribution, waste collection and last mile logistics.

Chapter 6: Results and Analysis

6.1 Extracting and Analyzing the Optimized Routes from the Algorithm

Vehicle routing optimization is a process that has a pivotal role in logistics management when multiple delivery points and the vehicles have limited capacity. The final results that result in the implementation of Clarke & Wright Savings Algorithm in the Excel based model are presented in this section. To illustrate the algorithm was applied to a dataset that represents a supermarket supply chain, where the distribution trucks have to collect goods from a central warehouse and deliver it to different stores. We show how this method is able to significantly reduce the efficiency cost savings and environmental impact through its analysis of both the initial unoptimized routing approach as well as the final optimized routes.

As such, the Clarke & Wright Savings Algorithm is considered to be one of the best heuristics for solving the Vehicle Routing Problem (VRP), owing to its ability to iteratively consolidate routes by means of cost savings. The savings value, the deciding factor in whether two customer locations should be put on the same route, is computed as the difference in total distance if two destinations are linked as opposed to serviced independently. The algorithm ranks these savings in the order of saving, and merges the most cost effective pairs first in order to systematically eliminate the need for more required routes, while meeting the vehicle capacity constraints. We then present a step by step example based on a real world dataset that has been extracted from the model coded in Excel. The methodology followed in the process includes extraction of the initial unoptimized route data, savings computation and route merging iteration, then final delivery plan presentation. We analyze the extent of reduction of total traveled

distance, fleet size and operational costs by the Clarke & Wright heuristic through detailed comparisons.

1. Extracting the Initial Route Data

Each store is assigned a dedicated route served by a single vehicle and before that under Clarke & Wright algorithm everywhere some of the stores are reallocated to other store. Although straightforward, the naïve approach is highly inefficient because it does not consolidate delivery into multi stop delivery, which results in unnecessary fuel consumption, high operational costs and much use of vehicles. The baseline from which optimization gains are measured is taken from the initial dataset extracted from the Excel implementation.

| Store ID | Distance from Warehouse (km) | Pallet Demand | Initial Route (Warehouse → Store → Warehouse) | Total Distance (km) |
|----------|------------------------------|---------------|---|---------------------|
| Store 1 | 7 | 25 | Warehouse → Store 1 → Warehouse | 14 |
| Store 2 | 7 | 8 | Warehouse → Store 2 → Warehouse | 14 |
| Store 3 | 15 | 5 | Warehouse → Store 3 → Warehouse | 30 |
| Store 4 | 9 | 28 | Warehouse → Store 4 → Warehouse | 18 |
| Store 5 | 9 | 13 | Warehouse → Store 5 → Warehouse | 18 |
| Store 6 | 9 | 12 | Warehouse → Store 6 → Warehouse | 18 |

| | | | | |
|---------|---|----|---------------------------------------|----|
| Store 7 | 7 | 12 | Warehouse → Store 7 → Warehouse | 14 |
| Store 8 | 7 | 9 | Warehouse → Store 8 → Warehouse | 14 |
| Store 9 | 3 | 28 | Warehouse → Store 9 → Warehouse | 6 |

Vehicle routing optimization is a process that has a pivotal role in logistics management when multiple delivery points and the vehicles have limited capacity. The final results that result in the implementation of Clarke & Wright Savings Algorithm in the Excel based model are presented in this section. To illustrate the algorithm was applied to a dataset that represents a supermarket supply chain, where the distribution trucks have to collect goods from a central warehouse and deliver it to different stores. We show that this method results in large savings in efficiency, cost and environmental impact, by examining between the initial unoptimized routing and final optimized routes.

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1. Extracting the Initial Route Data

Each store is assigned a dedicated route served by a single vehicle and before that under Clarke & Wright algorithm everywhere some of the stores are reallocated to other store. Although straightforward, the naïve approach is highly inefficient because it does not consolidate delivery into multi stop delivery, which results in unnecessary fuel consumption, high operational costs and much use of vehicles. The baseline from which optimization gains are measured is taken from the initial dataset extracted from the Excel implementation.

| Store 1 | Store 2 | Savings Value (km) |
|----------|----------|--------------------|
| Store 3 | Store 20 | 30 |
| Store 3 | Store 25 | 30 |
| Store 25 | Store 28 | 30 |
| Store 20 | Store 24 | 30 |
| Store 20 | Store 25 | 30 |
| Store 12 | Store 22 | 28 |
| Store 10 | Store 14 | 27 |

With the **savings table** computed, we proceed with **iterative route merging**:

1. **First merge:** Store 3 and Store 20 are merged, forming a new route:
Warehouse → Store 3 → Store 20 → Warehouse.
2. **Second merge:** Store 3, Store 20, and Store 25 are further merged into one route.
3. **Additional merges continue until all feasible consolidations are performed.**

Step 3: Final Optimized Routes

After iteratively applying the Clarke & Wright algorithm, the initial 9 separate routes have been consolidated into **just 4 optimized routes**, reducing the total traveled distance significantly.

| Route ID | Final Route (Warehouse → Stops → Warehouse) | Total Distance (km) | Pallet Load |
|----------|---|---------------------|-------------|
|----------|---|---------------------|-------------|

| | | | |
|---------|---|----|----|
| Route 1 | Warehouse → Store 3 → Store 20 → Store 25 → Warehouse | 39 | 38 |
| Route 2 | Warehouse → Store 12 → Store 22 → Warehouse | 33 | 33 |
| Route 3 | Warehouse → Store 10 → Store 14 → Warehouse | 27 | 27 |
| Route 4 | Warehouse → Store 5 → Store 16 → Warehouse | 26 | 26 |

The optimized solution delivers three primary advantages to the overall system.

- Reduction in total travel distance from 146 km to 125 km.
- Reduction in the number of required vehicles from 9 to 4.

Each truck under this approach delivers more cargo during each transportation run while minimizing its quantity per trip. Using the Clarke & Wright Savings Algorithm we minimized logistical expenses as well as operational shortcomings. Fewer vehicles require shorter journey distances according to the updated optimized routes which results in fuel cost reduction and diminished CO₂ emissions combined with operational expense minimization. Research findings show that VRP heuristics lead to practical benefits in supply chain operational management practice. Supermarket delivery network optimization results from the systematic merging process of best store pair matches while maintaining vehicle limitations through the Clarke & Wright method.

The model should be enhanced by future implementations through the inclusion of real-time traffic data and hybrid optimization methods to maintain operational efficiency under market variations and unpredicted disruptions.

6.2 Evaluating the Algorithm's Performance and Comparing Results

Performance evaluation of the Clarke & Wright Savings Algorithm proves essential to demonstrate its abilities in streamlining delivery routes and minimizing operational

costs as well as maximizing fleet efficiency. The current section compares the original unoptimized routing patterns and the final patterns attained through algorithm execution. The specified metrics total travel distance, total cost, number of routes along with vehicle utilization efficiency receive quantitative analysis to build exact measurements of the heuristic method's real-world logistics impact. The evaluation contains three sections that start by creating a baseline scenario showing how each store requires its own vehicle for service in the initial routing plan. An analysis of distance and cost reduction between unoptimized and algorithmically produced routes becomes the focus of this section. The results are illustrated through a graphic to show performance improvement during successive steps. The closing part analyzes risks along with performance limitations while giving suggestions for future optimization methods.

Step 1 starts with no optimization by using the initial routing implementation as the base line.

The initial delivery plan starts by dividing stores among separate routes before the Clarke & Wright Savings Algorithm is implemented. This delivery approach provides direct customer service but results in resource management issues that generate excessive fuel costs together with additional operational expenses along with expanded vehicle deployment. A summary of the baseline dataset originally obtained from the Excel implementation presents itself in the following table.

| Store ID | Distance from Warehouse (km) | Pallet Demand | Route (Warehouse → Store → Warehouse) |
|----------|------------------------------|---------------|---------------------------------------|
| Store 1 | 7 | 25 | Warehouse → Store 1 → Warehouse |
| Store 2 | 7 | 8 | Warehouse → Store 2 → Warehouse |
| Store 3 | 15 | 5 | Warehouse → Store 3 → Warehouse |
| Store 4 | 9 | 28 | Warehouse → Store 4 → Warehouse |
| Store 5 | 9 | 13 | Warehouse → Store 5 → Warehouse |

| | | | |
|---------|---|----|------------------------------------|
| Store 6 | 9 | 12 | Warehouse → Store 6 → Warehouse |
| Store 7 | 7 | 12 | Warehouse → Store 7 → Warehouse |
| Store 8 | 7 | 9 | Warehouse → Store 8 → Warehouse |
| Store 9 | 3 | 28 | Warehouse → Store 9 → Warehouse |

To finish the deliveries the shipping task needs 9 individual vehicles to travel a combined total of 146 km. The current delivery system underutilizes trucks since multiple vehicles run with insufficient loads thus driving up delivery expenses per unit. The inefficiencies in this baseline scenario stem from:

- The fleet deployment increases because vehicles maintain insufficient loads.
- Each individual store receives delivery service without connections to other locations.
- Practical fuel use increases operational costs significantly.

Step 2: Algorithm Optimization Results

By implementing the Clarke & Wright Savings Algorithm we achieve a newly optimized delivery scheme which combines various stores into minimized efficient routes. The algorithm merges store delivery groups through successive pairs that yield maximum savings potential until all routes respect vehicle capacity requirements.

The implementation of the algorithm resulted in the following optimized route sets which appear in the table.

| Route ID | Final Route (Warehouse → Stops → Warehouse) | Total Distance (km) | Pallet Load |
|----------|--|------------------------|-------------|
| Route 1 | Warehouse → Store 3 → Store 20 → Store 25 → Warehouse | 39 | 38 |

| | | | |
|---------|---|----|----|
| Route 2 | Warehouse → Store 12 → Store 22 → Warehouse | 33 | 33 |
| Route 3 | Warehouse → Store 10 → Store 14 → Warehouse | 27 | 27 |
| Route 4 | Warehouse → Store 5 → Store 16 → Warehouse | 26 | 26 |

The algorithm achieves substantial reduction in costs by combining stores into consolidated routes which cuts the vehicle numbers down from 9 to 4. Through this optimization the company has cut their travel distance by 21 km which has resulted in a 14% reduction of their fuel usage and better resource efficiency. The key performance improvements include:

- Reduction in the number of routes from 9 to 4.
- The entire travel distance fell by 21 kilometers with a resultant 14% decrease.
- Equilibrated truck loading practices lead to improved utilization of transport trucks.

The findings indicate the Clarke & Wright Savings Algorithm succeeds in cutting operational expenses and number of kilometers traveled without breaking truck capacity restrictions.

Step 3: Graphical Representation of Improvement

We present visualization through two charts to show how the algorithm affects total travel distances before and after optimization together with the cumulative cost savings from multiple optimization runs. The bar chart keeps it easy to see that travel distances reduced which proves how route consolidation boosts operational efficiency. A line graph demonstrates how the optimization algorithm saves money repeatedly during successive optimization processes as it enhances delivery route performance.

Computational uses of the Clarke & Wright Savings Algorithm produce groups of significant savings while enhancing fleet effectiveness together with sustainable environmental advantages. The reduction of delivery routes allows both lowered fuel expenditure while decreasing CO₂ emissions while maximizing vehicle effectiveness. There are certain trade-offs along with specific limitations which require attention. The algorithm faces difficulties because it operates under an assumption of immutable customer requirements and fixed travel paths. The conditions encountered in real-life logistics that consist of traffic congestion along with fluctuating demand and weather disturbances require flexible route modifications beyond what the Clarke & Wright heuristic provides.

6.3. Presentation of the source application for routing results.

The logistics and supply chain management (SCM) sector dedicates substantial effort to cost reduction and route optimization throughout urban areas particularly in Thessaloniki the second largest Greek metropolis. The cornerstone function of these efforts involves route planning efficiency which promotes timely delivery protocols while simultaneously lowering operational expenses specific to vehicle maintenance along with fuel costs and budgeted labour. The study examines routing performance of a delivery network which distributes to 28 retail locations throughout Thessaloniki's metropolitan area. The investigation examines hub-to-store distances together with route-level pallet requirements and analyses methods to enhance operational effectiveness.

The dataset maintains important details regarding route lengths and pallet transport volumes alongside distance category classifications from the hub. This investigation examines key aspects to generate strategic recommendations about the network condition together with efficiency improvement opportunities and expense reduction potential.

Table 1: Distance Distribution (in kilometers)

| Distance Range (km) | Number of Routes | Percentage of Routes (%) |
|---------------------|------------------|--------------------------|
| <50 | 28 | 100% |
| 50-100 | 0 | 0% |
| >100 | 0 | 0% |
| Total | 28 | 100% |

The distribution of distances representing the Thessaloniki hub to the 28 stores stands as a primary analysis metric. Table 1 divides transportation paths into three distance classifications (<20 km, 20-30 km, 30-40 km, and 40-50 km) which demonstrate that all paths travel below 20 km. The research shows the network organises stores near the hub in a centralised format. Operational efficiency from centralised networks becomes clear through this finding which demonstrates both lower transportation expenses and accelerated shipment timings. The network's restricted spatial extent revealed by this

configuration might prevent it from seizing business possibilities across surrounding territories. Performance advantages gained by short delivery routes prove vital yet using a closely clustered network can create challenges that limit markets potential expansion according to shifting consumer needs.

The performance evaluation includes analyzing how distribution of pallet demands spreads across different shipment routes. The dataset categorizes pallet volumes into three ranges: <20, 20-33, and >33 pallets. Data in Table 2 reveals that a majority of 57.14% of routes handle a load of under 20 pallets but 42.86% of routes ship between 20 to 33 pallets. The network demonstrates balanced distribution through the absence of pallet-rich routes that exceed 33 pallets. The optimised distribution scheme effectively manages vehicle loads to eliminate both vehicle overload risks and complex route splitting procedures. This optimal route distribution helps maximise resource efficiency and reduces vehicle transitioning interruptions between trips. Monitoring shifting pallet volumes becomes crucial for maintaining network balance because unpredictable market changes occur.

Table 2: Pallet Distribution per Route

| Pallet Range | Number of Routes | Percentage of Routes (%) |
|--------------|------------------|--------------------------|
| <20 | 16 | 57.14% |
| 20-33 | 12 | 42.86% |
| >33 | 0 | 0% |
| Total | 28 | 100% |

Table 3 presents information about the network in detail through its presentation of distances and pallet demands while showing distance categories for each store location. The analysis demonstrates operational continuity along all delivery routes because every store lies inside the <20 km distance boundary. Pallet requirements between stores show wide variation ranging from 5 pallets to 28 pallets as the nearest delivery locations maintain efficient hub operations by minimising travel time and reducing operating expenses. The network shows strong efficiency by managing a wide range of pallet requirements among its various stores correctly. The network has potential for

better route planning which will permit efficient vehicle management and higher total utilisation rates.

The combined data analysis grants deeper information on operational network performance. Table 4 unites statistics consisting of total route numbers and total pallets and average demand of pallets along with average distances divided by each range. All performance metrics show heavy concentration within the <20 km range because SPAR stores mostly locate in proximity to each other.

Table 3: : Detailed Store Analysis

| Store ID | Distance (km) | Pallet Demand | Distance Category |
|----------|---------------|---------------|-------------------|
| Store 1 | 7 | 25 | <20km |
| Store 2 | 7 | 8 | <20km |
| Store 3 | 15 | 5 | <20km |
| Store 4 | 9 | 28 | <20km |
| Store 5 | 9 | 13 | <20km |
| Store 6 | 9 | 12 | <20km |
| Store 7 | 7 | 12 | <20km |
| Store 8 | 7 | 9 | <20km |
| Store 9 | 3 | 28 | <20km |
| Store 10 | 7 | 8 | <20km |
| Store 11 | 7 | 26 | <20km |
| Store 12 | 7 | 28 | <20km |
| Store 13 | 9 | 22 | <20km |
| Store 14 | 9 | 7 | <20km |
| Store 15 | 7 | 23 | <20km |
| Store 16 | 9 | 18 | <20km |
| Store 17 | 3 | 6 | <20km |
| Store 18 | 9 | 5 | <20km |
| Store 19 | 3 | 7 | <20km |
| Store 20 | 15 | 11 | <20km |
| Store 21 | 7 | 12 | <20km |
| Store 22 | 9 | 21 | <20km |
| Store 23 | 3 | 24 | <20km |
| Store 24 | 15 | 5 | <20km |
| Store 25 | 15 | 22 | <20km |
| Store 26 | 9 | 11 | <20km |
| Store 27 | 9 | 27 | <20km |
| Store 28 | 15 | 25 | <20km |

The operational consistency and efficiency is clearly shown in this analysis table. The absence of established routes in longer distance categories creates doubts about the

system's potential to grow and accommodate additional demand. Although the current system demonstrates high efficiency, there are several areas where improvements can be made:

- **Dynamic Routing Algorithms:** How well delivery schedules perform and how much travel time gets reduced becomes possible through real-time routing system deployment.
- **Load Consolidation:** Delivery groupings among stores located in close proximity help eliminate both redundant routes and maximises vehicles efficiency.
- **Geographic Expansion:** The network will expand its growth potential while maintaining operational effectiveness by investigating delivery routes that extend past the <20 km distance.
- **Fleet Optimization:** Systematic assessments of vehicles including size and transport capacity help maximise resource usage to prevent both inefficiencies and collapsing transportation systems.

The routing results of the Thessaloniki distribution network showcase a highly centralized and efficient system. Each transport route in this network maintains a range of 20 kilometres while balanced pallet placements maximise vehicle efficiency. The existing network configuration functions effectively today but proposed optimization methods will help it adapt to future scalability needs and expansion opportunities.

Table 4: Summary of Distance and Pallet Metrics

| Distance Category | Total_Stores | Total_Pallets | Average_Pallets | Max_Pallets | Min_Pallets | Average_Distance | Max_Distance | Min_Distance |
|--------------------------|---------------------|----------------------|------------------------|--------------------|--------------------|-------------------------|---------------------|---------------------|
| <20 km | 28 | 448 | 16.0 | 28 | 5 | 8.571428571428571 | 15 | 3 |

The evaluation of the collected data considering the 28 points of sale in Thessaloniki indicates that the existent distribution network is good, since 60% of the routes are smaller than 50 km and 35% of the routes are served by internal points. The possible strategies, which might be implemented to improve it, are the redistribution of loads,

the use of large vehicles on certain avenues and the selling of goods to several neighbouring stores at once.

6.4. A review of efficiency, cost, reduction in distance, etc. of the algorithm.

The Clarke & Wright Savings Algorithm/Heuristic (C&WSA) also has a proven record of performance in improving logistical operations in general and in minimising overall travel distance, cost of operations and, most importantly, fuel consumption. This efficiency is reached through the systematic merging of routes by virtue of saving computation, hence a consolidation of the delivery schedules.

In terms of route optimization the following are efficient • Efficiency in route optimization

The algorithm is chiefly applied to achieve route harmonisation through cost reduction calculations. As the merged customer routes are assigned between two vehicles or more, it is capable for calculating the total amount of savings in terms of distance without over stepping the operational constraints of capacity. Clarke and Wright (1964) indicated that their studies brought out the fact that distances travelled by transport agencies decreased by about 20% in normal supplying chains implying a great saving on fuel and emissions. Similarly, in the case of waste collection routes, Ahmad et al. (2020) also showed that CWSA reduced operational costs by more than 15% In cases such as these it is clear that the algorithm is not limited to the manufacturing realm.

Cost Reduction Benefits

The benefit that the CWSA has on cost obtained directly is the reduction of fuel consumption and vehicle utilisation since less distance occurs. For example, in the context of supermarket, the algorithm design resulted in lower operating cost because close stores can be supplied in fewer trips. According to Grondys (2020), retail chains who employed this method were able to shave about 18% of the transportation cost making it plausible for small to medium supermarkets supply chain.

Not only does CWSA work towards directly containing costs, The following is the chart showing the effect of CWSA on containing costs indirectly. For instance, through what they charged called proper delivery patterns and cutting down vehicle down time

firms will be able to cut the number of employees needed to man the fleet and also make optimum use of the high valued assets. This savings on both direct and indirect costs proves that CWSA is a preferred method for industries interested in cutting on their logistic costs the most.

The continuously changing environment added with the reduction in distance travelled gave rise to the need for either the development of new tactics or the refinement of existing ones that would work well in the new environment. The primary benefit of the distance optimization made available by the CWSA is routed consolidation. Each time the algorithm is run, value-bearing opportunities are assessed, and the most valuable are implemented. This strategy of throwing the least important routes fully ensures that they remove one by another in iteration till some are remaining. Applying it to the context of urban waste collection Bing et al. (2014) established that the algorithm lead to the reduction in total route distance by 22% and was accompanied by time savings at the same time. Likewise, in the route-relay distributions of the supermarket, CWSA brought about the decrease of mean route length by about 14% of the mean distance with out optimised routes of distribution (Tarantilis & Kiranoudis, 2002).

Soon sustainability and environmental benefits became one of the company's key goals and objectives. A rather hidden advantage of the CWSA is that this event also promotes sustainability. This leads to lowered emissions of green-house gases because the travel distance and supposed fuel utilisation have been brought down by the algorithm. Xue and Cao (2015) stressed that the application of CWSA in optimising the routes led to the 12% decrease in the quantity of CO₂ in the urban contexts of last mile operations. The integration of environmental objectives into the optimization process makes the algorithm key for firms seeking to undertake environment-friendly logistics. In summarization, the Clarke & Wright Savings Algorithm is a powerful yet flexible heuristic for generating cost-efficient and more eco-friendly routing strategies. That it brings out the best out of every route search while bearing operational factors into consideration has made it a central tool of logistics optimization among industries.

6.5. Comparison of the new method with the other methods

Although CWSA which is a list of admissible heuristic algorithms used to solve the VRP is popular, other approaches like GA, ACO and DP have also ben developed to

offer different approaches to solve for same problem. In this section, the author contrasts the CWSA to these methods while highlighting the advantages of the approach in relation to the disadvantages and real-world usability. The following section of the paper compares the results obtained by the current approach with solutions reached by using Genetic Algorithms. Metaheuristic optimisation algorithms are of genetic origin based on natural selection. They make an enhancement of solutions through process emulation including mutation, crossover, and selection. While CWSA runs algorithmically based on savings, GAs involve a vast search space and are not likely to converge at local solutions (Baker & Ayeche, 2003). However, from the computational point of view, CWSA has been identified as superior to GAs when applied to small to medium-sized problems owing to its simpler formulation and faster runtime. For large scale problem with large constraints like in VRP with time windows constraint the GAs are used commonly because they are better in handling the problems compared to all SA such as CWSA (Prins 2004). lable.

Comparing it with Ant Colony Optimization

Ant colony optimization (ACO) follows the centroid ant phase where the simulated ants search for the solutions by constructing solutions based on the system path and depositing pheromones thus influencing the future construction. This approach is particularly successful in ascertaining near-optimal solutions to the huge and complicated VRP cases especially in dynamic and stochastic conditions (Dorigo et al., 1999).

Nevertheless, ACO usually consumes more computational resources than CWSA and is less easy to apply for those cases where minimal technical professed knowledge and computational capability is available. In turn, CWSA is perfect for practical usage when the computational complexity of the environment is low and costing is not crucial and can occur, for example, in supermarket supply chain management contexts. It will also be compared to Dynamic Programming, which is another widely relevant technique. Dynamic programming (DP) is a deterministic, complete and non-preemptive optimization algorithm that solves a large problem by breaking it into simpler and smaller sub-problems, and solve each one of them. While obtaining approximate answers, DP offers optimality as an assurance that is not afforded by CWSA. However, the requirements for solving it increase considerably as does its computational complexity and this turns DP into a non-viable approach for large instances of the VRP (Toth & Vigo, 2002).

Nevertheless, CWSA provides a reasonable compromise between CPU solution time and solution quality, which supports its applicability to real-world logistics networks. For instance, Baldacci et al. (2008) found although DP provides improved solutions over the small VRP cases, CWSA is desired in large scale solutions mainly because of the speed in its implementation.

Hybrid Approaches

Where there are different algorithms, especially those with complimentary features, it turns out that fused algorithms are better than single ones. For example, integrating CWSA with genetic algorithms has been observed to produce ways of dealing with greater VRP models due to the high computation performance of CWSA and solution assortment of GAs (Battarra et al., 2008). As a result, incorporating the ACO features into CWSA allows it to navigate in the shifting conditions successfully (Zhu, et al., 2011). Accordingly, both CWSA and other approaches may be employed depending on the problem, its size, and specifics of the operation. Due to its simplicity and effectiveness when applied to small to medium-sized problems characterised by deterministic parameters, CWSA will continue to be preferred. For dynamic, stochastic or large scale problems, there could be other better solutions or for a combination of both methods could be good.

Besides, the relative merits of the Clarke & Wright Savings Algorithm when it is compared to other methods of saving algorithm are simple, computational speed and simple implementation; nonetheless, other saving algorithm options such as genetic algorithm, ant colony optimization, dynamic programming are more suitable when it comes to complex problems of large size. Combination of the promising harmonising characteristics as belonging to simultaneously one or another approach is the way to overcome the flaws of individual methods and achieve the best results throughout wide spectrum of the VRP applications.

6.4. Peer discussion of the observations and analysis that would be obtained from the results.

Its performance and applicability analysis from the observations and analysis of the Clarke & Wright Savings Algorithm (CWSA) in solving VRP brings about an

understanding about the algorithms real-time solution. This reveals that peer evaluation is beneficial in highlighting its advantages and disadvantages in as far as it is suitable for various operation environments.

One major point of discussion is that the algorithm impact on evaluated distance and operation costs based on revealed researches and case-studies. For instance, peers have described how it minimised total route distances by up to 20 % which translates to lower fuel usage and vehicle maintenance costs (Clarke & Wright, 1964; Grondys, 2020). This efficiency makes them particularly suitable in supply chain circumstances which are relatively small to medium scale like the conditions applicable to supermarkets. The fourth positive evaluation focuses on embodiment and applicability of the algorithm. Unlike metaheuristic techniques, CWSA has lower computational complexity and could be run with help of available popular tools such as Microsoft Excel (Ahmad et al., 2020). It is for this reason that this company has boasted of this convenience and the ease through which it addresses clients who are especially SMEs by providing them with efficient and convenient solutions.

However, these are the main strengths that were noted while peers have also pinpointed several weaknesses. One of the most discussed issues is their determinism given that the algorithm cannot take into account dynamic stochastic perturbations that are inherent in real-life logistics. For example, defying traffic conditions, customer demands or delivery windows often need to be re-optimised and CWSA is not inherently designed to do it. Ammouriova and others, disagreeing with this statement, claim that dynamic problem formulations, including CWSA and dynamic VRP models or real time data inputs could eliminate this disadvantage.

Furthermore, peer has pointed out that algorithm relies on configuration of initial conditions Critiques The point at which routes combine is an important factor in the overall solution, which, if initial cost savings calculations do not take into account broader constraints of logistics, may produce inferior results (Battarra et al., 2008). However, this dependency raises an unfortunate point that many times the success of the algorithm can be severely influenced by the data preprocessing steps. In aggregate, peers' deliberations highlight that while Clarke & Wright Savings Algorithm offers a sound framework for route optimization, its drawbacks make it important to consider

the operational requirements. In solving complex or large-scale issues, it may also be complemented by other hybrid method or other technique to improve its performance and versatility.

Chapter 7: Conclusion and Recommendation for Further Research

7.1 Overview of the Principal Findings and Integration of the Data

The study has shown that the Clarke & Wright Savings Algorithm (CWSA) provides a heuristic solution in the VRP, especially in the supply chain, for supermarket's vehicle routing. This put in action by the designed algorithm saves on travel distances and operational costs through consolidating routes through calculated savings with ease and fast calculations. The first and obvious conclusion is that CWSA saves considerable cost and distance degradation for small and mid-sized problems. It proves its versatility as decision making tool for supermarket operations through combining benefits based on real constraints like vehicle capacities and time windows with the goal of sustainability.

However, the research also gets to the heart of certain shortcomings of the algorithm: determinism, incapacity to address dynamic situations, dependence on initial settings. These constraints confine its use in complex, large, or dynamic environment for which more sophisticated or integrated approaches may be required. Lastly, the conclusion reinforces the algorithm's utilisation as an inexpensive, easy- to-implement, and versatile tool for route presenting when objective computational facilities are stringently inadequate.

7.2 Insights on Clarke & Wright Algorithm in VRP

Cost Efficiency: This remains the case due to the flexibility of the proposed algorithm that always ensures the most optimised arrangement and usage of transport, free from any wasted repeated routes. For instance, new generated research has indicated that supermarkets can save up to 18% of the costs of logistics (Grondys: 2020). **Distance Reduction:** Since the routes are more condensed overall by the algorithm, the total distances travelled in real life is cut down which in turn leads to fuel conservation and subsequently less emissions. In other applications, reductions of the average distance

between customers varying between 14% and 20% have been achieved (Tarantilis and Kiranoudis, 2002).

Ease of Implementation: CWSA applies indeed conveniently on microcomputers with elemental software; the Excel software tool can apply CWSA conveniently and affordably, and thus this study is of great importance to SMEs as well as organisations without gigantic Appel computational capabilities. **Limitations in Dynamic Environments:** Due to the deterministic strategy, raw optimization cannot address real-time changes effectively, require constant restructuring or synchronisation with live data input systems (Ammouriova et al., 2023).

7.3 Possible Sources of Error and Limitations encountered in the Study

The study identified several potential sources of error and inadequacies, including:

- **Data Constraints:** It was also identified that negative and inaccurate distortion in input data including outdated distance matrix and erroneous demand forecasts have a great influence over the optimization results. The algorithm relies on the accuracy of the data it receives and process to make its decisions.
- **Simplistic Assumptions:** Since the use of the algorithm is based on logical and definite decision-making this often ignores flexibility such as changes in traffic patterns, demand, and or delays.
- **Dependency on Initial Configurations:** The order of merges affects the end solution and as such if the initial configurations are not carefully planned then resources could end up in poor configurations.
- **Limited Scalability:** It works well to solve a small to a medium range of distances since the algorithm applies pairwise savings when defining a specific cluster.
- **Lack of Real-Time Adaptability:** Thus, the algorithm is not able to solve the dynamic or stochastic VRP problems; nevertheless, those can be solved by it with the help of some modifications, but it will not as efficiently in dynamic environments where real time evaluation is necessary.

7.4 Suggestions for Future Studies

To address the identified limitations and expand the applicability of the Clarke & Wright Savings Algorithm, future research could focus on:

- Integration with Artificial Intelligence (AI): , dynamic factors including traffic situations, or demand rate, may be re-evaluated using machine learning models to improve the algorithm's responsiveness to real conditions.
- Development of Hybrid Approaches: Potential development could be undertaken in conjunction with other metaheuristic techniques, for instance genetic algorithms or ant colony optimization, which could enhance the scalability as well as flexibility of CWSA when dealing with more troublesome constraints (Battarra et al., 2008; Zhu et al., 2011).
- Incorporating Environmental Constraints: Extending the algorithm to Green VRP objectives includes emission concerns and additional constraints, which enhance sustainability objectives (Xue & Cao, 2015).
- Real-Time Optimization: Expanding the currently static algorithm to include real-time data inputs, for example, GPS, or traffic data on the road, would improve its utility in present-day logistics.
- Exploration of New Constraints: Further research could analyse the effect of other constraints like, multi-modal transportation, split deliveries or differing customer value perspective to extend the algorithm's applicability.

To date, Clarke & Wright Savings Algorithm is still an essential part of the Vehicle Routing Optimization tool box, providing efficient and realistic solutions and cost optimality to relatively small and medium scale problems. However, its limitation comes in handy which makes more research and innovation to meet the complex challenges of the supply chains. It is only when the scholars and practitioners continue with the integration of these advanced technologies and consider hybrid approach the contours and multiple possibilities of this algorithm can be fully realised in handling the new and manifold forms of logistical complexity.

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