REPUBLIQUE ALGERIENNE DEMOCRATIQUE ET POPULAIRE
الجمهورية الجزائرية الديمقراطية الشعبية

MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH
HIGHER SCHOOL IN APPLIED SCIENCES
--T L E M C E N--

المدرسة العليا في العلوم التطبيقية
École Supérieure en Sciences Appliquées

وزارة التعليم العالي والبحث العلمي
المدرسة العليا في العلوم التطبيقية
-تلمسان-

Final degree project

For Obtaining the Engineering diploma

Field: Industrial engineering
Major: Industrial management and logistics

Presented by:

Niama YAHIAOUI

Subject

Metaheuristic optimization of waste management in circular economy

Publicly defended, on 03/07/2024, in front of the jury composed of:

Mr Fouad MALIKI	MCA	ESSA. Tlemcen	President
Mr Mehdi SOUIER	Prof	Univ. Tlemcen	Thesis Director
Mr Abdelghani BEKRAR	Prof	UPHF Valenciennes	Thesis co-Director
Mr Mohammed BENNEKROUF	MCA	ESSA. Tlemcen	Examiner 1
Mr Abdessamad AIT EL KADI	Prof	UPHF Valenciennes	Examiner 2

School year : 2023 /2024

Gratitude

I would like to express my deepest gratitude to those who have supported and guided me throughout the course of this thesis.:

First and foremost, I extend my heartfelt thanks to my supervisors, Mr.Mehdi Souier and Mr.Bekrar Abdelghani. Despite his limited time and demanding workload, Mr.Mehdi Souier has been an incredible help, providing invaluable support and encouragement. Mr.Bekrar Abdelghani, with his brilliant ideas and expert guidance, has enriched this work with his vast knowledge and indispensable skills. I would also like to thank all the teachers who have helped and guided me in this journey, Mr.Ait El Kadi, Mr. Chergui and Mr.Bennekrouf, Your mentorship has been instrumental in the completion of this thesis.

I am profoundly grateful to Mr. Maliki Fouad, the Director of the Industrial Engineering Program, for his unwavering support and assistance. Your constant presence and readiness to help with everything we needed have been a great source of comfort and motivation.

Thank you to our school ESSAT for the great opportunities and assistance, and for all the great three years of studies.

A special thank you to the LAMIH laboratory at Université Polytechnique Hauts-de-France in Valenciennes for offering me this remarkable internship opportunity. The experience has been truly amazing and has greatly contributed to my professional and personal growth.

To all of you, I express my sincere appreciation and gratitude. Your collective support has made this journey a rewarding and unforgettable experience.

Acknowledgement

To my beloved parents, thank you for being the amazing parents that you are. Your unwavering support, constant encouragement, and endless love have provided me with the foundation to pursue my dreams. You have always ensured that I have everything I need to live a life full of opportunities and to thrive in the best conditions. Your sacrifices and guidance have been my pillars of strength.

To my sister, who has always been by my side, thank you for being my reliable confidant and my go-to person. Your presence in my life has been a constant source of comfort and support, and I am forever grateful for our bond.

To my extended family: Israa, Farah, Marouane, and Baker, thank you for believing in me and for your unwavering support. Your faith in my abilities and your encouragement have been instrumental in my journey. Your presence has made my path much clearer and more navigable.

To my best friends, Manel, Hadjer, and Safia, I cannot imagine how this year would have been without you. This school has gifted me friends for life. Manel, you have always been more than a friend; you are a part of my family. Hadjer, sharing the internship experience with you has been invaluable, and I could not have chosen a better partner to navigate this journey with. Safia, your joy and reassurance have brought so much light into my life.

Thank you all for believing in me and for being there through every step of my journey. Your support, love, and friendship have been the bedrock of my success, and I am eternally grateful for each and every one of you.

List of Figures

List of Tables

Contents

Abstract

The growing need for sustainable waste management has driven the adoption of circular economy principles to reduce environmental impact and resource depletion. This thesis develops a model for integrating these principles to optimize waste collection. Using the Discrete Particle Swarm Optimization (DPSO) algorithm, the study addresses the Vehicle Routing Problem (VRP) with capacity and time window constraints, and extends it to a Multi-Period Vehicle Routing Problem (MPVRP) for enhanced accuracy. By applying this model to real-world scenarios, we demonstrate its potential to significantly improve operational efficiency in waste management practices.

Key words: Circular Economy, Waste Management, Vehicle Routing Problem (VRP), Discrete Particle Swarm Optimization (DPSO), Multi-period Vehicle Routing Problem (MPVRP), time windows

Abstrait

Le besoin croissant de gestion durable des déchets a conduit à l'adoption de principes d'économie circulaire pour réduire l'impact environnemental. Ce mémoire développe un modèle d'intégration de ces principes pour optimiser la collecte des déchets. À l'aide de l'algorithme DPSO (Discrete Particle Swarm Optimization), l'étude aborde le problème de routage du véhicule (VRP) avec des contraintes de capacité et de fenêtre de temps, et l'étend à un problème de routage de véhicule multi-periodes (MPVRP) pour une précision accrue. En appliquant ce modèle à des scénarios réels, nous démontrons son potentiel d'amélioration significative de l'efficacité opérationnelle dans les pratiques de gestion des déchets.

Mots clés: Economie circulaire, gestion des déchets, problème de routage de véhicule (VRP), optimisation de essaim de particules discrètes (DPSO), problème de routage de véhicule multi-période (MPVRP), fenêtres de temps.

تلخيص

أدت الحاجة المتزايدة للإدارة المستدامة للنفايات إلى اعتماد مبادئ الاقتصاد الدائري للحد من الأثر البيئي واستنفاد الموارد. تطور هذه الأطروحة نموذجًا لدمج هذه المبادئ لتحسين جمع النفايات. باستخدام خوارزمية تحسين سرب الجسيمات المنفصلة (DPSO) ، تتناول الدراسة مشكلة توجيه السيارة (VRP) بقيود السعة والنافذة الزمنية، وتوسعها لتشمل مشكلة توجيه السيارة متعددة الفترات (MPVRP) لتعزيز الدقة. من خلال تطبيق هذا النموذج على سيناريوهات العالم الحقيقي، نثبت قدرته على تحسين الكفاءة التشغيلية بشكل كبير في ممارسات إدارة النفايات.

الكلمات المفتاحية: الاقتصاد الدائري، إدارة النفايات، مشكلة توجيه المركبات (VRP) ، تحسين أسراب الجسيمات المنفصلة (DPSO) ، مشكلة توجيه المركبات متعددة الفترات (MPVRP) ، النوافذ الزمنية

List of abbreviations

CE	: Circular Economy
IOT	: Internet of things
GPS	: Global positioning system
SWM	: Smart waste management
AI	: Artificial intelligence
VRP	: Vehicle routing problem
PSO	: Particle Swarm Optimization
DPSO	: Discrete Particle Swarm Optimization
HDPSO	: Hybrid Discrete Particle Swarm Optimization
TSP	: Traveling Salesman problem
CVRP	: Capacitated Vehicle Routing Problem
VRPTW	: Vehicle Routing Problem with Time Windows
MVRP	: Multi-Objective Vehicle Routing Problem
GA	: Genetic Algorithm

Introduction

This thesis demonstrates how integrating circular economy principles with technological innovations and advanced optimization algorithms can revolutionize waste management practices. By adopting these interdisciplinary approaches, we can move towards more sustainable, efficient, and cost-effective solutions, contributing to a more resilient and resource-efficient future.

In recent years, the pressing need for sustainable development has driven the global community to rethink traditional models of resource consumption and waste management. The concept of a circular economy (CE) has emerged as a promising strategy to address environmental challenges, reduce resource depletion, and foster sustainable practices. Unlike the linear "take, make, dispose" model, the circular economy emphasizes regenerative and cyclical flows, aiming to extend product life, minimize waste, and close resource loops. This shift is critical in mitigating environmental degradation and addressing the growing concerns over resource scarcity.

Among the technological advancements, the Internet of Things (IoT) have further propelled the transition towards more efficient and sustainable waste management practices. IoT-enabled smart systems facilitate real-time data collection, analysis, and decision-making, enabling cities and organizations to optimize operations and reduce costs. By integrating CE principles with technological innovations, there is a significant opportunity to enhance waste management systems, making them more resilient, resource-efficient, and environmentally sustainable.

In Chapter 1, This thesis explores the intersection of circular economy principles, technological innovation, and advanced optimization algorithms to improve waste management practices. We delve into the Vehicle Routing Problem (VRP) as a central theme, investigating its various extensions and their applications in smart waste management and reverse logistics. To provide a solid foundation for further research and analysis, we conduct a comprehensive literature review. We begin by discussing the fundamental principles of the circular economy and analyzing its implications for waste management across different industries. This involves exploring how the transition from a linear model to a circular economy can be achieved through sustainable sourcing, recyclable product design, and efficient production processes. The aim is to offer valuable insights into how businesses and communities can successfully transition towards more sustainable and efficient waste management practices. Additionally, we highlight the role of collaboration between different industries in promoting circularity within supply chains.

In the second Chapter, we delve into the VRP, a quintessential challenge in logistics and supply chain management. The VRP involves determining the optimal routes for a fleet of vehicles to service a set of geographically dispersed customers, starting and ending at one or multiple depots. The primary goal is to minimize travel costs while adhering to various constraints such as vehicle capacity, route length, and specific service requirements. The VRP holds critical importance due to its direct impact on operational efficiency and cost-effectiveness in delivery and collection operations. We explore several key VRP variants, including the Capacitated VRP (CVRP), VRP with Time Windows (VRPTW), Split Delivery VRP (SDVRP), and Dynamic VRP (DVRP), each presenting unique characteristics and complexities.

Metaheuristics provide a flexible and adaptive approach to optimization, allowing them to be applied across a wide range of problem domains, including logistics, scheduling, machine learning, and engineering design. Several well-known metaheuristic algorithms, such as Genetic Algorithms (GA), Simulated Annealing (SA), Tabu Search (TS), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO), are discussed for their roles in solving VRP and enhancing smart waste management practices.

Chapter 3, we focus on applying the VRP framework to the context of waste collection in reverse logistics. Reverse logistics involves moving goods from their final destination back to the origin for proper disposal, recycling, or reuse, making it a critical component of sustainable waste management practices. We formulate a mathematical model to represent the VRP in this context, incorporating key parameters such as vehicle and bin capacities, travel costs, distances, load times, and service time windows, we are looking to minimize the total travelling cost of this VRP. To solve this optimization problem, we employ a Discrete Particle Swarm Optimization (DPSO) algorithm, particularly well-suited for combinatorial optimization problems like VRP. We provide a detailed description of the DPSO algorithm, including particle construction, mutation, and crossover operations. Using real-world data from the municipality of Tlemcen [MBS18], Algeria, we test our model and evaluate multiple scenarios with varying numbers of bins and vehicles. Comparative analyses against solutions obtained from CPLEX, a well-known optimization solver, are conducted to assess the performance of DPSO in terms of solution quality and computational efficiency.

In the 4th Chapter, we also tested a Multi-Period Vehicle Routing Problem with time windows (MPVRP-TW), known as an advanced extension of the traditional VRP. MPVRP-TW involves planning and optimizing vehicle routes over multiple time periods within specific time intervals. This problem is highly relevant for real-world applications. The purpose is to demonstrate the increased complexity and computational requirements associated with multi-period routing problems. This chapter also provides insights into how dynamic and variable factors, such as fluctuating bin loads across periods, affect routing efficiency and decision-making.

Chapter 1

Circular Economy and Waste Management

Introduction

In recent years, the concept of circular economy (CE) has gained considerable attention as a promising strategy to address environmental problems, reduce resource consumption, and move towards sustainable development. This chapter dives into the fundamental principles of circular economy and analyses its implications for waste management across different industries. By investigating the incorporation of circular economy principles within supply chains and integrating advancements in technologies like the Internet of Things (IoT) and smart waste management systems, this chapter aims to offer valuable insights into how businesses and communities can successfully transition towards more sustainable and efficient waste management practices. The transition to a circular economy represents a change in the way goods are produced, consumed and disposed of. Unlike the traditional linear model of resource consumption, following a “take, make, dispose” approach, economics emphasizes regenerative and cyclical flows, extending product life , reducing waste and resource loops. Additionally, this chapter discusses the role of collaboration between different industries in promoting circularity within supply chains.

Advances in internet technology in smart sensors have paved the way for the Internet of Things (IoT), a transformative concept that enables machines, devices, and objects to connect and communicate. This section explores the intersection between IoT and the circular economy and explains how IoT technologies can improve circular resource management, optimize waste collection and facilitate real-time, data-driven decision-making in waste management practices. This section also describes the key components of smart waste management, including smart bins, waste level sensors, GPS tracking, and central monitoring systems. By harnessing the power of these technologies, cities and organizations can increase operational efficiency, reduce costs and minimize the environmental impact associated with waste management.

Finally, this chapter provides a literature review that includes various studies and research papers on the topics of circular economy, waste management, and Industry 4.0. By summarizing existing knowledge and identifying gaps in the literature, this section sets the stage for further research and analysis of the complex interplay between circular economy principles, technological advances and waste management practices.

1.1 Definitions and concept

1.1.1 Circular economy in supply chain

Circular economy (CE) is a concept that appeared in industries by the 20Th century focusing on regenerative and cyclical flows, this shift started to transform the industries, extending the product's lifetime, reducing waste and narrowing the resource loops. It is different from the traditional linear supply chain, it might include different actors facilitating horizontal collaboration in different industries [BPCG22]. The integration of supply chain in CE is also an important concept to adopt for a sustainable economy and waste minimization, this involves integrating circular thinking into the supply chain to enhance resource efficiency and reduce environmental impact [DGCMF21]. CE is an emerging alternative to linear and unsustainable production; industrial and academic literature focus on economic and environmental impacts rather than social ones, however transitioning towards a circular supply chain can depend on different methodological choices (economic efficiency, less resource consumption, normalizing procedures, etc) [CGB22]

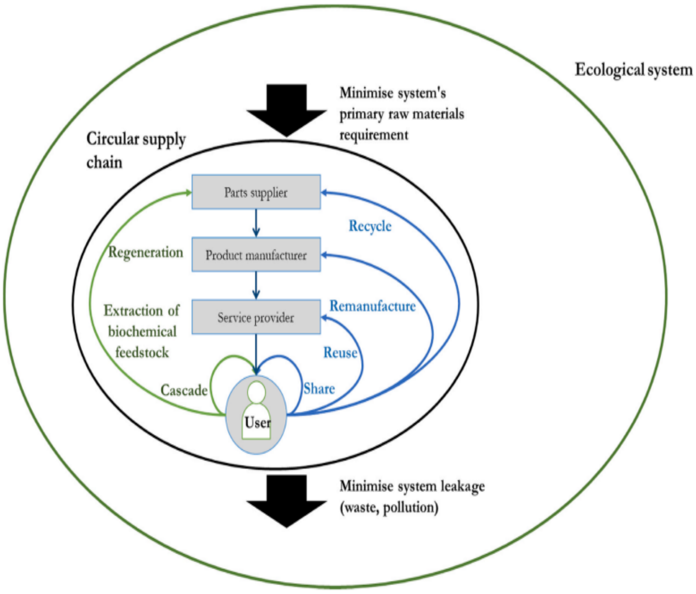

Figure 1.1: Circular Supply Chain as part of the Ecological system [BR15]

The key aspects of CE integration in supply chains are sustainable sourcing, recyclable and reusable product design, efficient production and logistics processes and leveraging technology such as IOT. By adopting these practices in operations research, it will lead to more sustainability, optimization and less waste. The principles of circular economy can be summarized as follows [Vel23]:

- **Design for Longevity and Durability:** Circular Economy promotes product layout that prioritizes durability. Products are supposed to have prolonged lifespans, lowering the want for replacements. This perception focuses on growing high-quality, robust, and dependable merchandise that may be used for an extended period, thereby lowering waste and useful resource consumption
- **Preserve and Extend Product Value:** Emphasis is on keeping and increasing the value of merchandise. This includes techniques such as repairability and upgradability. Repairing and upgrading merchandise as opposed to discarding and changing

them allows assets to stay in use for longer, minimizing waste generation and the depletion of raw materials.

- **Recycling and Material Recovery:** CE concepts prioritize recycling and product recovery. When merchandise can not be repaired or refurbished, they have to be disassembled, and their elements have to be recycled. This technique includes breaking down merchandise into their constituent substances for use as inputs for brand new merchandise, lowering the need for raw substances and mitigating environmental impacts.

- **Collaboration and Stakeholder Engagement:** The Circular Economy's success depends on different groups and stakeholders collaborating and working together, like businesses, governments, consumers, and NGOs. In order to make it work, everyone involved in the supply chain needs to team up, share ideas, and come up with new ways to be more innovative and sustainable.

- **Decentralization and Local Solutions:** Circular Economy principles encourage decentralized methods and local solutions. By encouraging local manufacturing, repair, and recycling centers, the CE can lessen the environmental consequences of transportation and boost regional economic growth. Localized systems are also more flexible in addressing regional demands and opportunities.

CE offers a road-map to shift away from a linear, wasteful economic model to one that's regenerative and sustainable. By integrating these principles into business strategies and policies, communities can decrease waste, conserve resources, and build a stronger, environmentally friendly industries.

1.1.2 Internet of things

The latest advancements in Internet technology, along with the integration of smart sensors and communication technologies, makes the connection of machines, devices, software, and objects possible and easy. This interconnected network facilitates communication and interaction among these entities without requiring direct human intervention. This transformative concept is commonly referred to as the Internet of Things (IoT).

It generally refers to situations in which network connectivity and computing power are extended to objects, sensors, and ordinary items. This enables these devices to generate, share, and process data with little to no human involvement. Currently, a diverse number of industry sectors, such as automotive, healthcare, manufacturing, home and consumer electronics, and beyond, are all considering the possibilities of integrating IoT technology into their products, services, and operations. [REC15]

IoT devices encompass a wide range, spanning from wearable fitness trackers to autonomous vehicles. Each device is equipped with sensors to gather data from the environment, which is then communicated to the IoT system through unique IP addresses. Based on the received information, these devices can initiate actions. The IoT system comprises various components, including sensors, actuators, IoT gateways, cloud infrastructure for data storage and processing, and user interfaces for interacting with the collected data. [RIKA19]

The IoT concept merges the physical and digital worlds, revolutionizing in our context, conventional waste collection and recycling methods into efficient, data-driven, and eco-friendly processes. This transformation ultimately fosters a more sustainable and efficient waste management ecosystem.

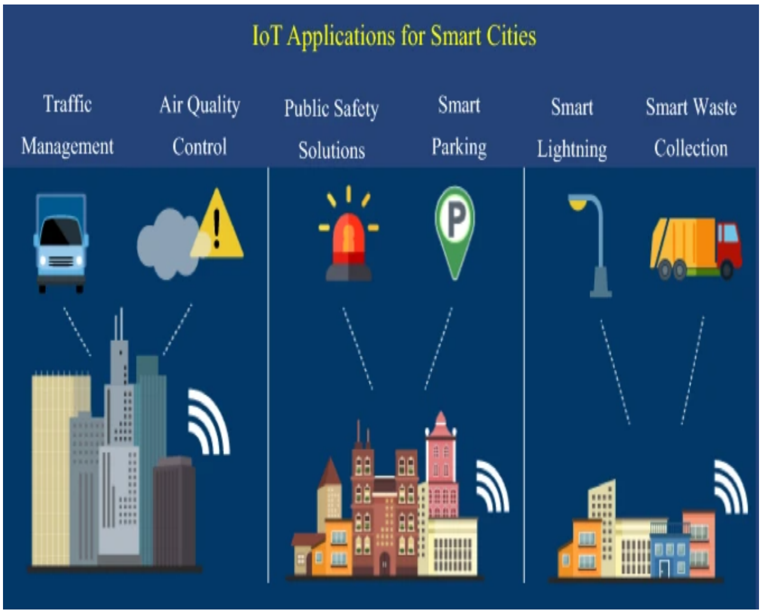

Figure 1.2: IOT application areas for smart cities[RIKA19]

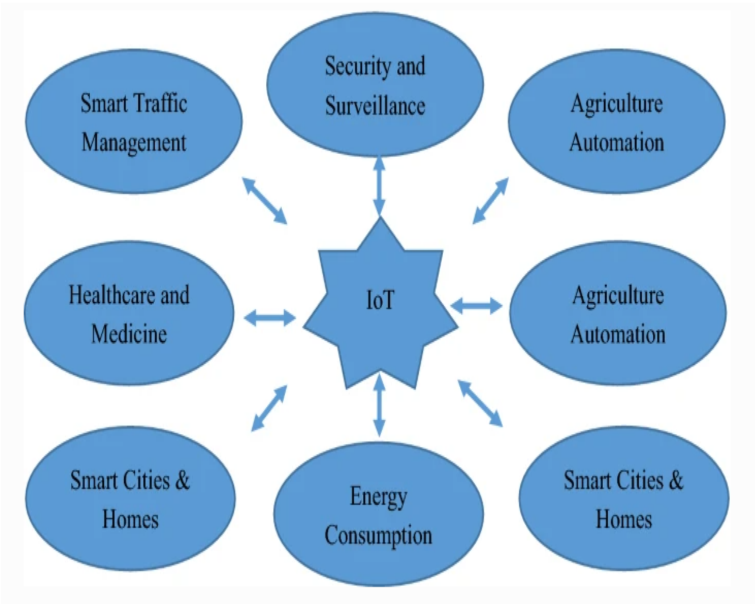

Figure 1.3: Potential application domains of IOT [RIKA19]

The Internet of Things (IoT) plays a crucial role in circular economy by improving circular resource management and reducing waste. With IoT technology, real-time data and analytics enable monitoring of products and waste throughout their life-cycle. This facilitates material tracking, end-of-life product collection, and efficient waste management. Its sensors also provide valuable data for decision-making and optimizing resource usage. By collecting data from various sensors, such as smart meters, IoT connects stakeholders across the value chain, offering real-time insights into the impact of their actions. This data can be leveraged to develop circular economy models based on IoT-captured data, enabling the evaluation of specific items like smartphones [GCT22].

Moreover, this technology has been widely used in waste management for sustainability in smart cities. Its efficient data collection capabilities and high accuracy enable data-driven decision-making models. Many companies utilize IoT technologies to share data within their supply chains and to track products, retaining product value [MKA].

In essence, IoT technology significantly boosts circular resource management and waste reduction by providing real-time data and analytics. Through meticulous monitoring of products and waste, IoT facilitates material tracking, end-of-life product collection, and efficient waste management, thereby promoting the transition to a circular economy [RSR+22].

1.1.3 Smart Waste management

Smart waste management (SWM), an integral part of the circular economy, harnesses technology and innovative solutions to optimize waste collection, disposal, and recycling procedures. Through the integration of smart waste management technologies such as IoT, data analytics, and real-time monitoring, cities and organizations can improve operational efficiency, lower expenses, and minimize environmental harmful impacts. Smart waste management systems also empower citizens to engage in responsible waste disposal practices, by contributing to cleaner, greener, and more sustainable communities. In addition to boosting efficiency and cutting costs, SWM systems also yield environmental advantages by reducing greenhouse gas emissions, encouraging recycling, and preserving natural resources. These efforts align closely with the principles of a circular economy. [Ear]

Our current throw-away culture demands a radical change if we want to achieve a zero-waste circular economy. Unfortunately, the reality paints a bleak picture – waste generation is on the rise, jeopardizing environmental sustainability. The challenge is multifaceted. It requires collaboration between various stakeholders, a shift in consumer behavior, and a complete renovation of existing waste management systems. The good new however is that Smart technologies can be the catalyst for this transformation. By embracing these advancements, we can usher in a circular economy where waste becomes a valuable resource. [Lin]

Managing waste responsibly and effectively has become increasingly difficult in many economies due to the rising volume and diversity of waste generated. Concepts related to the Circular Economy (CE) are offering new perspectives and potentially more efficient technical approaches compared to current dominant practices worldwide. [ZVL+19]

With the potential for continuous technological progress, there's an opportunity to employ real-time monitoring and automated control systems for waste disposal. The conventional method of monitoring waste bins proves highly inefficient for waste management, falling short of the standards expected in smart city initiatives. Recently, sophisticated algorithms have significantly enhanced information technology, opening new avenues for improvement in waste management practices. [RMKM22] The most important common smart waste management technologies can be summarized as follow according to [Hau]

- **Smart waste bins:** Smart bins are waste bins or containers operating with various sensors to optimize waste collection processes. this bins are designed to monitor are communicate their fill level and provide real time date to management centers to choose the best collection times, they also can detect, sort and compress the types of waste. these bins use IOT technologies to transmit the data wirelessly. smart waste bins offer a highly effective solution for managing waste in a more sustainable way.

- **Waste Level Sensors:** These sensors are placed in the trash bins to monitor their fill levels, ensuring that bins are emptied before they overflow, these waste levels data can also help predict the filling times and the busy areas where collection should be preformed more often than other.

- **GPS (Global Positioning System):** GPS can be integrated in smart bins as a very important element, to help provide real-time location tracking, optimize collection routes, and improve operational efficiency. it includes features like real time monitoring of a specific area, and route optimization to help trucks take the shortest roads or avoid traffic. [BGS+22]
- **Central monitoring systems:** These systems act as central platforms, collecting data from multiple smart waste management technologies (smart bins for instance) to simplify the process of waste collection and disposal. They receive all the data on fill levels, locations and even trucks, and can signal the nearest ones to collect the almost filled or overfilled bins. These systems are important to improve operations efficiency and reduce time and costs in waste collection by eliminating unnecessary trips and protecting public health from overflow. [RMKM22]

However, when discussing waste management in a circular economy, there are some aspects that need to be considered in addition to the smart sides, such as and most importantly the waste collection.

Waste collection encompasses the process of transporting solid waste from its point of disposal to treatment facilities or landfills. This includes the gathering of recyclable materials from curbside bins. In economically advanced countries, household waste is typically placed in designated containers or recycling bins for collection by waste management vehicles. However, in many developing countries, waste left by the roadside may remain uncollected unless residents directly engage with waste collectors [PLA]. The frequency of collection, distance traveled, service type, and local climate are key factors influencing the selection of an optimal collection route. This task is particularly challenging in large, densely populated cities. An ideal route maximizes the efficiency of labor and equipment usage. Waste collection in rural areas presents its own set of challenges due to low population densities, resulting in higher unit costs [Enc].

Recent technologies such as artificial intelligence (AI), automated vacuum collection systems, and specialized software are revolutionizing waste collection and management practices by enhancing efficiency and providing real-time data insights. Smart waste bins as mentioned above, equipped with advanced sensors and AI algorithms, are improving the efficiency of operations, improving security, and even detecting illegal waste disposal activities. Automated vacuum collection systems are automating waste collection processes, facilitating real-time data analysis, and simplifying user interaction. Additionally, dedicated software solutions are automating e-waste processing, enabling efficient material recovery, and minimizing environmental impact [Cle].

Choosing the most efficient collection route causes a challenging task, particularly in urban areas with dense populations. An optimal route is defined by its ability to minimize labor and equipment utilization, necessitating sophisticated computer analyses to consider numerous constraints and variables within a complex network. These variables encompass factors such as collection frequency, distance traveled, service type, and local climate conditions. Moreover, waste collection in rural ares presents its own set of challenges, as low population densities result in elevated costs.[Enc]

The presence of the data provided by IOT sensors, presents fresh opportunities to optimize the efficiency of waste management systems. However, it also raises important questions regarding the design of operations that are economically viable, environmentally sustainable, and socially equitable. In addition to providing real-time fill level data, historical sensor information enables the calculation of bin accumulation rates with greater

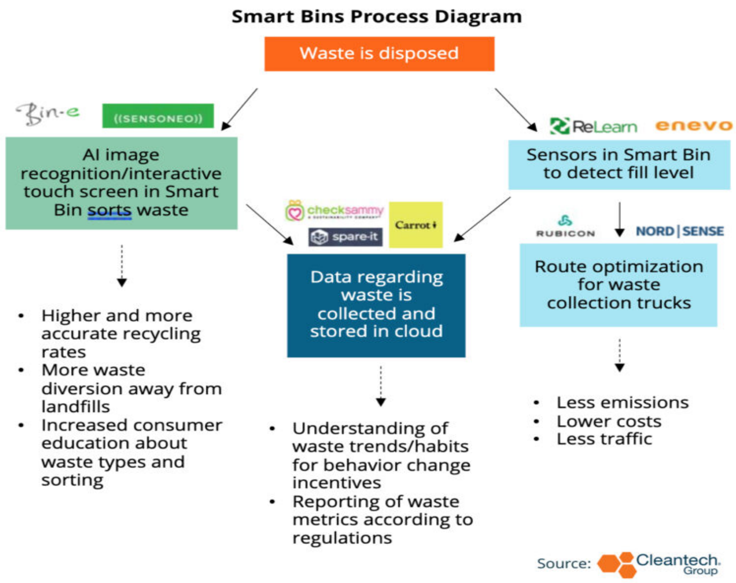

Figure 1.4: Smart Bins Process Diagram [Cle]

precision. Access to these data represents a significant shift towards the development of decision-support methodologies that not only know the present but also predicts the future. This transition from conventional "blind" collection practices to more intelligent, data-driven operations marks a pivotal shift towards enhanced efficiency and effectiveness [JARBP22]. These procedures will largely help waste collectors, optimizing time consumption by only visiting the filled or overfilled bins, avoiding unnecessary trips, reducing gas emissions and pollution.

Conventional waste collection methods face numerous challenges, including ineffective routing, lack of real-time data concerning fill levels and waste composition, and inadequate attention to environmental concerns. These shortcomings often result in elevated operational costs, prolonged collection duration, traffic congestion, and increased carbon emissions [MHG23]. Some other challenges that can be faced in Waste collection are for example the dynamic nature of waste generation, as it is not constant and can fluctuate on daily basis or seasonally, also the vehicle or bins capacity constraints where it requires multiple vehicles and multiple trips per day and lastly the complexity of Urban areas, each area is built according to its population densities and networks, so it may complicate the optimization process, and it requires knowledge of each area and its traffic [Sma].

In order to address these challenges, it requires a comprehensive understanding of current local conditions, possible innovative technology solutions such as IOT integration, and effective collaboration among stakeholders involved in waste management.

1.1.4 Smart bins in SWM

In the face of growing urban populations and the resultant waste management challenges, smart cities worldwide are turning to innovative solutions to enhance sustainability and efficiency. This context sets the stage for the integration of Smart Trash Bins within the framework of smart waste management. Utilizing Internet of Things (IoT) technologies, such as sensors, image processing, and spectroscopy, Smart Trash Bins represent a groundbreaking shift toward automating and optimizing waste segregation. [HCS21] discusses the design and benefits of a smart trash bin model to improve waste management in smart cities specifically in South Korea, the paper proposes an Internet of Things (IoT)-based smart trash bin model that aims to reduce the workload and cost associated with trash separation using: Sensor Technology, Image Processing and Spectroscopy. However deploying these advanced technologies come with several challenges such as the cost and complexity of implementation. [FA19] in BIN-CT: Urban Waste Collection based on Predicting the Container Fill Level, discusses an intelligent waste management system called BIN-CT (BIN for the CiTy). This system enhances urban waste collection efficiency through computational learning algorithms that forecast container fill levels and plan optimal collection routes. it calculates optimal routes for waste collection trucks, reducing operational costs and environmental impact by avoiding unnecessary trips and minimizing the distance traveled. [PRD+20] which introduces an IoT-based smart waste management system designed to enhance urban sanitation by utilizing technology to monitor and manage waste more efficiently. The system aims to improve environmental sustainability by reducing overflow incidents and the number of collection trips, thus decreasing emissions from waste collection vehicles.

1.1.5 Sustainability

Sustainability is a holistic concept that aims to meet the needs of the present without compromising the ability of future generations to meet theirs. It involves the balanced integration of three core dimensions, environmental, social and economic [BM10].

[SZ18] talks about Environmental sustainability and production, it discusses how the field of production and operations management has integrated environmental sustainability increasingly over the past 55 years. It defines sustainability as the practice of making decisions and taking actions in the interest of protecting the natural world, particularly emphasising on preserving the capability of the environment to support human life

[Sar19] aims to explore the intersection of corporate sustainability and supply chain management, it argues that Sustainability in supply chains includes considerations for ecological impacts, corporate social responsibility (CSR), and sustainable development goals (SDGs).

[DLK+19] discusses that proper Solid waste management is a crucial component of broader environmental sustainability efforts. The adoption of advanced technologies, such as smart waste bins and automated collection systems, is presented as a way to enhance the sustainability of SWM systems. These technologies can improve efficiency, reduce operational costs, and lower environmental impacts. This article highlights several sustainable practices, including waste reduction at the source, recycling, and composting.

[PMP19] provides an extensive review of various approaches to business model innovation (BMI) for circular economy (CE) and sustainability. The goal is to synthesize the existing methodologies and frameworks, examining their application and effectiveness in promoting CE and sustainability within businesses.

[LE10] addresses the critical importance of sustainability in modern business practices. It explains that how companies respond to sustainability challenges will remarkably impact their competitiveness and, potentially, their survival. It also argues that sustainability is emerging as a megatrend with predictable trajectories, much like previous business megatrends such as quality and information technology revolutions.

[WHG01] discusses the crucial need for sustainable development in modern business practices. It emphasizes that sustainability should be integrated into the core strategies of organizations rather than being treated as a peripheral issue. Sustainability is not only a moral and environmental obligation but also a driver of competitive advantage, innovation, and long-term profitability. Key elements to transition towards sustainability are summarized to include reducing environmental impact, improving resource efficiency, and fostering social responsibility.

[GF13] emphasizes the necessity for a shift from traditional economic and industrial practices to more sustainable ones that consider environmental, social, and economic impacts. it outlines the basic and fundamental concepts of sustainability, stressing the importance of balancing these three pillars to achieve long-term viability and health of both natural and human systems.

[KF10] establishes a comprehensive review that explores the evolution and varying interpretations of sustainability as a policy concept. It delves into the origins of sustainability, tracing its conceptual journey from the Brundtland Report of 1987, which highlighted the balance between human objectives and natural limitations. They criticise the modern understanding of sustainability, which has been expanded to include social, economic, and environmental dimensions, arguing that this shift dilutes the original focus on the environmental aspect and obscures the inherent conflicts between welfare and conservation.

1.2 Literature revue

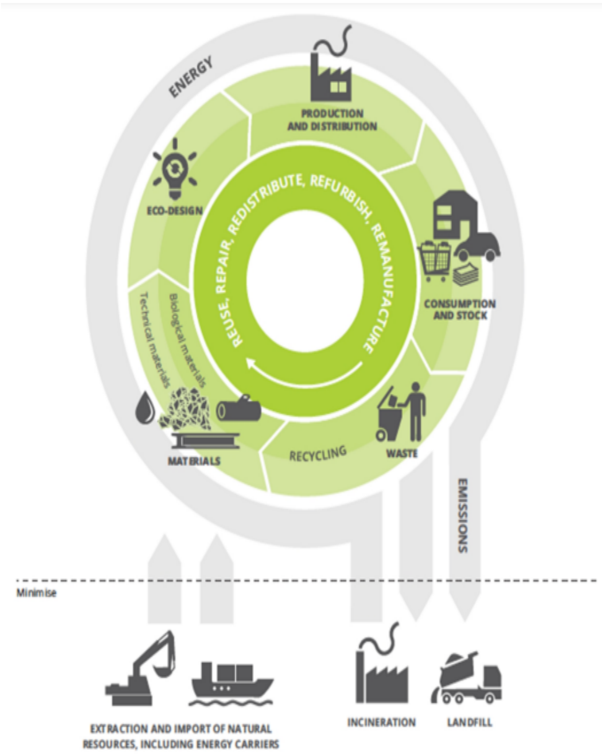

Figure 1.5: The circular economy concept [LSB+17]

In order to provide further details and clarity about the aim of this study, this section provides an overview of some of the papers dealing with circular economy and waste management routing optimization using smart bins.

Starting with a systematic literature review by [MGS21] who has assessed 252 articles on how Closed-Loop Supply Chain (CLSC) modeling supports the transition towards a circular Economy transition at supply chain level and also tried to identify the gaps in the literature for further research development. The results showed that although CLSC has gotten significant attention recently, its research lacks focus on the circular economy principles and the mathematical models should start considering economic, environmental and social criteria. [WKD17] has elaborated on the development of the CE concept in different countries, there is no specific record to when it was really created, but the rapid pace of growth in economy and manufacturing has pushed countries such as china, Russia and Germany to capitalize on material flow, recycling and balance economic development with efficient resource use. Therefore, the shift towards CE aims to change the production methods, emphasising on sustainable methods and preventing environmental damage, focusing on the metrics to measure the impact of these methods such as (costs and revenues, emissions, energy consumption, jobs created...etc) [CGB22]. [KRH17] has analyzed a 114 definitions of circular economy, the research indicates that CE can be summarized in the 3Rs: reduce, reuse and recycle, and it is highly linked to sustainability, environmental and economic prosperity. [SUPP24] has also emphasized the Circular economy 4 R's: Reduce, Reuse, Recycle, Recover, it also discusses waste sorting, treatment, recovery, and economic, social, environmental aspects. They propose key facets for a circular economy-driven solid waste management system and highlights the importance of integrating CE with solid waste management. [CGB21] examined circular economy practices in European Multi-National enterprises through their sustainability reports, most companies implement practices related to renewable energy, resource efficiency, reduction and recycling but the reuse concepts were overlooked. [GAFK17] also emphasized the impact of CE on the environment by comparing carbon emissions of circular vs. linear supply chain systems, it has noted that circular economy is not just about reducing the environment as a sink for waste but also creating sustainable production systems where materials and products are used over and over again, the results demonstrated that although CE show great advantages through a lifestyle Assessment, it is less attractive facing the economical challenges of the pricing and supply.

Another issue facing waste management in circular economy is the constant increase in the diversity of waste generated. The lack of regulatory pressures, environmental education and market demands those are common barriers, other ones like innovation barriers are important to consider, given that technology is rapidly changing, and so organizations need the capacity to be equipped with these technologies and stay up to date, and also have to implement an innovation culture that would allow them to develop their circular supply chain and firms [ZVL+19].

1.2.1 Circular economy in 4.0 industries

Always in the theme of circular economy, the book [MN20] "circular economy with the industry 4.0" has elaborated a detailed study on CE and it's impact on waste management. The main concern is about finding a clear definition of CE and balancing the wasteful present with a waste-less future and rising other questions about sustainability, issues of global warming, resources scarcity and biodiversity losses. According to the authors, international cooperation is crucial if we want to ever reach circularity along with global public support and effective governance, facilitated by technologies like digitalization and artificial intelligence. This transition also requires rethinking societal norms, promoting product reuse, and efficient waste management. Industry 4.0 has helped this revolution of thinking, it has blurred the boundaries between physical, chemical, and biological sectors, with automation and digitalization driving change Naturally with the rapid increase in population and consumption, waste management forms a critical challenge for modern societies, affecting the human health, environment, and various economic sectors, this would especially affect low- and middle-income countries. Advanced economies and countries demonstrate that a proper waste management can significantly reduce negative impacts, global environmental issues and even contribute to resource re-circulation and job creation. A strong and sustainable waste management system can be achieved with just the right balance between the technical, legislative and financial elements to unlock great economic potential and even develop new enterprises. The book has considered

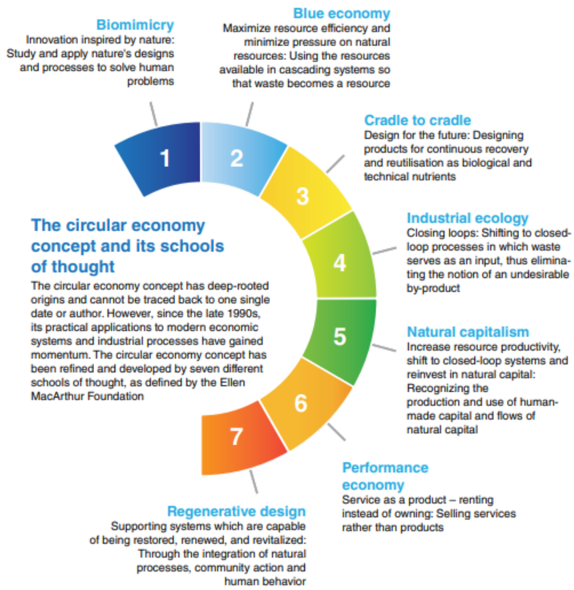

Figure 1.6: CE Concept, and its schools of thought[MN20]

multiple aspects that will be explained as follow:

- **Industry 4.0:** Industry 4.0, originating in 2011, aims to seamlessly integrate mechanical and virtual systems into comprehensive cyber-physical systems, with the goal of enhancing global productivity. Relying on advancements in AI, machine-to-machine connectivity, and real-time data management, Industry 4.0 leverages decreasing costs of sensors, processors, and bandwidth to enable widespread implementation. Its influence goes beyond manufacturing, reaching sectors like energy, healthcare, and mobility services. Despite these strides, Industry 4.0 is still in its early stages, with further outcomes to unfold. The concept invites ongoing discussions regarding the value it should generate and the beneficiaries of its advancements. The key aspects of industry 4.0 include: Data-driven Decision Making, Interconnected Systems and Innovative Concepts such as Predictive Maintenance when forecasting machine components' lifespans based on data that allows this planned maintenance. Digital twins, Smart factories, Edge computing, etc.

- **Waste Hierarchy:** Waste management hierarchy is a guideline that helps prioritizing actions to reduce and manage waste effectively. Generally portrayed as a ladder or pyramid diagram, and has been a fundamental aspect of waste management policies globally for the past three decades. The hierarchy provides guidance for decision-making and has influenced legislation in various countries. However with the emergence of CE concept, that's main objective is reducing waste and optimizing waste management, it was necessary to reevaluate this hierarchy, and asses how waste management strategies align with it's principles.

- **Industry 4.0 and Waste Management:** Relying on fossil energy sources has become increasingly unsustainable by the end of the 20th century, leading to the exploration of alternative options for energy. Moving forward to Industry 4.0 (IND4.0),

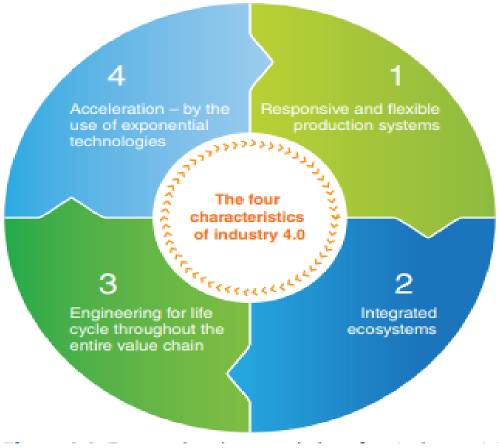

Figure 1.7: 4 main characteristics of an industry 4.0 business environment [MN20]

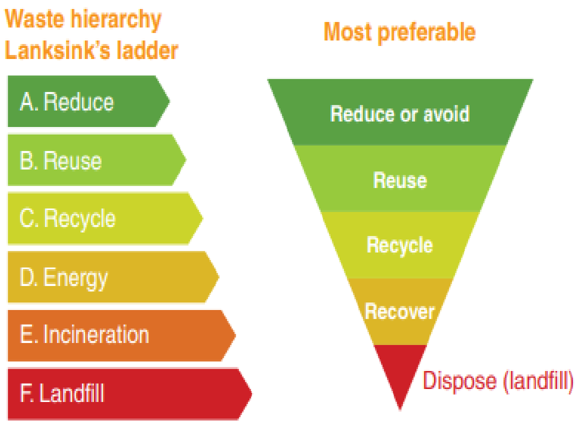

Figure 1.8: Lansink's ladder and Pyramid form of waste hierarchy [MN20]

information emerges as a critical resource. The digitalization of processes aims to facilitate the supply of required information, but it also requires significant energy inputs for collection, organization, transmission, storage, and retrieval. Waste streams will consist of a combination of existing waste streams and new ones impacted and created by IND4.0 advances. These waste streams will vary from one country to another based on the level of industrialization, progress in IND4.0, and each country's role in global supply and value chains. However, certain waste streams will have global significance and demand special attention.

- **Food Wastes and plastics:** One of the most common waste categories on a global scale is food and green waste, making up to approximately 44percent of the total waste generated in 2016. The large presence of organic waste, including municipal organic waste (MSW), presents a substantial challenge for waste management in urban areas. To tackle this issue, various initiatives have been undertaken, like the establishment of composting and anaerobic digestion facilities. The strategic placement of these facilities is determined by factors like population size and logistical considerations, and recommendations are made accordingly to ensure efficient waste management practices. food waste is an important and crucial global concern, studies estimate that roughly 1.3 billion tonnes of food are wasted annually, amounting to about 30percent of cereals, 40-50percent of root crops, fruits, and vegetables, and

20percent of oil seeds, meat, and dairy products. This waste represents a significant loss of resources, including land, water, labor, and energy, and contributes to climate change through greenhouse gas emissions.

Moreover, Plastics have become a remarkable global waste stream, with 242 million tonnes generated in 2016, comprising 12percent of all municipal solid waste (MSW). Despite increasing awareness of the environmental impact of plastic waste, consumption continues to rise, exacerbating the problem. Despite corporate commitments and efforts to reduce plastic waste and increase recycling, challenges persist. The cost between recycled and virgin plastics, along with projected growth in plastic production, presents obstacles to effective waste management. Therefore, the efficacy of recycling initiatives has been questioned, with concerns that they may serve as an excuse for continued plastic production and consumption. Addressing plastic waste a comprehensive and multifaceted approach is necessary, that includes waste reduction, alternative materials, improved waste management infrastructure, and policy interventions at both local and global levels.

The book has proceeded to mention further details about Industry 4.0 and how can it be utilized to benefit circularity, it exposes the flaws of the current linear industrial paradigm and calls for a redefinition of value creation. Addressing these challenges, highlighting the role of economics, sociology, philosophy, history, biology, industrial ecology, and complexity science. Systemic approaches are deemed essential for understanding and navigating the transition to a circular economy within the context of IND4.0. The transformation of the waste management strategies is not merely modifying the existing business models; it represents a fundamental and remarkable shift into uncharted territory. The combination of the circular economy and Industry 4.0 signifies a revolution that will not only alter processes but also redefine the identity of those involved in waste management.The next economic paradigm will be shaped by innovative entrepreneurs, visionary politicians, and dedicated workers in waste management.

1.2.2 Circular Economy, Industrial Ecology

the concepts of circular economy, industrial ecology, and short supply chains have gained attention as potential solutions to shift production and consumption methods towards more sustainable practices, particularly on regional scales. In opposition to the linear model of resource consumption,CE aims to optimize resources usage and reduce waste. This book [GL16] emphasizes industrial ecology and short supply chains as key components of circular economy to potentially contribute to sustainable regional development. It has elaborated even on the social impacts of creating new jobs, contribute to the longevity of activities and strengthen social relation.

The concept of industrial ecology has developed over time, with early definitions focusing on the reuse of waste materials to minimize pollution and resource depletion. industrial ecology provides concrete solutions for sustainable development by shifting away from traditional "end of pipe" solutions and adopting systemic approaches to environmental problems. One of the fundamental principles of the circular economy is transitioning from the usual common model of selling goods to a "functional service economy." This involves shifting towards a model where goods are rented or leased, rather than being sold outright. By adopting this approach, waste generation is minimized, promoting a more sustainable use of resources.

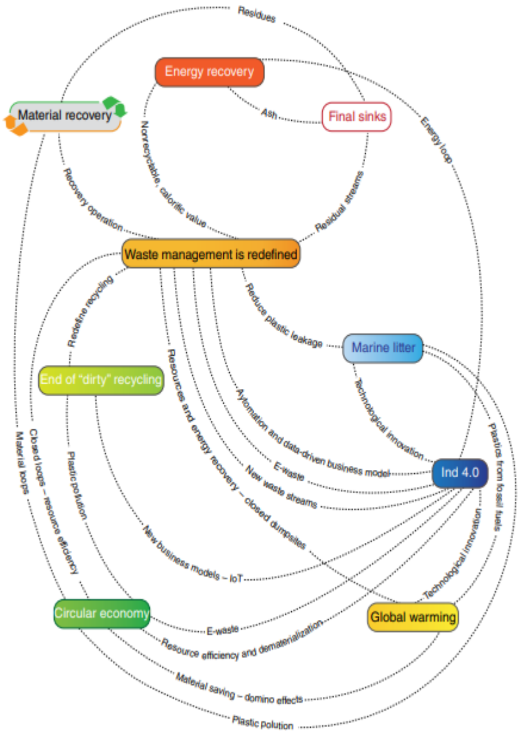

Figure 1.9: A mind map with the interconnections of the five trends [MN20]

1.2.3 Circular economy and classical supply chain

The transition from traditional linear supply chains to circular economy models has gained significant attention due to increasing environmental concerns and the need for sustainable development. The classical supply chain focuses on maximizing efficiency and profit through a linear process of production and consumption, often resulting in significant waste and resource depletion. Conversely, the circular economy aims to create a sustainable loop where products and materials are reused, repaired, and recycled, thereby minimizing environmental impact and resource use. The following table highlights the key differences between classical supply chain management and the circular economy. [GSBH17] [Chr16]

Table 1.1: Comparison between Classic Supply chain and Circular economy

Aspect	**Classical Supply Chain**	**Circular Economy**
Objective	Maximize efficiency and profit by minimizing costs and lead times.	Minimize resource input and waste output, emphasizing sustainability.
Resource Utilization	Linear approach: raw materials → products → waste.	Circular approach: raw materials → products → reuse/recycle.
Waste Management	Disposal of waste at the end of product life.	Reuse, recycling, and remanufacturing of waste materials.
Product Life Cycle	Short, often driven by consumer demand for new products.	Extended, with focus on durability and reparability.
Design Philosophy	Products designed for functionality and cost-effectiveness.	Products designed for longevity, reparability, and recyclability.
Economic Model	Based on selling as many products as possible.	Based on value retention through reuse and recycling.
Supply Chain Structure	Linear supply chain from supplier to end consumer.	Closed-loop supply chain with reverse logistics for returns and recycling.
Environmental Impact	Higher carbon footprint and resource depletion.	Lower carbon footprint and resource conservation.
Innovation Focus	Process optimization and cost reduction.	Product and process innovation for sustainability.
Regulatory Influence	Compliance with environmental regulations as a secondary concern.	Proactive adoption of sustainable practices driven by regulations and market demand.
Stakeholder Engagement	Limited to suppliers, manufacturers, and customers.	Extensive, including recyclers, refurbishers, and policymakers.
Market Drivers	Consumer demand, cost pressures, and competition.	Environmental regulations, corporate sustainability goals, and consumer awareness.
Risk Management	Focus on supply chain disruptions and cost volatility.	Focus on resource scarcity and regulatory risks.

Conclusion

In conclusion, combining circular economy principles with technological innovation is a promising path towards more sustainable and efficient waste management practices. In recent years, the shift from a linear model of resource consumption to a circular economy paradigm has gained momentum due to growing concerns about environmental degradation and resource scarcity. The principles of the circular economy, which emphasize regeneration and circular flows, provide a holistic framework for rethinking how goods are produced, consumed and disposed of. By prioritizing sustainable sourcing, recyclable product design and efficient production processes, companies and communities can minimize waste generation, conserve resources and reduce environmental impact.

Advances in internet technology, particularly the Internet of Things (IoT), have revolutionized waste management practices by enabling real-time data collection, analysis, and decision-making. IoT-enabled smart waste management systems equipped with sensors, GPS tracking and central monitoring systems enable cities and organizations to optimize waste collection routes, improve operational efficiency and minimize costs. Furthermore, the literature review conducted in this chapter highlights the growing number of research papers and studies focusing on circular economy, waste management and Industry 4.0. By synthesizing existing knowledge and identifying areas for further exploration, this review highlights the importance of interdisciplinary approaches and collaborative efforts in improving our understanding of circular economy principles and their implications for waste management practices.

In essence, the combination of circular economy principles and technological innovation offers a transformative opportunity to solve the complex challenges of waste management while promoting sustainable development. By adopting a circular economy, businesses, governments and communities can work together to create a more resilient, resource efficient and environmentally sustainable future for generations to come.

Chapter 2

Mono-Objective Vehicle Routing Problem and Metaheuristics

Introduction

In the realm of logistics and supply chain management, the Vehicle Routing Problem (VRP) stands as a quintessential challenge. It involves determining the optimal routes for a fleet of vehicles to service a set of geographically dispersed customers, starting and ending at one or multiple depots. The primary goal is to minimize travel costs while adhering to various constraints such as vehicle capacity, route length, and specific service requirements. The VRP holds critical importance due to its direct impact on operational efficiency and cost-effectiveness in delivery and collection operations.

The VRP encompasses a wide range of variations, each presenting unique characteristics and complexities. These variations, including Capacitated VRP (CVRP), VRP with Time Windows (VRPTW), Split Delivery VRP (SDVRP), and Dynamic VRP (DVRP), have been extensively studied in the literature. Each variant adds layers of complexity making VRP a rich area of research with significant practical implications. The solutions to these problems are crucial for various industries, including transportation, logistics, and smart waste management, where efficient routing directly translates to cost savings and improved service levels.

Metaheuristics are high-level problem-independent algorithmic frameworks that guide underlying heuristics to efficiently explore and exploit the search space for optimal or near-optimal solutions. Metaheuristics provide a flexible and adaptive approach to optimization, allowing them to be applied across a wide range of problem domains, including logistics, scheduling, machine learning, and engineering design. Several well-known metaheuristic algorithms have been developed, each with its unique mechanisms and strategies. Some of the most prominent metaheuristics include Genetic Algorithms (GA), Simulated Annealing (SA), Tabu Search (TS), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO).

This chapter aims to provide a detailed understanding of VRP and the role of PSO in solving these complex routing problems. By exploring the various types of VRP, their applications in smart waste management, and the advancements in PSO algorithms, we aim to highlight the significant contributions of these methodologies to the field of logistics and supply chain optimization.

2.1 Vehicle Routing Problem

The Vehicle Routing Problem (VRP) is a fundamental logistics problem including the optimization of delivery or collection routes from one or multiple depots to various geographically dispersed cities/customers, while respecting certain constraints that ensure vehicle routes meet capacity and length restrictions or Sub-tour elimination constraints that establish the number of vehicles needed 2.1 VRP holds significant importance in the domains of physical distribution and logistics. The VRP involves a wide range of variations, which have been extensively studied and documented in the literature [Lap92]. This chapter aims to provide an overview of the primary exact and approximate algorithms developed to address the VRP and explores a selection of solution approaches, considering both deterministic and heuristic methodologies. We will explore the types of VRP and how it is used in the context of smart waste management.

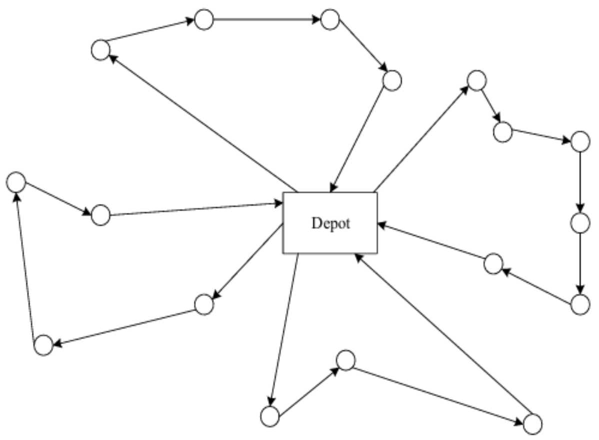

Figure 2.1: Vehicle Routing Problem [ZGYT22]

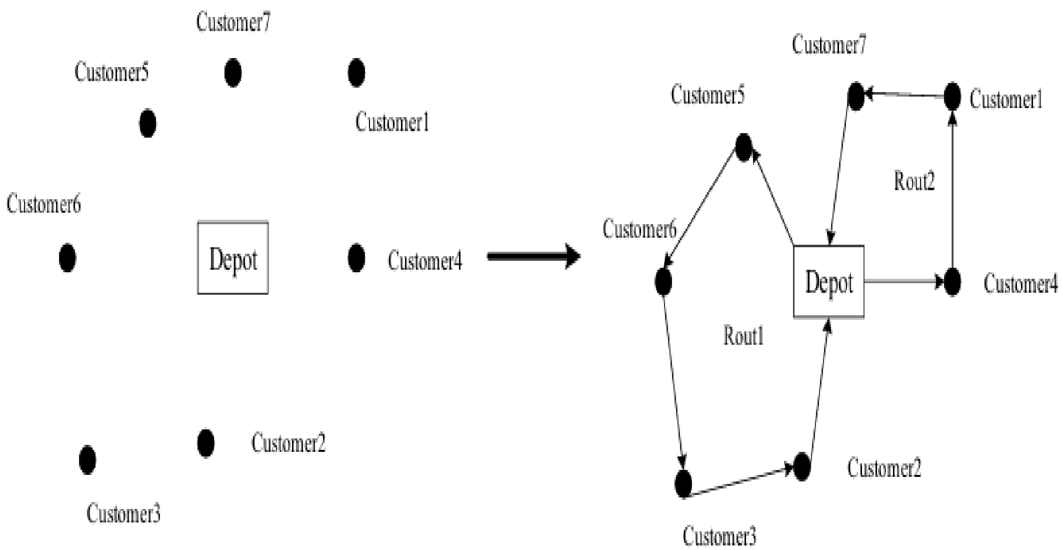

Figure 2.2: Cpacitated Vehicle Routing Problem [ZGYT22]

2.1.1 VRP classification

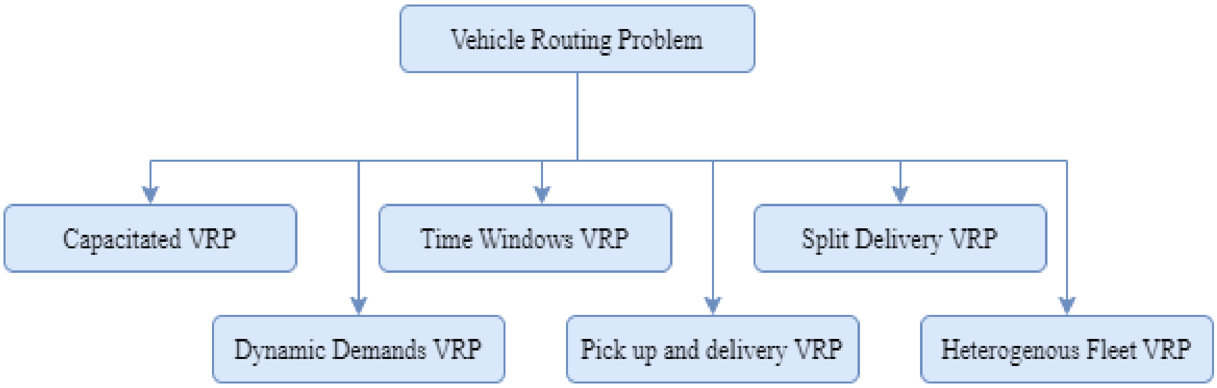

Figure 2.3: VRP Classification

The Vehicle Routing Problem (VRP) encompasses several variations and classifications to address diverse logistical needs. It involves finding the optimal set of routes for a fleet of vehicles to deliver goods to a set of customers. Each vehicle starts from a depot, visits several customers, and returns to the depot 2.2 The objective is to minimize total travel cost while satisfying constraints such as vehicle capacity and customer demand. the most common constraints are: Capacity Constraints, Time Windows, Route Length, Service Priority.

According to [ZGYT22] In the classification of VRP we have:

- Classical VRP (CVRP): or also called Capacitated VRP, Focuses on capacity constraints where each vehicle has a maximum load limit. The goal is to minimize the number of vehicles or the total distance traveled, which involves finding the least-cost simple cycles that start and end at the depot while covering all customer demands [LLE04]. The CVRP is significant in practical applications, driving the development of various heuristic and exact algorithms to efficiently solve the problem, such as branch-and-cut, branch-and-cut-and-price, and other advanced methods. These capacity constraints require a comprehensive optimization process that considers the interdependent relationships between the number of vehicles, cargo distribution, and path planning to achieve the shortest total travel distance. [Zir08] Noted that in practical solutions, two main issues often arise:
  - Constraints limit the generation of new solutions for optimization, reducing the algorithm's global search capability and making it prone to getting stuck in local optima. As the types and strengths of constraints increase, this effect becomes more pronounced.
  - The fusion of constraints with VRP problems makes it challenging to achieve overall coordination and efficiency in terms of algorithm structure, computational complexity, and solution accuracy.
- VRP with Time Windows (VRPTW): Customers must be visited within specified time windows. This adds a layer of complexity as the scheduling of visits becomes crucial. It is an extension of the classic Vehicle Routing Problem (VRP) that incorporates scheduling constraints, making it highly relevant for real-world applications. The VRPTW optimizes the use of a vehicle fleet to serve a set of customers, specifying which customers should be served by each vehicle and in what sequence, with

the goal of minimizing the overall cost. This optimization is subject to both vehicle capacity constraints and specific time windows within which each customer must be served [Zir08]. An other paper [BG05] offers a comprehensive overview of various metaheuristics applied to solve the VRPTW, using Tabu search, Simulated annealing and genetic algorithms metaheuristics. The Time window constraints have been incorporated in the algorithms, and they concluded that Proper handling of time windows is crucial for the effectiveness of metaheuristics in solving VRPTW.

- Split Delivery VRP (SDVRP): According to [?] SDVRP allows a single customer's demand to be split across multiple deliveries. This can reduce the number of vehicles needed and optimize the usage of vehicle capacities.

- Dynamic VRP (DVRP): Deals with situations where customer demand, traffic conditions, or other factors change in real-time.[PWK16] the DVRP is an extension of the classic Vehicle Routing Problem (VRP). It incorporates real-time information and changes that occur during the execution of vehicle routes. Unlike the static VRP, where all inputs are known and fixed beforehand, DVRP deals with dynamic elements such as new customer requests, traffic conditions, and vehicle breakdowns. The goal is to continually adapt and optimize the vehicle routes in response to these changes to minimize costs, improve service levels, and increase efficiency.

  - Dynamic Demand VRP (DDVRP): Focuses on changing customer demands during the routing process. Real-Time Traffic VRP (RTVRP): Considers real-time traffic information affecting vehicle routes.

  - Dynamic Demand and Real-Time Traffic VRP (DDRVRP): Combines dynamic customer demands with real-time traffic information for the most complex scenarios.

- VRP with Pickup and Delivery (VRPPD): Vehicle routing problems are often more complex than the classical VRP. A significant complication is that goods need to be both delivered to customers and picked up from customers to be brought back to the depot. This is known as the Vehicle Routing Problem with Pick-Up and Delivery (VRPPD), also referred to as the Vehicle Routing Problem with Backhauls (VRPB) in the literature. Vehicles perform both delivery and pickup tasks within the same route. The VRPPD can be effectively divided into two separate Capacitated Vehicle Routing Problems (CVRPs): one for delivery (linehaul) customers and another for pickup (backhaul) customers.[Zir08]

- Heterogeneous Fleet VRP (HFVRP): Involves a fleet of vehicles with different capacities and costs.

2.1.2 Solution Methods

The figure 2.4 provides a taxonomy of solution methods for the Vehicle Routing Problem (VRP), categorizing them into three main groups: Exact Methods, Approximate Methods, and Hybrid Methods. Exact Methods, such as Mixed Integer Linear Programming and Dynamic Programming, guarantee finding the optimal solution. Approximate Methods, including heuristics like trajectory-based approaches like Local Search, offer faster, good-enough solutions without guaranteeing optimality. Hybrid Methods combine elements from both exact and approximate techniques, incorporating meta-heuristics like Genetic Algorithms and Particle Swarm Optimization to use the strengths of each approach for more efficient problem-solving.

[Alm13] provides a comprehensive exploration of various methods to solve different vehicle routing problems (VRP)

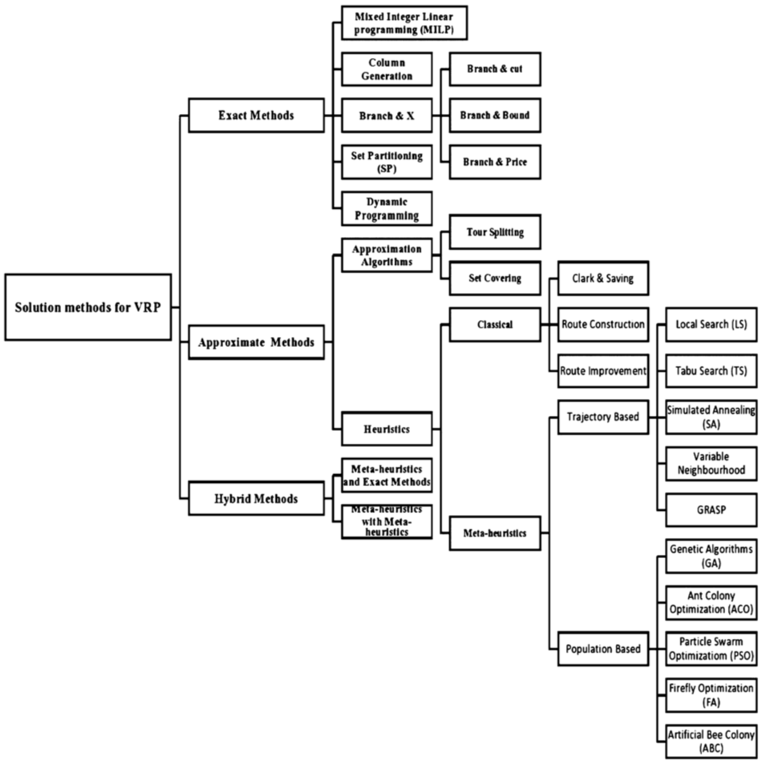

Figure 2.4: Solution Methods [GB20]

Exact Algorithms:

They are optimization techniques that guarantee finding the optimal solution to a given problem by exploring all possible solutions. These methods are useful for solving combinatorial optimization problems. Exact methods use mathematical formulations to systematically search the solution space, ensuring that the best possible solution is identified. Despite their computational intensity, exact methods are important in situations where optimality is crucial and where problem sizes are manageable within computational limits. The exact algorithms include a bunch of methods that explore all possible solutions systematically and ensure finding optimality, some of these methods are:

1. **Branch and Bound** Branch and Bound is a tree-based method used for solving integer and combinatorial optimization problems. It explores the branches of a solution tree, where each branch is a representation of a subset in the solution space. The method involves calculating bounds on the best possible solution within each branch and pruning branches that cannot give better solutions than the current best-known one.

2. **Branch and Cut** Branch and Cut is an extension of the Branch and Bound method that incorporates cutting planes to improve efficiency. Cutting planes are additional linear constraints added to the problem to tighten the linear relaxation of the solution space, thereby reducing the feasible region and speeding up convergence. The process involves branching to create subproblems, bounding to evaluate their potential, and adding cuts to prune infeasible or suboptimal regions.

Classical Heuristics

Classical heuristics are straightforward, rule-based methods used to find feasible solutions for complex optimization problems such in Vehicle Routing Problems (VRP). These heuristics prioritize simplicity and speed over finding the optimal solution, aiming instead to produce good-enough solutions within a reasonable timeframe. They are particularly useful for large-scale problems where exact methods may be computationally infeasible. if a problem has a lot of constraints, or a very big search space, the number of feasable solutions will be huge, therefore so it will be hard to find the optimal solution. Amongst these classical heuristics we have:

1. **Constructive Heuristics** It consists of building a solution from scratch, adding one element at a time based on specific criteria. For example, in the context of VRP, a constructive heuristic might start at the depot and repeatedly add the nearest customer that hasn't been visited yet until all customers are served, or randomly select a customer that has not yet been visited. This method is simple and fast but doesn't always guarantee finding the best solution.

2. **Two-Phase Methods** This method divides the problem-solving process into two distinct phases. The first phase generally involves constructing an initial solution, while the second phase focuses on improving this solution. In VRP, the first phase might involve creating initial routes for the vehicles, and the second phase might involve optimizing these routes by swapping customers between them or rearranging their order to reduce total travel distance.

2.1.3 Mathematical Formulation of a Mono-Objective VRP:

The Vehicle Routing Problem (VRP) can generally be formulated mathematically using the following notations and equations. The classic VRP formulation involves minimizing the total distance traveled by a fleet of vehicles to serve a set of customers, starting and ending at a depot.

$$\text{Minimize} \sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij} x_{ij} \tag{2.1}$$

where:

- n is the number of customers.
- c_{ij} is the distance or cost from customer i to customer j.
- x_{ij} is a binary variable that is 1 if the vehicle travels directly from customer i to customer j, and 0 otherwise.

Constraints

Each customer is visited exactly once:

$$\sum_{j=0, j \neq i}^{n} x_{ij} = 1 \quad \forall i = 1, \ldots, n \tag{2.2}$$

$$\sum_{i=0, i \neq j}^{n} x_{ij} = 1 \quad \forall j = 1, \ldots, n \tag{2.3}$$

Vehicle capacity constraints:

$$\sum_{i=0}^{n}\sum_{j=1}^{n} d_i x_{ij} \leq Q \tag{2.4}$$

where d_i is the demand of customer i and Q is the vehicle capacity.

Sub-tour elimination constraints:

$$u_i - u_j + Qx_{ij} \leq Q - d_j \quad \forall 1 \leq i \neq j \leq n \tag{2.5}$$

where u_i is the load of the vehicle after visiting customer i.

2.1.4 VRP in Smart waste management

For our case, the Vehicle Routing Problem (VRP) in smart waste management is used to optimize the collection and transportation of waste by determining the most efficient routes for a fleet of vehicles, it helps in route planning that waste collection vehicles should take, while ensuring to minimize distances, costs or time spent, it also allows to take into account various constraints such as time windows for example waste collection hours, and capacity constraints considering the capacity of each vehicle, ensuring that the routes are planned in such a way that the vehicles are filled to optimal capacity without overloading [GKKP20]. IoT enables dynamic and mobile communication systems that collect, process, and analyze data from connected vehicles. This integration aims to enhance the logistics and distribution processes in cities.By harnessing data from various sources such as vehicle sensors and external traffic data, the system can make informed decisions that optimize routes and schedules.

[HAMR+23] discusses a new approach to handle municipal solid waste using an integrated smart waste management (ISWM) system. This system uses Internet of Things (IoT) technology for optimizing routes and schedules for waste collection to maximize efficiency and minimize costs, also to gather data, enabling dynamic and efficient routing and scheduling of waste collection. By optimizing waste management operations, the model not only aims to improve environmental sustainability but also enhances economic efficiency by reducing costs associated with waste collection and disposal.

[RdMBP18] Presents an advanced operational management approaches to enhancing the efficiency of waste collection systems using Internet of Things (IoT) technologies. Limited Approach using capacitated Vehicle Routing Problem (CVRP) model to build a heuristic to decide which bins to collect, Smart Collection Approach and a Smarter Collection Approach includes a comprehensive optimization model that dynamically selects bins and routes daily to maximize operational efficiency. The study shows significant improvements in operational efficiency, such as reduced travel distances, improved service levels, and better use of resources. Implementing these advanced routing strategies can lead to substantial economic benefits, reductions in greenhouse gas emissions due to fewer and more efficient routes, and improved service levels in urban waste management.

Another article that explores a novel approach to waste management that integrates Internet of Things (IoT) [SAAHK+22] in "Designing an effective two-stage, sustainable, and iot based waste management system" proposes a two-stage model for waste management. The first stage focuses on the collection and routing of waste using smart bins that communicate real-time data to optimize routes. The second stage deals with the separation and recovery of materials to maximize resource recovery and economic benefits. They used a Green Capacitated Vehicle Routing Problem (GCVRP) emphasizing on sustainability by aiming to reduce environmental impacts through efficient routing (reducing emissions).

2.2 Metaheuristics for VRP in SWM

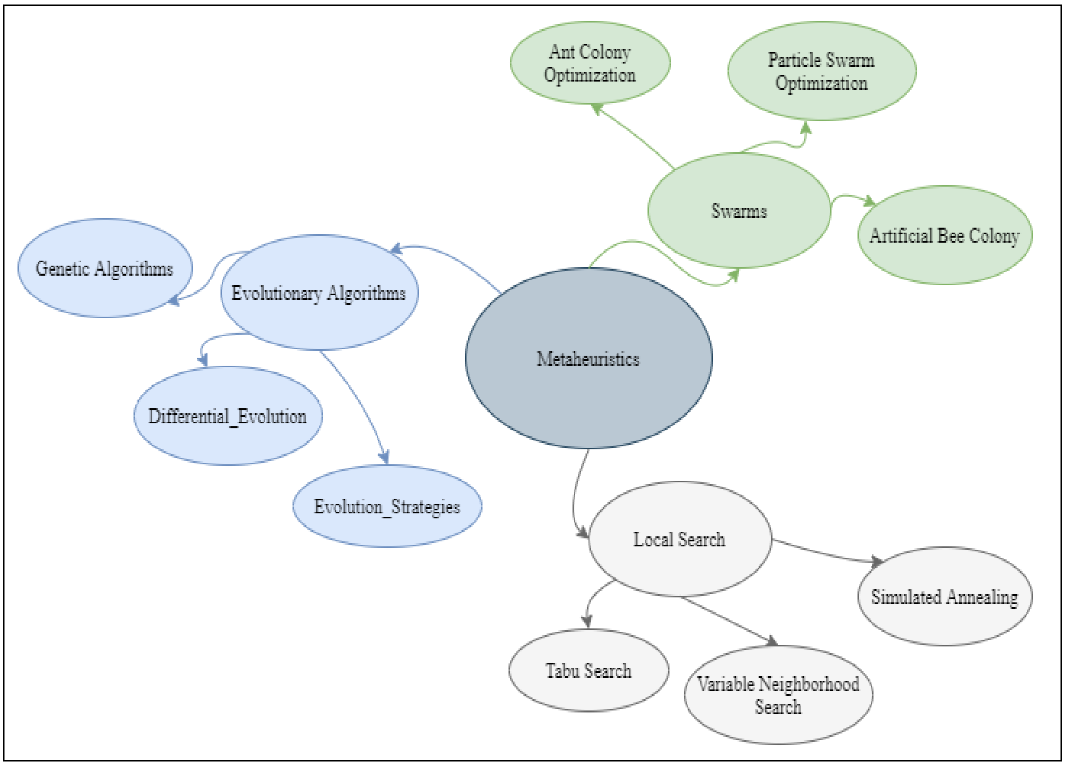

Figure 2.5: Metaheuristics

Metaheuristics are high-level problem-independent algorithmic frameworks that guide underlying heuristics to efficiently explore and exploit the search space for optimal or near-optimal solutions. In the context of smart waste management, metaheuristic algorithms, such as Genetic Algorithms (GA), Simulated Annealing (SA), Tabu Search (TS), and Hybrid Metaheuristics, have been widely adopted to solve VRP due to their flexibility and ability to provide high-quality solutions within acceptable computational times.

[JARBP22] discusses the development and implementation of a hybrid metaheuristic to address smart waste collection problems with workload concerns. They used a look-Ahead Heuristic which decides the collection days and identifies bins that need collection based on current and predicted fill levels. and a hybrid Simulated Annealing and Neighborhood Search (SANS) to determine the bins profitable to collect and optimize the collection routes, The hybrid metaheuristic achieved a profit at least 45per-cent higher than the current methods used by a major waste management company, It also ensured better compliance with maximum shift durations and improved route workload balance.

[SAAHK+22] Has designed a two-Stage Sustainable Waste Management System, the first stage focuses on optimizing waste collection routes using Green Capacitated Vehicle Routing Problem (GCVRP). The goal is to minimize transportation costs, CO2 emissions, social impact, and the number of unvisited bins the second stage involves separating and transferring waste to recovery centers using Green Split Pick-up Vehicle Routing Problem (GSPVRP), it applies various metaheuristics and hybrid algorithms, including Simulated Annealing (SA), Social Engineering Optimizer (SEO), Genetic Algorithm (GA), Keshtel Algorithm (KA), Particle Swarm Optimization (PSO), and hybrid methods (KAGA and GAPSO). The hybrid algorithms KAGA and GAPSO demonstrated enhanced performance in intensification and diversification phases.

[RMKM22] used Variable Neighborhood Search (VNS) which xplores different neighborhood structures to find near-optimal solutions for vehicle routing and Ant Colony Optimization (ACO) that generates initial solutions by simulating the behavior of ants searching for the shortest path. Imposes a time-dependent penalty on waste management authorities if bins are not emptied on time and aims to minimize total costs, including bin allocation, routing, driver wages, and penalty costs. The hybrid VNS-ACO algorithm outperformed advanced versions of Genetic Algorithm (GA) and ACO in terms of total costs and computational efficiency.

[AHB15] the paper presents an effective approach to improving solid waste collection efficiency using the Particle Swarm Optimization algorithm. The study uses (PSO) algorithm to solve the VRP, considering constraints like time windows, vehicle capacities, and waste levels. It showed impressive results in optimizing routes, particularly when only bins filled to a certain threshold were considered.

[WTY20] this article focuses on optimizing urban waste collection and transportation with high-priority waste bins, it incorporates environmental concerns by minimizing greenhouse gas (GHG) emissions and conventional waste management costs. Combines Particle Swarm Optimization (PSO) for initial solution generation and Simulated Annealing (SA) for global optimization, the hybrid algorithm outperformed PSO alone in terms of total distance, GHG emissions, and total costs.

Another study introduces a robust hybrid metaheuristic (I-HFPSO) for optimizing municipal solid waste collection routes [Kay23] it Combines firefly algorithm (FA) and PSO, utilizing the fast convergence of PSO and the local search strengths of FA, enhanced with a mixed local search strategy including swap, insert, and invert operations.

[HAB+18] Focuses on optimizing waste collection routes considering vehicle capacities and the fill levels of bins. Modified PSO is applied to solve the CVRP, leveraging its ability to find optimal or near-optimal solutions efficiently. The study concludes The PSO-based CVRP model significantly improves waste collection efficiency compared to traditional methods, reducing travel distance, fuel consumption, and greenhouse gas emissions while ensuring timely collection of waste bins.

The application of various metaheuristic algorithms, including Genetic Algorithms, Simulated Annealing, Ant Colony Optimization, and hybrid methods like PSO-based approaches, has significantly enhanced the efficiency and effectiveness of smart waste management systems. These algorithms have demonstrated substantial improvements in optimizing waste collection routes, minimizing costs, reducing greenhouse gas emissions, and ensuring timely waste collection.

2.2.1 Particle Swarm Optimization

Since 1995, Particle Swarm Optimization (PSO) has seen significant advancements and numerous new versions have emerged. As a population-based search algorithm, PSO involves a group of randomly initialized individuals exploring the search space simultaneously and ultimately converging on the optimal solution. Unlike other evolutionary computation techniques, PSO is inspired by the behavior of bird flocking or fish schooling. In PSO, individuals in the population, known as particles, are associated with velocities and adjust their velocities dynamically based on historical search experiences. The design and implementation of PSO are straightforward and easy to grasp. Additionally, PSO algorithms exhibit strong global search capabilities, rapid convergence speeds, and robustness. These attributes make PSO a powerful optimization technique. In recent years, PSO algorithms have been extensively applied across a wide range of fields.

The original Particle Swarm Optimization (PSO) is designed for continuous optimization tasks. Each particle i in the population is represented by three D-dimensional vectors: the velocity vector $\mathbf{V}_i = [V_i^1, V_i^2, \ldots, V_i^D]$, the current position vector $\mathbf{X}_i = [X_i^1, X_i^2, \ldots, X_i^D]$, and the previous best position vector $\mathbf{pBest}_i = [pBest_i^1, pBest_i^2, \ldots, pBest_i^D]$. The dimensionality of the search space is denoted by D. The population also maintains a global best-so-far position vector $\mathbf{gBest} = [gBest^1, gBest^2, \ldots, gBest^D]$.

In each iteration of the optimization process, each particle updates its velocity $\mathbf{V}_i$ and position $\mathbf{X}_i$ by learning from its own best search experience ($\mathbf{pBest}_i$) and the swarm's best search experience (**gBest**). The velocity and position update rules are as follows:

$$V_i^d = \omega \times V_i^d + c1 \times \text{rand}_1^d \times (pBest_i^d - X_i^d) + c2 \times \text{rand}_2^d \times (gBest^d - X_i^d) \tag{2.6}$$

$$X_i^d = X_i^d + V_i^d \tag{2.7}$$

Here, ω is the inertia weight, $c1$ and $c2$ are the acceleration coefficients for self-cognitive and social influences respectively, and rand_1^d and rand_2^d are random numbers uniformly distributed over $[0, 1]$. i represents the current particle, and d represents the current dimension.

Liang et al. proposed a PSO variant called Comprehensive Learning PSO (CLPSO), which uses a novel velocity update rule to prevent premature convergence:

$$V_i^d = \omega \times V_i^d + c \times \text{rand}^d \times (pBest_{f_i(d)}^d - X_i^d) \tag{2.8}$$

Here, $f_i(d) \in \{1, 2, \ldots, M\}$ (where M is the population size) determines which particle's $pBest$ the current particle should follow for dimension d. The decision for $f_i(d)$ depends on a probability P_c. If a randomly generated number rand (in the range $[0, 1]$) is larger than P_c, the particle follows its own $pBest$; otherwise, it employs a tournament selection to choose another particle's $pBest$. Experimental results demonstrated that CLPSO performs well on complex multimodal optimization problems. The following flowchart 2.6 illustrates the process of a Particle Swarm Optimization (PSO) algorithm.

2.2.2 Mono-Objetive Discrete Particle Swarm Optimization (DPSO) Algorithm

Mono-objective Particle Swarm Optimization (PSO) is a type of metaheuristic algorithm specifically designed to solve optimization problems with a single objective. Unlike multi-objective optimization, which seeks to optimize multiple conflicting objectives simultaneously, mono-objective PSO focuses on finding the best solution with respect to one objective function.

[MMD10] Discusses the development and implementation of a hybrid algorithm that integrates Particle Swarm Optimization (PSO) with several metaheuristic techniques to effectively solve a mono-objective Vehicle Routing Problem (VRP), it uses the pso algorithm and the following algorithms: Multiple Phase Neighborhood Search-Greedy Randomized Adaptive Search Procedure (MPNS-GRASP) to enhance the generation of initial solutions. Expanding Neighborhood Search (ENS) to improve local search capabilities and path relinking (PR) to intensify the search by exploring trajectories between high-quality solutions.

[SQLL21] Another paper addressing mono-objective PSO focusing on addressing traffic congestion in urban areas using a Particle Swarm Optimization (PSO) algorithm with linearly decreasing weight (LDW-PSO). The main objective of this study is to optimize traffic signal control in real-time to minimize queue length and average waiting time at intersections.

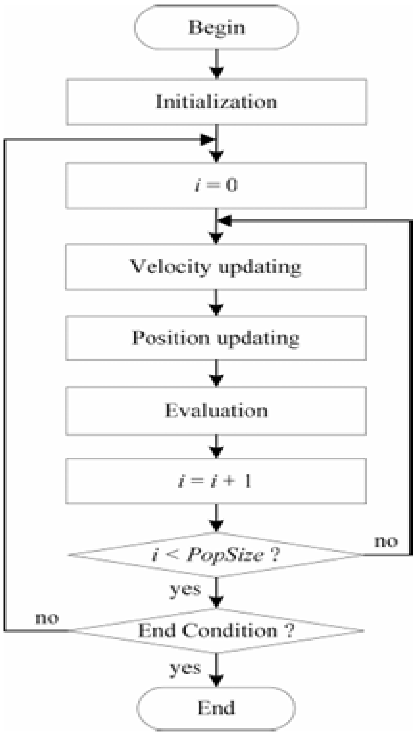

Figure 2.6: Flowchart of PSO algorithms [GZL+11]

The DPSO algorithm is adapted from the standard particle swarm optimization (PSO) algorithm, designed for combinatorial problems by representing particles as discrete job permutations. The key Components of DPSO are the particle representation which means each particle represents a job permutation, and Position Update signifying that the position of a particle is updated using a combination of its current position, personal best position, and global best position, with specific operations (insert, crossover) to generate new permutations.

[PWTZ08] This paper introduces a hybrid discrete particle swarm optimization (HDPSO) algorithm for the no-wait flow shop scheduling problem, focusing on minimizing the makespan. The no-wait flow shop scheduling problem is a critical task in manufacturing systems where jobs must be processed without waiting times between consecutive operations. Traditional PSO is continuous and not directly applicable to combinatorial problems. The paper addresses this by adapting PSO to work in a discrete space, enabling its application to scheduling problems. The proposed HDPSO combines the global exploration capabilities of DPSO with local exploitation through a local search algorithm. This balance ensures effective search and optimization of solutions. Resolution approach:

- Representation and Initialization: The HDPSO uses permutation representation for particles (job sequences) and initializes the population with one particle generated by a heuristic

- Velocity and Position Update: The algorithm updates the position of particles using a combination of personal best (pbest) and global best (gbest) information, adjusted by crossover operators to ensure exploration and exploitation

- Local Search Integration: After updating positions, the algorithm applies a local search to the global best particle to refine solutions further. This local search is based on the insert neighborhood to find locally optimal permutations.

- Annealing-Like Strategy: To maintain diversity in the swarm, an annealing-like strategy is employed for updating personal bests, allowing for probabilistic acceptance of worse solutions early in the iterations to avoid premature convergence

In this algorithm, the position of a particle represents a potential solution to the VRPSPD. Specifically, it is a permutation of the customers that the vehicle needs to visit, and velocity is not a physical quantity but rather a metaphorical one that represents how a particle's position should be updated. In the context of this algorithm, velocity can be understood as the set of operations or transformations that move a particle from its current position to a new position. These operations are based on the differences between the current position, the personal best position, and the global best position.

Another paper that used this discrete method is [PWTZ08] proposes a hybrid approach combining Particle Swarm Optimization (PSO) with Variable Neighborhood Descent (VND) to solve the Vehicle Routing Problem with Simultaneous Pickup and Delivery (VRPSPD). The core resolution approach involves hybridizing PSO with VND. PSO is used for global search to explore the solution space, while VND is used for local search to refine solutions. This combination aims to balance exploration and exploitation in the search process. Solutions are represented as giant tours without trip delimiters. This representation is transformed into feasible routes using a split procedure adapted from Prins (2004) for capacitated VRP. An annealing-like strategy is employed to update the personal best positions of particles to preserve swarm diversity and prevent premature convergence. This strategy allows worse solutions to be selected as personal bests with a probability that decreases over time.

[MA11] presents a real-value version of the Particle Swarm Optimization (PSO) algorithm for solving the Open Vehicle Routing Problem (OVRP). The OVRP is a variant of the traditional Vehicle Routing Problem (VRP) where vehicles do not return to the depot after servicing the last customer. It starts with Swarm Initialization, the algorithm initializes a swarm of particles, where each particle represents a potential solution (route) to the OVRP. Each particle has a position and a velocity in the search space. Also, Initialize Positions and Velocities where particles are given initial random positions and velocities. The personal best position and the global best position are also initialized. The update of velocity is done using the equation (2.6) and (2.7) The third step is: The decoding method, it involves constructing routes by decoding the position vector of each particle into a sequence of customer visits. This process sorts the customers based on their positions and assigns them to routes while ensuring that capacity constraints are not violated. The feasibility of each generated route is then checked to confirm that capacity constraints are met. Additionally, the quality of the solution is further improved using the one-point move method. This technique involves making small adjustments to the routes by moving a customer from its current position and inserting it into another position in the same or a different route if it leads to an improved solution. The following table 2.1 gives a global comparison on the differences between classic and discrete PSO

Explanation This table 2.1 provides a detailed comparison between Classic Particle Swarm Optimization (PSO) and Discrete PSO (DPSO) across various features, highlighting their differences and application areas. Here is an explanation of each feature in the table:

- **Problem Domain** - Classic PSO: Designed for continuous optimization problems where variables are real numbers. - Discrete PSO: Adapted for combinatorial optimization problems where variables are discrete, such as integers or permutations.
- **Particle Representation** - Classic PSO: Uses real-valued vectors to represent the positions of particles in the search space. -Discrete PSO: Uses discrete permuta-

Table 2.1: Comparison between Classic PSO and Discrete PSO

Feature	**Classic PSO**	**Discrete PSO**
Problem Domain	Continuous optimization problems	Combinatorial optimization problems
Particle Representation	Real-valued vectors	Discrete permutations or integer vectors
Velocity Update	Uses real-valued velocity vectors	Uses discrete operations (e.g., swaps, insertions)
Position Update	Adds velocity to position	Applies discrete changes to position
Application Areas	Function optimization, neural network training	Scheduling, routing, assignment problems
Cognitive Component (c1)	Influences particle's own best-known position	Similar concept, but applied to discrete positions
Social Component (c2)	Influences global best-known position	Similar concept, but applied to discrete positions
Update Equations	Velocity: $$V_i^d = \omega V_i^d$$ $+\text{c1} \cdot\text{rand} \cdot (pBest_i^d - X_i^d)$ $+\text{c2} \cdot\text{rand} \cdot (gBest^d - X_i^d)$ Position: $$X_i^d = X_i^d + V_i^d$$	Various, often involves swap, insert, or reordering operations
Convergence Criteria	Reduction in velocity magnitude or improvement in objective value	Similar, but focused on permutation changes and solution quality
Hybridization	Often combined with other continuous optimization techniques	Frequently hybridized with local search and other combinatorial optimization techniques
Examples of Applications	Engineering design, economic modeling, scientific research	Traveling Salesman Problem (TSP), Job Shop Scheduling, Vehicle Routing Problem (VRP)

tions or integer vectors to represent particle positions, suitable for problems like the Traveling Salesman Problem (TSP) or Job Shop Scheduling.

- **Velocity Update** - Classic PSO: Updates velocity using real-valued vectors, which influences the direction and speed of particle movement. - Discrete PSO: Uses discrete operations such as swaps, insertions, or reordering to update velocity.
- **Cognitive Component (c1)** - Classic PSO: Influences a particle's movement based on its own best-known position, guiding it towards previously found good solutions. - Discrete PSO: Similar concept, but applied to discrete positions, guiding particles based on their best-known discrete configurations.
- **Social Component (c2)** - Classic PSO: Influences a particle's movement based on the global best-known position, encouraging collaboration and sharing of good

solutions. - Discrete PSO: Similar concept, applied to discrete positions, fostering collective learning among particles.

- **Update Equations** - Classic PSO: Uses equations involving inertia, cognitive, and social components to update velocities and positions. - Discrete PSO: Employs various update mechanisms often involving swap, insert, or reordering operations to update positions.
- **Convergence Criteria** - Classic PSO: Convergence is often determined by the reduction in velocity magnitude or continuous improvement in the objective value. - Discrete PSO: Similar criteria but focused on permutation changes and the quality of the solution in a discrete space.
- **Hybridization** - Classic PSO: Often combined with other continuous optimization techniques to enhance performance. - Discrete PSO: Frequently hybridized with local search techniques and other combinatorial optimization methods to improve solution quality.

This comparison highlights how Classic PSO and Discrete PSO are tailored to different types of optimization problems, each leveraging specific techniques to handle their respective domains effectively.

Conclusion

In this chapter, we have provided a comprehensive overview of the Vehicle Routing Problem (VRP) and its various extensions, highlighting their significance in logistics and smart waste management. The classic VRP involves optimizing the routes of a fleet of vehicles to minimize total travel cost while meeting specific constraints, such as vehicle capacity and customer demand. We presented the mathematical formulation for the classic VRP, including the objective function and constraints, and discussed how these formulations change for different VRP variants.

We explored several key VRP variants, including the Capacitated VRP (CVRP), VRP with Time Windows (VRPTW), Split Delivery VRP (SDVRP), Dynamic VRP (DVRP), VRP with Pickup and Delivery (VRPPD), and Heterogeneous Fleet VRP (HFVRP). Each variant addresses unique logistical challenges and constraints, emphasizing the need for tailored optimization approaches.

In the context of smart waste management, VRP plays a crucial role in optimizing waste collection and transportation routes. By leveraging Internet of Things (IoT) technologies, smart waste management systems can dynamically adjust routes based on real-time data, enhancing efficiency and reducing costs. Various metaheuristic algorithms, including Genetic Algorithms, Simulated Annealing, Tabu Search, and Hybrid Metaheuristics, have been effectively applied to solve VRP in smart waste management, demonstrating significant improvements in operational efficiency and environmental sustainability.

Furthermore, we delved into the Particle Swarm Optimization (PSO) algorithm, a powerful population-based search technique inspired by the behavior of bird flocking and fish schooling. PSO has shown strong global search capabilities, rapid convergence, and robustness, making it a valuable tool for continuous and combinatorial optimization problems. We provided a detailed comparison between Classic PSO and Discrete PSO (DPSO), highlighting their differences in particle representation, velocity update mechanisms, and application areas.

Chapter 3

A Mono-Objective Vehicle Routing Problem for Waste collection

Introduction

In this chapter, we delve into the Vehicle Routing Problem (VRP), emphasizing the optimization of garbage collection routes. Reverse logistics involves the process of moving goods from their final destination back to the origin for the purpose of proper disposal, recycling, or reuse, making it a critical component of sustainable waste management practices. The primary objective in our study is to minimize the traveling cost of garbage collection vehicles while ensuring compliance with various operational constraints such as vehicle capacities and specified service time windows.

We begin by formulating a mathematical model to represent the VRP in this context. The model incorporates several key parameters: the capacities of vehicles and bins, the unit cost of travel, distances between bins, load times at each bin, and the earliest and latest service times for each bin. The decision variables include whether a vehicle takes a specific route, visits a particular bin, or is chosen for the operation, as well as the order of visits and the instance of arrival at each bin. The primary objective function is designed to minimize the total traveling cost across all routes and vehicles.

To solve this mono-objective optimization problem, we employ a Discrete Particle Swarm Optimization (DPSO) algorithm. DPSO is a heuristic method particularly well-suited for combinatorial optimization problems like VRP. The algorithm's effectiveness relies on the initialization and evolution of particles, which represent potential solutions. Each particle's position is updated through discrete operations such as mutation and crossover, enabling the exploration of new solutions while adhering to constraints like vehicle capacity and time windows.

The chapter provides a detailed description of the DPSO algorithm, including particle construction, mutation, and crossover operations.

We utilize real-world data from the municipality of Tlemcen, Algeria, to test our model. This includes actual distance data, randomly generated bin loads, fixed vehicle capacities, and time windows. The DPSO algorithm is evaluated across multiple scenarios, each with varying numbers of bins and vehicles. Comparative analyses are conducted against solutions obtained from CPLEX, a well-known optimization solver, to assess the performance of DPSO in terms of solution quality and computational efficiency.

3.1 Problem description

3.1.1 General Description

In the context of a circular economy, efficient waste collection is paramount to ensuring sustainable operations and minimizing environmental impact. We have developed a sophisticated vehicle routing model that addresses this need by incorporating capacity constraints and time windows. Specifically, our model focuses on optimizing the routes for waste collection vehicles, which start from a central depot, visit a series of designated waste bins, and return to the depot. The primary objective of this model is to minimize the total distance traveled, factoring in the cost associated with each unit of distance.

The problem is formalized as follows: we have a set of potential waste bins B, where each bin is indexed as B where:{ b = 1, . . . , B } These bins must be serviced by a fleet of vehicles V, where each vehicle is indexed as V: { v = 1, . . . , V } . Each vehicle has a specific load capacity that it cannot exceed, and this capacity varies depending on the vehicle type. The load for each bin is denoted as LB_i representing the amount of waste that needs to be collected from bin i.

3.1.2 Hypothesis

The following model focuses on vehicle routing problem with capacity and time window constraints

- In a smart city, divided into regions, each region has its own depot and set of vehicles V: { v = 1, . . . , V } and bins B:{ b = 1, . . . , B }
- The vehicles assigned to each region are responsible for collecting waste from the bins within that region during specific time windows and transporting the waste back to the region's designated depot.
- Each vehicle in the fleet has a limited capacity, which must be respected in order to ensure efficient and safe waste collection operations.
- The bins are not pre-assigned to specific vehicles, allowing for dynamic routing based on current conditions and constraints.
- The total travel distance incurs a cost proportional to the distance traveled, emphasizing the importance of optimizing routes to minimize operational expenses.

3.1.3 problem formulation

Notations:

$\mathbf{VC}_v$: Vehicle Capacity
$\mathbf{BC}_b$: Bin Capacity
$\mathbf{C}$: Unit Cost of travelling
$\mathbf{D}_{ij}$: Distance travelled from i to j
$\mathbf{LB}_b$: Load of the Bin b
$\mathbf{LV}_v$: Load of the Vehicle v
$\mathbf{E}_i$: Earliest service time of bin b
$\mathbf{F}_i$: Latest service time of bin b
Sp : Fixed value representing the speed of all the vehicles
S : Loading time at each bin

Decision variables:

$$X_{ijv} : \begin{cases} 1 & \text{if Vehicle } v \text{ takes the trajectory from } i \text{ to } j \\ 0 & \text{otherwise} \end{cases}$$

$$Y_{iv} : \begin{cases} 1 & \text{if Bin } i \text{ is visited by vehicle } v \\ 0 & \text{otherwise} \end{cases}$$

$$UV_v : \begin{cases} 1 & \text{if vehicle } v \text{ is chosen} \\ 0 & \text{otherwise} \end{cases}$$

U_b : Order of visits

T_{iv} : Instance of arriving at bin i by vehicle v

Objective function:

$$Z1 = \min\left(\sum_i \sum_j \sum_v C \cdot X_{ijv} \cdot D_{ij}\right) \tag{3.1}$$

The objective function 3.1 aims to minimize the total cost of traveling for all vehicles over all routes chosen, by multiplying the unit cost with the distance between each two bins, if that arc i to j is chosen.

Constraints:

$$\sum_v \sum_j X_{vij} = 1 \quad \forall\, i \neq 1 \tag{3.2}$$

$$\sum_v \sum_i X_{vij} = 1 \quad \forall\, j \neq 1 \tag{3.3}$$

$$\sum_{j \neq 1} X_{v1j} = UV_v \quad \forall\, v \tag{3.4}$$

$$\sum_i \sum_j \sum_v X_{vij}\,(LB_i + LB_j) < VC_v \quad \forall\, b \tag{3.5}$$

$$\sum_j X_{vij} = \sum_j X_{vji} \quad \forall\, v \forall\, i \tag{3.6}$$

$$X_{iiv} = 0 \quad \forall\, v \forall\, i \tag{3.7}$$

$$X_{ijv} \leq UV_v \quad \forall\, v \forall\, i \forall\, j \tag{3.8}$$

$$T_i + S + D_{ij}/SP - T_j \leq M \cdot (1 - X_{ijv}) \quad \forall\, i \forall\, v \forall\, j \neq 1 \tag{3.9}$$

$$E_i \leq T_i \leq F_i \quad \forall\, i \tag{3.10}$$

$$U_j \geq U_i + X_{ijv} - (B-2) \cdot (1 - X_{ijv}) + (B-3) \cdot X_{ijv} \quad \forall\, i \forall\, j \forall\, v \tag{3.11}$$

Equations 3.2 and 3.3 mean that every bin is visited only once in a tour except for the depot, it can be visited more than once since it indicates the beginning and end of the tour. Constraint 3.4 means that the vehicle should only leave the depot once, the sum of the outgoing arcs from the depot of that vehicle v should be 1. 3.5 explains that the sum of the loads in bins i and bins j if the trajectory (i,j) is chosen, does not exceed the capacity of the vehicle v. 3.6 is for preserving flow. 3.7 ensures that there is no trajectory from one bin to itself. 3.8 means if the vehicle visited at least one node, the UV should be equal to 1, meaning the vehicle was chosen. 3.9 calculates the arrival times at each bin, which is the start time at the previous bin plus the traveling time from the bin i to bin j and the loading time S if that trajectory is taken. The second time window constraint 3.10 puts the obligation of arriving at each bin within the time window, respecting the upper and lower bound for each bin. The last constraint 3.11 is to avoid sub-tours.

3.2 Resolution approaches

3.2.1 CPLEX and Gurobi Solvers

This model was tested and solved using IBM ILOG CPLEX OPTIMIZATION STUDIO 12.8.0.0 and Gurobi Solver 11.0.0 integrated in python 3.9 on an i5-11 GEN CPU with 8GB RAM computer.

Discrete Particle Swarm Optimization

DPSO is an adaptation of the traditional Particle Swarm Optimization (PSO) algorithm designed for continuous optimization problems. While PSO operates in a continuous space using real-valued vectors, DPSO operates in a discrete space suitable for combinatorial optimization problems such as the Traveling Salesman Problem (TSP), Vehicle Routing Problem (VRP), job scheduling, and routing problems.

In DPSO, particles represent potential solutions in the form of permutations or discrete sequences rather than continuous values. The concept of velocity and position updates in the traditional PSO is modified to handle discrete operations such as swaps, insertions, and reordering to explore and exploit the search space effectively.

3.2.2 Solution Encoding

Common Encoding Schemes in DPSO:

- **Binary Encoding:** This is used for situations where variables can only be in two distinct states, like boolean "yes/no" decisions or on/off settings. Each element in the solution is represented by a 0 (off/no) or 1 (on/yes).
- **Integer Encoding:** Generally used when variables can take on a specific set of whole numbers. Each element directly corresponds to an integer value representing a choice within the problem.
- **Permutation Encoding:** This is applied to problems where the order of elements is important, like scheduling tasks or finding the shortest route. Here, the solution might be represented as a permutation (unique ordering) of all possible elements.

For our case, we are working with an integer vector encoding, the bins and depot are already presumed located, we have one depot, V vehicles and B bins.

- The Bins are indexed from 1 to B: $b = \{n = 1, \dots, B\}$
- The Vehicles are indexed from 1 to V: $v = \{n = 1, \dots, V\}$

Particle Construction Heuristic

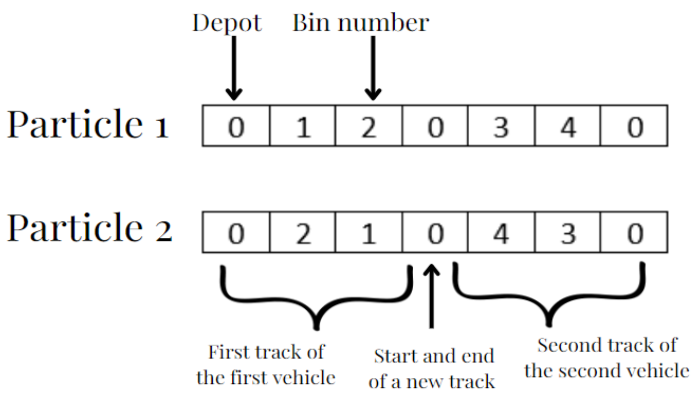

Figure 3.1: Particles Representation

In a discrete particle swarm optimization (DPSO) algorithm for a vehicle routing problem, the initialization and evolution of particles are crucial. For an example with four bins and one depot (B=5) and two vehicles (V=2), we begin by generating an initial population of particles. The figure 3.1 represents a population of two particles. Each particle represents a potential solution to the routing problem.

To construct each particle, we initialize a vector Particle[0] with 0, indicating the depot as the starting point. An empty set, selected indices, is maintained to keep track of the bins already included in the particle, ensuring that no bin is selected more than once.

During the particle construction, random bin indices are generated and added to the particle vector. The corresponding bin index is then moved to the selected indices set. As indices are appended to the particle, the algorithm simultaneously checks if the vehicle's capacity and time window constraints are satisfied. If a constraint is violated, a 0 is inserted into the particle to denote the start of a new route for another vehicle.

The process involves two primary operations: mutation and crossover, enabling the exploration of new potential solutions. This continuous evolution aims to find the optimal routing solution that minimizes travel cost while respecting vehicle capacities and time window constraints.

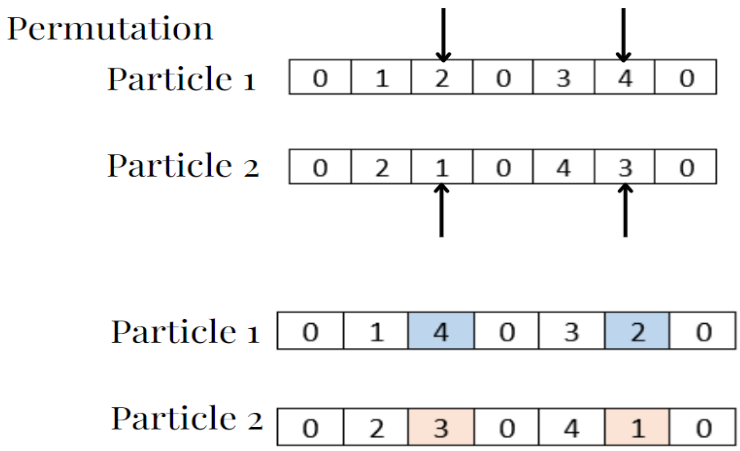

Figure 3.2: Mutation

Mutation

In the context of DPSO, the mutation operation involves creating a new sequence (or mutation) of bin visits that need to be scheduled. This operation is crucial for combinatorial problems where the order in which bins are visited can significantly affect the objective function (total cost).

Initial mutation: each particle represents a potential solution, which is a permutation of bin positions. Velocity and Position Update, unlike continuous PSO, where positions are updated using velocities, in DPSO, particles are updated using discrete operations. The velocity here can be thought of as a set of swap or insertion operations that modify the current position to explore new solutions. The technique used in mutation-based DPSO is the insert operator. It involves selecting a bin from its current position and inserting it into a new position within the particle, thus creating a new sequence.

Crossover Operations

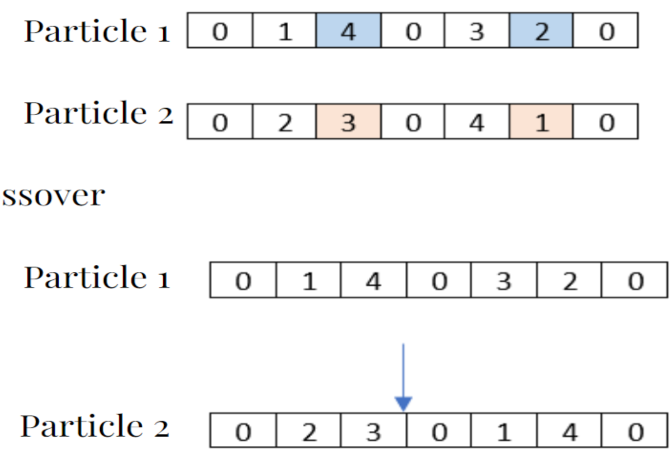

Figure 3.3: Crossover

Crossover operations in DPSO are inspired by genetic algorithms and are used to combine the features of two parent particles (permutations) to create new offspring. The goal is to inherit the best characteristics from both parents, thus generating potentially better solutions.

In this method, two cut points are randomly selected. The segment between these two points from the first parent is preserved, and the remaining positions are filled with bin numbers from the second parent in the order they appear, excluding those already present in the preserved segment.

Given the discrete nature of the problem, the crossover ensures that the offspring are valid permutations without duplicates and include all bin indices exactly once. This is crucial for maintaining the feasibility of solution.

In this case, the crossover operation is performed twice, once with the personal (or local) best and once with the global best.

- **Crossover with Local Best:** Each particle in the swarm has a personal best position (local best) it has achieved during the search process. This local best represents the best solution found by the particle up to that point.
- **Crossover with Global Best:** The global best particle is the best solution found by the entire swarm across all iterations. It represents the most promising solution discovered so far.

The crossover operation in the Discrete Particle Swarm Optimization (DPSO) algorithm proceeds as follows to build the offspring:

1. Select a Random Position in Parent 1: Begin by selecting a random point in the first parent particle. This point will determine how many elements from Parent 1 will be included in the offspring initially.
2. Copy Elements from Parent 1: Copy all elements from Parent 1 up to the randomly selected point into the offspring. This initial segment forms the basis of the offspring.
3. Add Non-Repeated Elements from Parent 2: Next, take Parent 2 (which could represent either the personal best or the global best particle) and sequentially add its elements to the offspring. Ensure that any element from Parent 2 that is added to the offspring does not already exist in it. This step ensures that the offspring contains all unique elements.

By following these steps, the offspring will include an initial segment from Parent 1, followed by non-repeated elements from Parent 2, maintaining the diversity of elements and adhering to the constraints of the problem.

The figure 3.3 explains this operation, if particle 1 is the global best for example, and we chose the position indicated by the arrow, we keep the first elements of the second particle, and fill the rest of it with the other elements from the global best.

3.2.3 DPSO ALGORITHM

The provided figure 3.4 illustrates the flowchart of the Discrete Particle Swarm Optimization (DPSO) algorithm. This DPSO is an adaptation of the traditional Particle Swarm Optimization (PSO) method, tailored for discrete and combinatorial optimization problems.

The algorithm begins with the initialization of parameters such as inertia weight, the number of particles, and the total number of iterations. An initial population of particles is then randomly generated. The fitness of each particle is evaluated based on the objective functions.

The algorithm updates the personal best position for each particle if the current position offers a better fitness value. It also identifies the global best position among all particles in the swarm. Depending on certain conditions, the algorithm performs crossover and

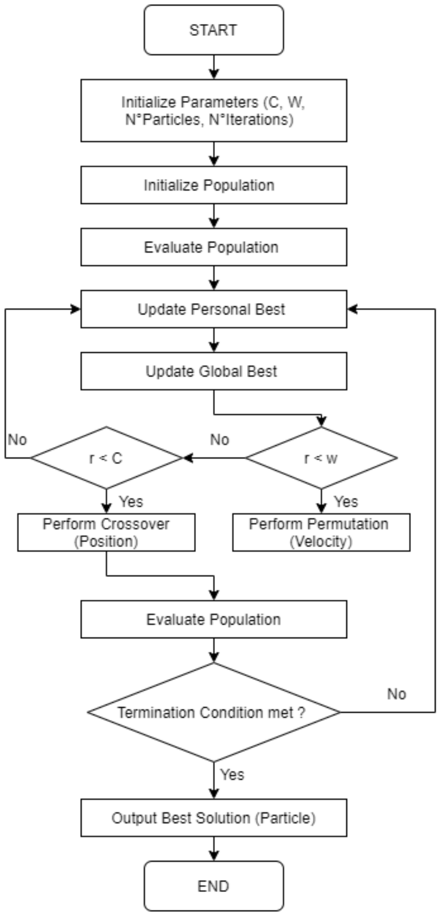

Figure 3.4: Discrete PSO

permutation operations. If a randomly generated number is less than a defined crossover threshold, the crossover operation is executed, combining elements from two parent particles to create offspring, ensuring diversity and potential improvement in solutions. If the random number is less than a permutation threshold, a permutation operation is performed, modifying the sequence of elements within a particle to explore new solutions.

After these operations, the population is re-evaluated for fitness. The algorithm checks if the termination condition, such as reaching a maximum number of iterations or achieving a satisfactory fitness level, is met. If the condition is satisfied, the best solution found by the algorithm is outputted.

3.3 Application

3.3.1 Data

The Distances data used in the proposed model is real data of the municipality of Tlemcen, Algeria from [MBS18]. The Loads of bins were randomly generated between 0 and 0.4 tons, which the maximum bin capacity [ind]. All vehicles have a fixed capacity of 6 tons [isu]. The traveling Cost is a fixed cost of 0.5 euros per meter travelled. The time windows are randomly generated, from 8AM to 12PM for the upper bound and 11AM to 4PM for the lower bound. The speed of vehicles is fixed to 17 meters per second (17 m/s) and the loading time at each bin is 120s (2 minutes)

Algorithm :

Data: C: Cognitive coefficient **W**: Inertia weight **N**: Number of particles **N_iter**: Number of iterations **Population**: Set of particles

```
Result: Best Solution
Function DPSO(C, W, N_particles, N_iterations)
Initialize Particle: Initialize parameters C, W, N_particles , N_iterations
Initialize Population : Initialize a population of particles with random positions and velocities
Evaluate Population: Calculate the fitness of each particle in the population.
While Termination Condition Not met:
  Do
    For each particle:
        Update personal best if the current position is better
        Update global best based on the personal best positions of all particles
    End For
    For each particle:
        If a random number r < W:
            Perform Permutation to update Velocity
            Else if a random number r < C:
                Perform crossover to update position
            End If
        End If
        Update Position based on the new velocity
    End For
    Evaluate the updated population
  End Do
End While
Return Best Solution Found
```

Figure 3.5: DPSO Algorithm inspired from [PWTZ08]

Parameter	**Value**
Distance Data	Real data
Bin Loads	Randomly generated between 0 and 0.4 tons
Vehicle Capacity	6 tons
Traveling Cost	0.5 euros per meter
Time Windows Upper Bound	8AM to 12PM
Time Windows Lower Bound	11AM to 4PM
Vehicle Speed	17 meters per second (17 m/s)
Loading Time at Each Bin	120 seconds (2 minutes)

Table 3.1: Summary of Model Parameters

3.3.2 Scenarios

The model was evaluated and tested through four different scenarios, each characterized with the number of bins and vehicles available. Only one depot is used. The details of the scenarios is summerized as follows:

Scenario	Nb of Bins	Nb of Vehicles
Scenario 01	4	2
Scenario 02	9	3
Scenario 03	14	5
Scenario 04	19	8

Table 3.2: Scenarios

3.3.3 Results

Scenario	**CPLEX**	**DPSO**	**GAP**
Scenario 1	844.3	844.3	0%
Scenario 2	1413.25	1425.71	0.8%
Scenario 3	1820.2	1912.82	4%
Scenario 4	1996.15	2074.64	4.5%

Table 3.3: Comparison of CPLEX and DPSO results with the corresponding GAP values.

Scenario	**CPLEX**	**DPSO**
Scenario 1	0.17s	0.28s
Scenario 2	0.31s	1.6s
Scenario 3	24s	24.6s
Scenario 4	100s	320s

Table 3.4: Comparison of Execution Times for CPLEX and DPSO

Key Observations and Analysis

From the following tables 3.2 and 3.4 we can deduce the following analysis:

Scenario 1:

- The gap 0% indicates that DPSO performed as well as CPLEX, finding an optimal or near-optimal solution.
- DPSO takes slightly longer than CPLEX, but the difference is minimal.

Scenario 2:

- The small gap 0.8% suggests that PSO's solution is very close to that of CPLEX, demonstrating its effectiveness in this scenario.
- PSO takes longer to execute, which might be due to the complexity of operations involved in its heuristic approach.

Scenario 3:

- This moderate gap 4% indicates that while DPSO's solution is not as optimal as CPLEX's, it is still reasonably close, showing DPSO's potential for producing good solutions.
- Both CPLEX and DPSO have similar execution times, indicating that for larger problems, DPSO can achieve comparable execution times to CPLEX

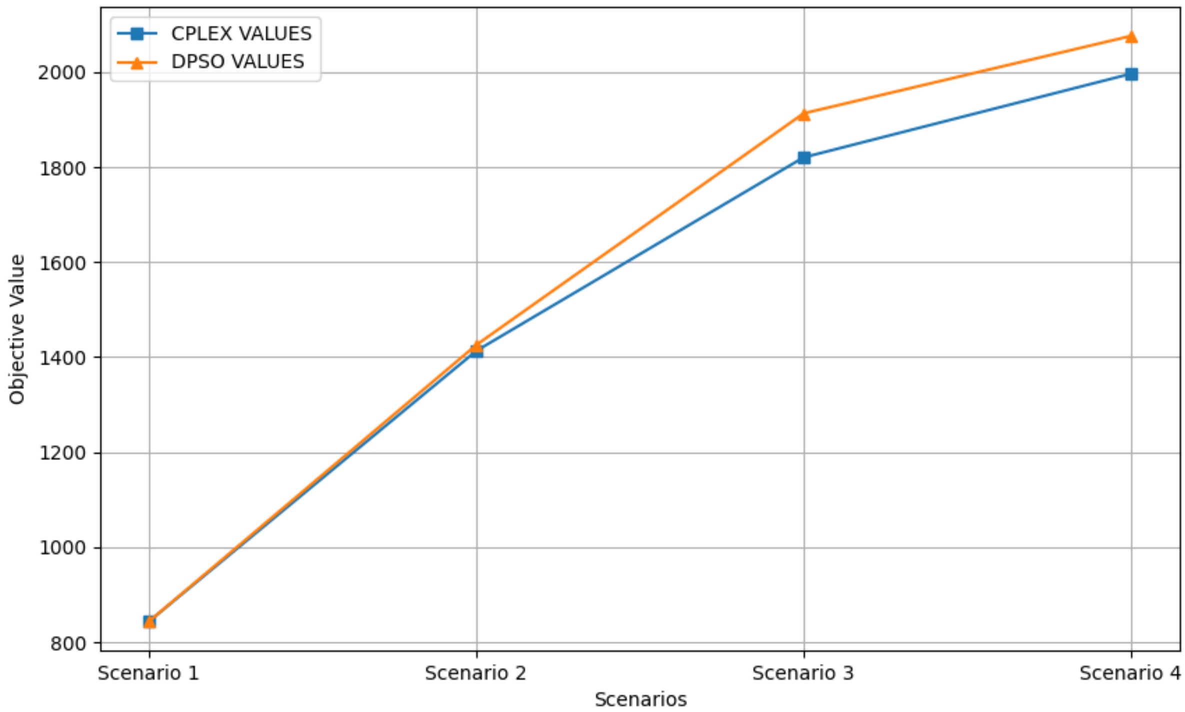

Figure 3.6: Comparison of CPLEX and DPSO results

Scenario 4:

- In Scenario 4, DPSO showed an acceptable gap of 4.5% compared to CPLEX, indicating a difference in solution quality for this more complex scenario.
- The execution time for DPSO was much longer than that of CPLEX, taking more than three times longer to complete. This suggests that as the problem size and complexity increase, DPSO's computational efficiency decreases.

Analysis of the GAP

- The GAP between CPLEX and DPSO results slightly increases with the complexity and size of the scenarios. This suggests that while DPSO is effective for simpler problems, it may struggle to find solutions as close to the optimal ones as CPLEX when the problem complexity increases.
- DPSO is a heuristic method, which means it doesn't guarantee finding the optimal solution but aims for a good approximation within a reasonable time frame.
- the GAP reaches 4.5% in the most complex scenario. DPSO's performance remains within a reasonable range. This demonstrates DPSO's ability to handle complexity effectively, even though it doesn't always match the precision of exact solvers like CPLEX. The results are still practical and useful for large-scale problems where computational resources and time may be limited.

Conclusion

The evaluation of different scenarios revealed several key insights about the performance of the Discrete Particle Swarm Optimization (DPSO) algorithm in solving the Vehicle Routing Problem (VRP) for reverse logistics. In simpler scenarios, DPSO performed similar to CPLEX, managing to find optimal or near-optimal solutions with minimal gaps. This indicates that DPSO is highly effective in less complex situations, providing reliable and accurate solutions comparable to those obtained from an exact optimization method like CPLEX.

However, as the complexity of the problem increased, the gap between DPSO and CPLEX solutions widened, which is totally logical given the increased complexity and variability in the data. The inherent nature of heuristic methods like DPSO, which aim for good approximations within a reasonable time frame rather than guaranteed optimal solutions, contributes to this widening gap. Small differences in distances and other parameters can have a significant impact on the objective function, making it more challenging for DPSO to match the precision of exact solvers like CPLEX in more complex scenarios.

The nature of DPSO allows it to handle larger problems more efficiently in terms of computational time. This is a significant advantage, particularly in applications where exact methods like CPLEX may become impractically slow. By balancing cost minimization with operational efficiency, the DPSO algorithm proves to be a robust optimization framework for sustainable waste management, aligning with the principles of a circular economy. This chapter underscores the applicability and effectiveness of DPSO in addressing the complex challenges of reverse logistics in garbage collection, contributing valuable insights to the field of sustainable logistics and waste management. The increase in computational time and gap as problem complexity grows is a natural consequence of the intricate data and varying distances, further emphasizing the need for heuristic methods in large-scale, real-world applications.

Chapter 4

A Vehicle Routing Problem for Reverse Logistics

Introduction

This chapter delves into the complexities of the Multi-Period Vehicle Routing Problem with time windows (MPVRP-TW), an advanced extension of the traditional Vehicle Routing Problem (VRP). Unlike the standard VRP, which typically addresses a single period, the MPVRP-TW involves planning and optimizing vehicle routes over multiple time periods withing specific time intervals. This problem is highly relevant for real-world applications such as retail distribution, waste collection, and scheduling, where routing decisions span several days or weeks.
We explore the integration of multiple depots and time windows within the MPVRP framework, highlighting the use of advanced optimization techniques such as CPLEX and Gurobi solvers. By analyzing different scenarios and their respective computational results, we aim to demonstrate the increased complexity and computational requirements associated with multi-period routing problems. This chapter also provides insights into how dynamic and variable factors, such as fluctuating bin loads across periods, affect routing efficiency and decision-making.

4.1 Multi-Period Vehicle Routing Problems

The Multi-Period Vehicle Routing Problem (MPVRP) is an extension of the traditional Vehicle Routing Problem (VRP) that involves planning and optimizing vehicle routes over multiple time periods. Unlike the standard VRP, which typically focuses on a single day or period, the MPVRP addresses the need to service customers over a series of days or weeks, incorporating additional temporal constraints and objectives [PKRG21]. The MPVRP is particularly relevant for real-world applications where routing decisions need to be made over extended time horizons, such as in retail distribution, waste collection and scheduling.

[PKRG21] This article primarily focuses on extending the traditional Vehicle Routing Problem (VRP) to a more complex scenario involving multiple depots and multiple periods, referred to as MDMPVRP-TW (Multi-Depot Multi-Period Vehicle Routing Problem with Time Windows). MPVRP is complex due to the additional temporal constraints and the need to consider customer orders over several periods. This problem was solved using The hybrid Tabu Search (TS) and Variable Neighbourhood Search (VNS) algorithm, it is shown to be effective and robust for the MDMPVRP-TW, providing stable and optimal solutions.

[AJS15] This paper dives into the complexities of planning and optimizing vehicle routes over multiple periods, specifically focusing on urban freight distribution. This problem involves a dedicated fleet of vehicles that must serve customer orders originating from a single depot, adhering to specific period and time windows. It proposes two new exact strategies for providing efficient lower bounds to the MPVRPTW. These strategies exploit the special structure of the multi-period problem, and their efficiency is validated against benchmarks used in other approaches.

[WCLL10] Addresses the challenge of optimizing vehicle routes over multiple time periods, with a focus on dynamic and time-sensitive elements. The main aspects to retain include its examination of how customer demands and traffic conditions vary over different periods, requiring adaptive and flexible routing strategies. The study explores the integration of dynamic programming and heuristic methods to efficiently solve the problem, emphasizing the need for real-time decision-making capabilities to handle unexpected changes in demand or traffic conditions.

[Ath11] focuses on the Dynamic Multi-Period Vehicle Routing Problem (DMPVRP), which involves planning and optimizing vehicle routes over multiple periods (days or weeks) while customer orders are dynamically revealed over time. The main objectives are to minimize total travel costs, minimize customer waiting times, and balance daily workloads over the planning horizon.

[ABMS09] This article primarily addresses a dynamic vehicle routing problem where a fleet of uncapacitated vehicles must handle online pick-up requests over a finite time horizon. The focus is on developing strategies to manage requests with deadlines of one or two days, balancing immediate service and postponable requests. Each day, vehicles start from a central depot and must return by day's end, with some requests known beforehand and others arriving throughout the day.

[DCGR15] Develops an advanced optimization method to tackle the complexities of planning vehicle routes over multiple time periods. The Multi-Period Vehicle Routing Problem (MPVRP) involves not only determining efficient daily routes but also considering the interactions and dependencies between these routes across several days or weeks.The authors use the branch and price approach to explore the solution space by creating subproblems and bounding their potential solutions.

The MPVRP research provides a robust foundation for developing innovative and efficient solutions for complex, multi-period routing challenges. The literature highlights its significant complexity and practical relevance in various real-world applications such as urban freight distribution, retail distribution, and waste collection.

4.2 Problem Description

4.2.1 General Description

In the context of multiple-period vehicle routing problem, we will be using the same model as in section 3.1, with addition of the multiple depots parameters.

We have a set of potential waste bins B, where each bin is indexed as B where:{ b = 1, . . . , B } These bins must be serviced by a fleet of vehicles V, where each vehicle is indexed as V: { v = 1, . . . , V }. Each vehicle has a specific load capacity that it cannot exceed, and this capacity varies depending on the vehicle type. The load for each bin is denoted as LB_{ip} representing the amount of waste that needs to be collected from bin i, and we have a set of periods P where:{ p = 1, . . . , P } such that the loads of bins LB_{ip} vary from one period to another.

4.2.2 Hypothesis

The following model focuses on a multi-period vehicle routing problem with capacity and time window constraints fpr a vehicle routing problem in waste collection. The hypothesis are the same as in section 3.1.2 with the following changes

- In a region there is one depot and set of vehicles V: { v = 1, . . . , V } and bins B:{ b = 1, . . . , B } and time periods P:{ p = 1, . . . , P }
- The vehicles are responsible for collecting waste from the bins during specific time windows and transporting the waste back to the region's designated depot in each period.
- Each time period represents a week, waste is collected once a week.
- The loads of the bins vary every week, this is related to how some periods have more waste generation than others.

Notations:

$\mathbf{VC}_v$	: Vehicle Capacity
$\mathbf{BC}_b$	: Bin Capacity
$\mathbf{C}$	: Unit Cost of travelling
$\mathbf{D}_{ij}$	: Distance travelled from i to j
$\mathbf{LB}_{bp}$	: Load of the Bin b in the period p
$\mathbf{LV}_v$	: Load of the Vehicle v
$\mathbf{E}_i$	: Earliest service time of bin b
$\mathbf{F}_i$	: Latest service time of bin b
$\mathbf{Sp}$	: Fixed value representing the speed of all the vehicles
$\mathbf{S}$	: Loading time at each bin

Decision variables:

$$X_{ijvp} : \begin{cases} 1 & \text{if Vehicle } v \text{ takes the trajectory from } i \text{ to } j \text{ in a period } p \\ 0 & \text{otherwise} \end{cases}$$

$$Y_{ivp} : \begin{cases} 1 & \text{if Bin } i \text{ is visited by vehicle } v \text{ in a period } p \\ 0 & \text{otherwise} \end{cases}$$

$$UV_{vp} : \begin{cases} 1 & \text{if vehicle } v \text{ is chosen in a period } p \\ 0 & \text{otherwise} \end{cases}$$

U_{bp} : Order of visits in each period p

T_{ivp} : Instance of arriving at bin i by vehicle v in period p

Objective function:

$$Z1 = \min \left(\sum_i \sum_j \sum_v C \cdot X_{ijvp} \cdot D_{ij} \right) \tag{4.1}$$

The objective function 4.1 aims to minimize the total cost of traveling for all vehicles over all routes chosen, by multiplying the unit cost with the distance between each two bins, if that arc i to j is chosen.

Constraints:

$$\sum_v \sum_j X_{vijp} = 1 \quad \forall\, i \neq 1 \tag{4.2}$$

$$\sum_v \sum_i X_{vijp} = 1 \quad \forall\, j \neq 1 \tag{4.3}$$

$$\sum_{j \neq 1} X_{v1jp} = UV_{vp} \quad \forall\, v \tag{4.4}$$

$$\sum_i \sum_j \sum_v X_{vijp} \left(LB_{ip} \right) < VC_v \quad \forall\, b \tag{4.5}$$

$$\sum_j X_{vijp} = \sum_j X_{vjip} \quad \forall\, v \forall\, i \tag{4.6}$$

$$X_{iivp} = 0 \quad \forall\, v \forall\, i \tag{4.7}$$

$$X_{ijvp} \leq UV_{vp} \quad \forall\, v \forall\, i \forall\, j \tag{4.8}$$

$$T_{ip} + S + D_{ij}/SP - T_{jp} \leq M \cdot (1 - X_{ijvp}) \quad \forall\, i \forall\, v \forall\, j \neq 1 \tag{4.9}$$

$$E_i \leq T_{ip} \leq F_i \quad \forall\, i \tag{4.10}$$

$$U_{jp} \geq U_{ip} + X_{ijvp} - (B-2) \cdot (1 - X_{ijvp}) + (B-3) \cdot X_{ijvp} \quad \forall\, i \forall\, j \forall\, v \tag{4.11}$$

Equations 4.2 and 4.3 mean that for every period, every bin is visited only once in a tour except for the depot, it can be visited more than once since it indicates the beginning and end of the tour. Constraint 4.4 means that the vehicle should only leave the depot once in a period, the sum of the outgoing arcs from the depot of that vehicle v should be 1. 4.5 Explains that the sum of the loads in bins i and bins j if the trajectory (i,j) is chosen, does not exceed the capacity of the vehicle v. 4.6 Is for preserved flow. 4.7 ensures that there is no trajectory from one bin to itself. 4.8 Means if the vehicle visited at least one node in a period, the UV should be equal to 1, meaning the vehicle was chosen. 4.9 Calculates the arrival times at each bin in a time period, which is the start time at the previous bin plus the traveling time from the bin i to bin j and the loading time S if that trajectory is taken. The second time window constraint 4.10 puts the obligation of arriving at each bin within the time window, respecting the upper and lower bound for each bin. The last constraint 4.11 is to avoid sub-tours.

4.3 Resolution approaches

4.3.1 CPLEX and Gurobi Solvers

This model was tested and solved using IBM ILOG CPLEX OPTIMIZATION STUDIO 12.8.0.0 on an i5-11 GEN CPU with 8GB RAM computer.

4.4 Application

4.4.1 Data

The Distances data used in the proposed model is real data of the municipality of Tlemcen, Algeria from [MBS18]. The Loads of bins depend on the period, for each period they were randomly generated between 0 to 2 tons, a little more than bin capacity [ind], indicating overflows. The number of periods is set to 5 periods. All vehicles have a fixed capacity of 6 tons [isu]. The traveling Cost is a fixed cost of 0.5 euros per meter travelled. The time windows are randomly generated, from 8AM to 12PM for the upper bound and 11AM to 4PM for the lower bound. The speed of vehicles is fixed to 17 meters per second (17 m/s) and the loading time at each bin is 120s (2 minutes) , The difference however is the Loads that will start depending on the period. Each period has different loads, the Loads are generated randomly from 0 to 2, a little more than bin capacity, indicating overflows.

Parameter	**Value**
Distance Data	Real data
Bin Loads	Randomly generated between 0 and 2 tons
Periods	5 periods
Vehicle Capacity	6 tons
Traveling Cost	0.5 euros per meter
Time Windows Upper Bound	8AM to 12PM
Time Windows Lower Bound	11AM to 4PM
Vehicle Speed	17 meters per second (17 m/s)
Loading Time at Each Bin	120 seconds (2 minutes)

Table 4.1: Summary of Model Parameters

4.4.2 Scenarios and Results

After running the model on Cplex with different instances, these are the results we obtained:

Scenario	**CPLEX**	**Execution time**	**Number of bins**
Scenario 1	4553.8	0.18s	4
Scenario 2	7558.2	6s	9
Scenario 3	9988.35	4440s	14

Table 4.2: Multi-Period Cplex Results

The table 4.2 presents the results of running the multi-period model using CPLEX across three different scenarios, each involving multiple time periods. The first scenario, which includes 4 bins, completed in 0.18 seconds. The second scenario, with 9 bins,

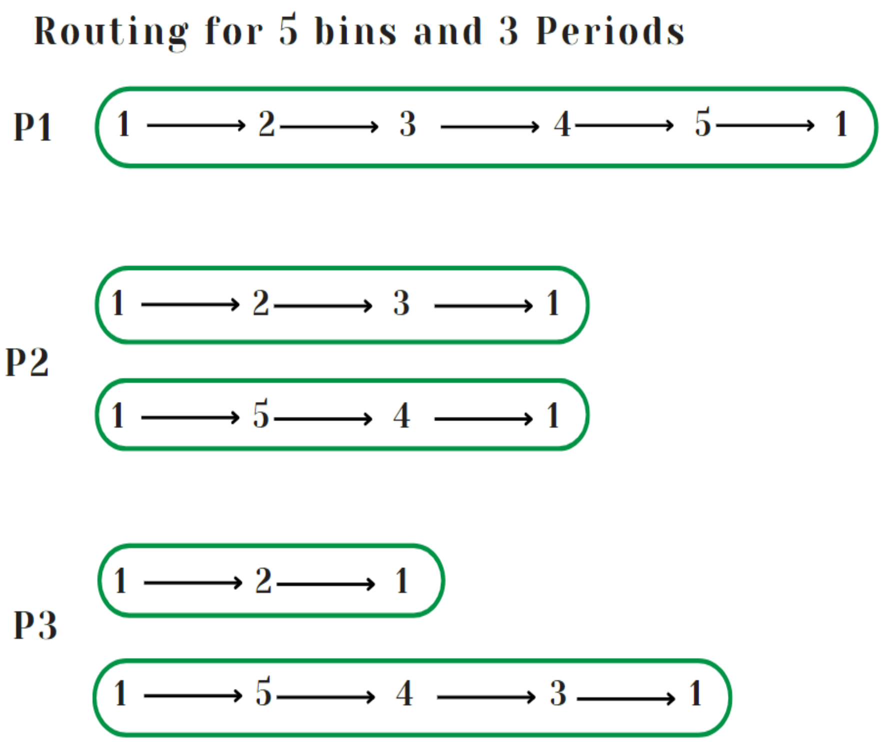

Figure 4.1: Multi-period Routes

required 6 seconds to run. The third scenario, involving 14 bins, reached the computational limit, running for 4440 seconds with a gap of 36.42%. These results illustrate the increasing computational complexity and execution time as the number of bins increases.

The figure 4.1 presents the routing solution of CPLEX using as an example 5 nodes and 3 periods. the differences of the routes depend on the changes of the loads over the time periods. The models tries to find the optimal solution for each period with its associated loads.

The multi-period vehicle routing problem with time windows is an extremely complex issue, demanding significant computational time and rigorous calculations. This problem model was tested to reflect a more realistic approach to real-life waste management operations. In practice, bin loads fluctuate over different time periods, leading to varying routing requirements. Thus, this model aids in predicting optimal routes based on estimated bin loads, providing a practical solution for dynamic waste collection scenarios.

Conclusion

In conclusion, this chapter has delved into the complexities of the Multi-Period Vehicle Routing Problem with Time Windows (MPVRP-TW), underscoring its complexity and relevance to real-world applications. By extending the traditional VRP to handle multiple periods, we introduced additional temporal constraints and objectives, thereby illustrating the challenge of optimizing vehicle routes over extended time horizons. The results obtained from running the multi-period model using CPLEX across various scenarios highlight the escalating computational complexity with an increasing number of bins. Specifically, smaller instances with 4 and 9 bins were completed in relatively short times (0.18 seconds and 6 seconds, respectively), while the model reached its computational limit with 14 bins, running for 4440 seconds and stopping with a significant gap of

36.42%. These findings emphasize the limitations of exact solvers like CPLEX in handling larger instances of MPVRP, pointing to the necessity for more efficient or heuristic-based approaches to tackle such complex problems effectively. Additionally, the dynamic nature of bin loads across periods adds another layer of complexity to routing decisions, reinforcing the need for advanced optimization techniques to achieve practical and near-optimal solutions. This model, by accommodating the variability in bin loads and routing requirements, provides a more realistic and practical approach to waste management in real-life scenarios.

General Conclusion

This thesis has thoroughly explored the transformative potential of integrating circular economy principles with advanced technological innovations to enhance waste management practices. Through a comprehensive examination of the Vehicle Routing Problem (VRP) and its various extensions, we have demonstrated how these combined approaches can lead to more sustainable, efficient, and economically viable waste management solutions.

We began with an in-depth discussion of the circular economy, emphasizing the shift from a linear model of resource consumption to a circular paradigm. This transition is crucial due to growing concerns about environmental degradation and resource scarcity. Circular economy principles, which focus on regeneration and circular flows, provide a holistic framework for rethinking how goods are produced, consumed, and disposed of. By prioritizing sustainable sourcing, recyclable product design, and efficient production processes, businesses and communities can significantly reduce waste generation, conserve resources, and mitigate environmental impact.

Advances in Internet of Things (IoT) technology have played a pivotal role in revolutionizing waste management practices. IoT-enabled smart waste management systems, equipped with sensors, GPS tracking, and central monitoring, allow for real-time data collection, analysis, and decision-making. These systems optimize waste collection routes, enhance operational efficiency, and minimize costs. The literature review highlighted the increasing number of studies focusing on the integration of circular economy principles, waste management, and Industry 4.0 technologies. This interdisciplinary approach underscores the importance of collaboration in advancing our understanding and implementation of sustainable waste management practices.

Building on this foundation, we delved into the VRP and its various extensions, highlighting their significance in logistics and smart waste management. We presented the mathematical formulation for the classic VRP and discussed how these formulations adapt for different VRP variants, each addressing unique logistical challenges and constraints.

In the context of smart waste management, VRP is crucial for optimizing waste collection and transportation routes. By leveraging IoT technologies, smart waste management systems can dynamically adjust routes based on real-time data, enhancing efficiency and reducing costs. Various metaheuristic algorithms, including Genetic Algorithms, Simulated Annealing, Tabu Search, and Hybrid Metaheuristics, have been effectively applied to solve VRP in smart waste management, demonstrating significant improvements in operational efficiency and environmental sustainability.

We also tackled the evaluation of the Discrete Particle Swarm Optimization (DPSO) algorithm for solving the VRP in reverse logistics. DPSO presents a valuable tool for scenarios that require quick, good approximations rather than exact solutions. By balancing cost minimization with operational efficiency, the DPSO algorithm proves to be a robust optimization framework for sustainable waste management, aligning with the principles of a circular economy.

In conclusion, this thesis underscores the transformative potential of combining circular economy principles with technological innovation and advanced optimization algorithms to address the complex challenges of waste management. The insights gained from this research contribute valuable knowledge to the field of sustainable logistics and waste management, offering a pathway toward a more resilient, resource-efficient, and environmentally sustainable future.

Bibliography

[ABMS09] Enrico Angelelli, Nicola Bianchessi, Renata Mansini, and Maria G Speranza. Short term strategies for a dynamic multi-period routing problem. *Transportation Research Part C: Emerging Technologies*, 17(2):106–119, 2009.

[AHB15] Mahmuda Akhtar, MA Hannan, and Hassan Basri. Particle swarm optimization modeling for solid waste collection problem with constraints. In *2015 IEEE 3rd International Conference on Smart Instrumentation, Measurement and Applications (ICSIMA)*, pages 1–4. IEEE, 2015.

[AJS15] Claudia Archetti, Ola Jabali, and M Grazia Speranza. Multi-period vehicle routing problem with due dates. *Computers & Operations Research*, 61:122–134, 2015.

[Alm13] Samira Almoustafa. *Distance-constrained vehicle routing problem: exact and approximate solution (mathematical programming)*. PhD thesis, Brunel University, School of Information Systems, Computing and Mathematics, 2013.

[Ath11] Theodore Athanasopoulos. *The multi-period vehicle routing problem and its applications*. PhD thesis, PhD thesis, Department of Financial & Management Engineering, University of ..., 2011.

[BG05] Olli Bräysy and Michel Gendreau. Vehicle routing problem with time windows, part ii: Metaheuristics. *Transportation science*, 39(1):119–139, 2005.

[BGS+22] Asmit Roy Burman, Anurupa Goswami, Hitesh Sharma, et al. Smart waste management system using gis paired with iot-based smart waste collection bins. In *2022 International Conference on Smart and Sustainable Technologies in Energy and Power Sectors (SSTEPS)*, pages 229–232. IEEE, 2022.

[BM10] Gro Harlem Brundtland and K Mansour. World commission on environment and development (wced). 1987. *Our common future*, page 2010, 2010.

[BPCG22] Meletios Bimpizas-Pinis, Tommaso Calzolari, and Andrea Genovese. Exploring the transition towards circular supply chains through the arcs of integration. *International Journal of Production Economics*, 250:108666, 2022.

[BR15] Jacqueline Maria Bloemhof-Ruwaard. *Sustainable Logistics Management: from castle on the cloud to cathedral*. Wageningen University, Wageningen UR, 2015.

[CGB21] Tommaso Calzolari, Andrea Genovese, and Andrew Brint. The adoption of circular economy practices in supply chains–an assessment of european multi-national enterprises. *Journal of Cleaner Production*, 312:127616, 2021.

[CGB22] Tommaso Calzolari, Andrea Genovese, and Andrew Brint. Circular economy indicators for supply chains: A systematic literature review. *Environmental and Sustainability Indicators*, 13:100160, 2022.

[Chr16] Martin Christopher. *Logistics and Supply Chain Management: Logistics & Supply Chain Management*. Pearson UK, 2016.

[Cle] Cleantech Group. Smart waste collection.

[DCGR15] Iman Dayarian, Teodor Gabriel Crainic, Michel Gendreau, and Walter Rei. A branch-and-price approach for a multi-period vehicle routing problem. *Computers & Operations Research*, 55:167–184, 2015.

[DGCMF21] Manlio Del Giudice, Roberto Chierici, Alice Mazzucchelli, and Fabio Fiano. Supply chain management in the era of circular economy: the moderating effect of big data. *The International Journal of Logistics Management*, 32(2):337–356, 2021.

[DLK+19] Subhasish Das, S-H Lee, Pawan Kumar, Ki-Hyun Kim, Sang Soo Lee, and Satya Sundar Bhattacharya. Solid waste management: Scope and the challenge of sustainability. *Journal of cleaner production*, 228:658–678, 2019.

[Ear] Earth.org. Smart waste management.

[Enc] Encyclopædia Britannica. Solid waste management - solid waste collection.

[FA19] Javier Ferrer and Enrique Alba. Bin-ct: Urban waste collection based on predicting the container fill level. *Biosystems*, 186:103962, 2019.

[GAFK17] Andrea Genovese, Adolf A Acquaye, Alejandro Figueroa, and SC Lenny Koh. Sustainable supply chain management and the transition towards a circular economy: Evidence and some applications. *Omega*, 66:344–357, 2017.

[GB20] Rajeev Kr Goel and Sandhya Rani Bansal. Hybrid algorithms for rich vehicle routing problems: a survey. In *Smart delivery systems*, pages 157–184. Elsevier, 2020.

[GCT22] Michael J. Gawrysiak, James R. Carl, and Brett W. Tuckman. Examining the effects of mindfulness-based interventions on psychological well-being in university students: A meta-analysis. *Frontiers in Psychology*, 13:866361, 2022.

[GF13] Elena Giovannoni and Giacomo Fabietti. What is sustainability? a review of the concept and its applications. *Integrated reporting: Concepts and cases that redefine corporate accountability*, pages 21–40, 2013.

[GKKP20] Sotiris P Gayialis, Grigorios D Konstantakopoulos, EP Kechagias, and GA Papadopoulos. An advanced transportation system based on internet of things. In *Proceedings of the 10th Annual International Conference on Industrial Engineering and Operations Management (IEOM 2020), Dubai, United Arab Emirates*, pages 10–12, 2020.

[GL16] Delphine Gallaud and Blandine Laperche. *Circular economy, industrial ecology and short supply chain*, volume 4. John Wiley & Sons, 2016.

[GSBH17] Martin Geissdoerfer, Paulo Savaget, Nancy MP Bocken, and Erik Jan Hultink. The circular economy–a new sustainability paradigm? *Journal of cleaner production*, 143:757–768, 2017.

[GZL+11] Yue-Jiao Gong, Jun Zhang, Ou Liu, Rui-Zhang Huang, Henry Shu-Hung Chung, and Yu-Hui Shi. Optimizing the vehicle routing problem with time windows: A discrete particle swarm optimization approach. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 42(2):254–267, 2011.

[HAB+18] MA Hannan, Mahmuda Akhtar, RA Begum, H Basri, A Hussain, and Edgar Scavino. Capacitated vehicle-routing problem model for scheduled solid waste collection and route optimization using pso algorithm. *Waste management*, 71:31–41, 2018.

[HAMR+23] Omid Hashemi-Amiri, Mostafa Mohammadi, Golman Rahmanifar, Mostafa Hajiaghaei-Keshteli, Gaetano Fusco, and Chiara Colombaroni. An allocation-routing optimization model for integrated solid waste management. *Expert Systems with Applications*, 227:120364, 2023.

[Hau] Haulla.com. 9 innovative waste management technologies.

[HCS21] Jun-Ho Huh, Jae-Hyeon Choi, and Kyungryong Seo. Smart trash bin model design and future for smart city. *Applied sciences*, 11(11):4810, 2021.

[ind] 1400 l wheeled dustbin. https://www.indiamart.com/proddetail/1400-l-wheeled-dustbin-21314090091.html. Accessed: 2024-05-28.

[isu] Isuzu 6 ton small light garbage compactor truck. https://www.isuzuvehicles.com/product/isuzu-6-ton-small-light-garbage-compactor-truck/. Accessed: 2024-05-28.

[JARBP22] Diana Jorge, António Pais Antunes, Tânia Rodrigues Pereira Ramos, and Ana Paula Barbosa-Póvoa. A hybrid metaheuristic for smart waste collection problems with workload concerns. *Computers & Operations Research*, 137:105518, 2022.

[Kay23] Serkan Kaya. A hybrid firefly and particle swarm optimization algorithm with local search for the problem of municipal solid waste collection: a real-life example. *Neural Computing and Applications*, 35(9):7107–7124, 2023.

[KF10] Tom Kuhlman and John Farrington. What is sustainability? *Sustainability*, 2(11):3436–3448, 2010.

[KRH17] Julian Kirchherr, Denise Reike, and Marko Hekkert. Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, conservation and recycling*, 127:221–232, 2017.

[Lap92] Gilbert Laporte. The vehicle routing problem: An overview of exact and approximate algorithms. *European journal of operational research*, 59(3):345–358, 1992.

[LE10] David A Lubin and Daniel C Esty. The sustainability imperative. *Harvard business review*, 88(5):42–50, 2010.

[Lin] Link Labs. Top 5 reasons to use smart waste management.

[LLE04] Jens Lysgaard, Adam N Letchford, and Richard W Eglese. A new branch-and-cut algorithm for the capacitated vehicle routing problem. *Mathematical programming*, 100:423–445, 2004.

[LSB+17] Peter Lee, Edward Sims, Olivia Bertham, Harry Symington, Nia Bell, Lucie Pfaltzgraff, Pernilla Sjögren, Henning Wilts, and Meghan O'Brien. *Towards a circular economy: waste management in the EU; study*. Europ. Union, 2017.

[MA11] SA MirHassani and N Abolghasemi. A particle swarm optimization algorithm for open vehicle routing problem. *Expert Systems with Applications*, 38(9):11547–11551, 2011.

[MBS18] Khalid Mekamcha, Mohamed Bennekrouf, and Mehdi Souier. Improvement of the municipal waste collection: the real case of city center of tlemcen, algeria. In *2018 International Colloquium on Logistics and Supply Chain Management (LOGISTIQUA)*, pages 140–145. IEEE, 2018.

[MGS21] Azar MahmoumGonbadi, Andrea Genovese, and Antonino Sgalambro. Closed-loop supply chain design for the transition towards a circular economy: A systematic literature review of methods, applications and current gaps. *Journal of Cleaner Production*, 323:129101, 2021.

[MHG23] Seyedsahand Mousavi, Ali Hosseinzadeh, and Abooali Golzary. Challenges, recent development, and opportunities of smart waste collection: A review. *Science of The Total Environment*, page 163925, 2023.

[MKA] MKAI. The role of iot in advancing circular economy models.

[MMD10] Yannis Marinakis, Magdalene Marinaki, and Georgios Dounias. A hybrid particle swarm optimization algorithm for the vehicle routing problem. *Engineering Applications of Artificial Intelligence*, 23(4):463–472, 2010.

[MN20] Antonis Mavropoulos and Anders Waage Nilsen. *Industry 4.0 and circular economy: Towards a wasteless future or a wasteful planet?* John Wiley & Sons, 2020.

[PKRG21] Arjun Paul, Ravi Shankar Kumar, Chayanika Rout, and Adrijit Goswami. Designing a multi-depot multi-period vehicle routing problem with time window: hybridization of tabu search and variable neighbourhood search algorithm. *Sādhanā*, 46(3):183, 2021.

[PLA] PLAEX. How is waste collected and where is it taken?

[PMP19] Marina PP Pieroni, Tim C McAloone, and Daniela CA Pigosso. Business model innovation for circular economy and sustainability: A review of approaches. *Journal of cleaner production*, 215:198–216, 2019.

[PRD+20] Kellow Pardini, Joel JPC Rodrigues, Ousmane Diallo, Ashok Kumar Das, Victor Hugo C de Albuquerque, and Sergei A Kozlov. A smart waste management solution geared towards citizens. *Sensors*, 20(8):2380, 2020.

[PWK16] Harilaos N Psaraftis, Min Wen, and Christos A Kontovas. Dynamic vehicle routing problems: Three decades and counting. *Networks*, 67(1):3–31, 2016.

[PWTZ08] Quan-Ke Pan, Ling Wang, M Fatih Tasgetiren, and Bao-Hua Zhao. A hybrid discrete particle swarm optimization algorithm for the no-wait flow shop scheduling problem with makespan criterion. *The International Journal of Advanced Manufacturing Technology*, 38:337–347, 2008.

[RdMBP18] Tania Rodrigues Pereira Ramos, Carolina Soares de Morais, and Ana Paula Barbosa-Povoa. The smart waste collection routing problem: Alternative operational management approaches. *Expert Systems with Applications*, 103:146–158, 2018.

[REC15] Karen Rose, Scott Eldridge, and Lyman Chapin. The internet of things: An overview. *The internet society (ISOC)*, 80(15):1–53, 2015.

[RIKA19] Md. Abdur Rahman, Md. Saiful Islam, Humaun Kabir, and Mohiuddin Ahmad. A comprehensive study on internet of things (IoT) towards 5G wireless systems. *Journal of Big Data*, 6(1):1–33, 2019.

[RMKM22] Arindam Roy, Apurba Manna, Jungmin Kim, and Ilkyeong Moon. Iot-based smart bin allocation and vehicle routing in solid waste management: A case study in south korea. *Computers & Industrial Engineering*, 171:108457, 2022.

[RSR+22] Abderahman Rejeb, Zailani Suhaiza, Karim Rejeb, Stefan Seuring, and Horst Treiblmaier. The internet of things and the circular economy: A systematic literature review and research agenda. *Journal of Cleaner Production*, 350:131439, 2022.

[SAAHK+22] Amirhossein Salehi-Amiri, Navid Akbapour, Mostafa Hajiaghaei-Keshteli, Yuvraj Gajpal, and Armin Jabbarzadeh. Designing an effective two-stage, sustainable, and iot based waste management system. *Renewable and Sustainable Energy Reviews*, 157:112031, 2022.

[Sar19] Joseph Sarkis. The handbook on the sustainable supply chain: An introduction. In *Handbook on the sustainable supply chain*, pages 1–10. Edward Elgar Publishing, 2019.

[Sma] SmartRoutes. Route optimization for solid waste collection.

[SQLL21] Yanjun Shi, Yuhan Qi, Lingling Lv, and Donglin Liang. A particle swarm optimisation with linearly decreasing weight for real-time traffic signal control. *Machines*, 9(11):280, 2021.

[SUPP24] Sidhartha Sondh, Darshit S Upadhyay, Sanjay Patel, and Rajesh N Patel. Strategic approach towards sustainability by promoting circular economy-based municipal solid waste management system-a review. *Sustainable Chemistry and Pharmacy*, 37:101337, 2024.

[SZ18] Joseph Sarkis and Qingyun Zhu. Environmental sustainability and production: taking the road less travelled. *International Journal of Production Research*, 56(1-2):743–759, 2018.

[Vel23] Rafael A. Vela. Circular economy and supply chain management: Circular scm, a sustainable pathway for the future, 2023.

[WCLL10] Min Wen, Jean-François Cordeau, Gilbert Laporte, and Jesper Larsen. The dynamic multi-period vehicle routing problem. *Computers & Operations Research*, 37(9):1615–1623, 2010.

[WHG01] Adrian Wilkinson, Malcolm Hill, and Paul Gollan. The sustainability debate. *International Journal of Operations & Production Management*, 21(12):1492–1502, 2001.

[WKD17] Kiara Winans, Alissa Kendall, and Hui Deng. The history and current applications of the circular economy concept. *Renewable and Sustainable Energy Reviews*, 68:825–833, 2017.

[WTY20] Hailin Wu, Fengming Tao, and Bo Yang. Optimization of vehicle routing for waste collection and transportation. *International Journal of Environmental Research and Public Health*, 17(14):4963, 2020.

[ZGYT22] Haifei Zhang, Hongwei Ge, Jinlong Yang, and Yubing Tong. Review of vehicle routing problems: Models, classification and solving algorithms. *Archives of Computational Methods in Engineering*, pages 1–27, 2022.

[Zir08] Mourad Zirour. Vehicle routing problem: models and solutions. *Journal of Quality Measurement and Analysis JQMA*, 4(1):205–218, 2008.

[ZVL+19] Abraham Zhang, Venkatasmany G Venkatesh, Yang Liu, Ming Wan, Ting Qu, and Donald Huisingh. Barriers to smart waste management for a circular economy in china. *Journal of Cleaner Production*, 240:118198, 2019.