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A Sustainable Bi-objective Vehicle Routing Problem in Waste Collection

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Contents

Abstract

Sustainability and emissions reduction are paramount in modern waste management. This thesis explores the integration of circular economy principles with advanced optimization techniques to enhance resource efficiency and minimize environmental impact. By focusing on Multi-objective vehicle routing problems (VRP) and employing the optimization algorithm of Non-dominated Sorting Genetic Algorithm II (NSGA-II) for Bi-objective models. the research aims to optimize travel costs and CO2 emissions. The study demonstrates significant improvements in operational efficiency and sustainability, highlighting NSGA-II's effectiveness in providing near-optimal solutions for complex, large-scale optimization challenges.

Key words: Circular Economy, Waste management, CO2 EMissions, Bi-objective Vehicle Routing Problem, Non-dominated Sorting Genetic Algorithm II (NSGA-II).

Abstrait

La durabilité et la réduction des émissions sont primordiales dans la gestion moderne des déchets. Cette thèse explore l'intégration des principes de l'économie circulaire avec des techniques d'optimisation avancées pour améliorer l'efficacité des ressources et minimiser l'impact environnemental. En se concentrant sur les problèmes de routage de véhicules multi-objectifs (VRP) et en utilisant l'algorithme d'optimisation de l'algorithme de tri génétique non dominé II (NSGA-II) pour les modèles bi-objectifs. la recherche vise à optimiser les coûts de déplacement et les émissions de CO2. L'étude démontre des améliorations significatives de l'efficacité opérationnelle et de la durabilité, soulignant l'efficacité de NSGA-II à fournir des solutions presque optimales pour les défis d'optimisation complexes à grande échelle.

Mots clés: Economie circulaire, Gestion des déchets, CO2 EMissions, Problème de routage de véhicule bi-objectif, Algorithme génétique de tri non dominé II (NSGA-II).

تلخيص

تعتبر الاستدامة وخفض الانبعاثات أمرًا بالغ الأهمية في إدارة النفايات الحديثة. تستكشف هذه الأطروحة دمج مبادئ الاقتصاد الدائري مع تقنيات التحسين المتقدمة لتعزيز كفاءة الموارد وتقليل الأثر البيئي. من خلال التركيز على مشاكل توجيه المركبات متعددة الأهداف (VRP) واستخدام خوارزمية التحسين لخوارزمية الفرز الجيني الثانية غير المهيمنة (NSGA-II) للنماذج ثنائية الهدف. ويهدف البحث إلى تحسين تكاليف السفر وانبعاثات ثاني أكسيد الكربون. توضح الدراسة تحسينات كبيرة في الكفاءة التشغيلية والاستدامة، وتسلط الضوء على فعالية NSGA-II في توفير حلول شبه مثالية لتحديات التحسين المعقدة والواسعة النطاق.

الكلمات المفتاحية: الاقتصاد الدائري، إدارة النفايات، انبعاثات ثاني أكسيد الكربون، مشكلة توجيه المركبات ثنائية الهدف، الخوارزمية الوراثية غير المهيمنة للفرز الثاني (NSGA-II) .

List of abbreviations

CE	: Circular Economy
IOT	: Internet of things
GPS	: Global positioning system
SWM	: Smart waste management
AI	: Artificial intelligence
NSGA-II	: Non-dominated Sorting Genetic Algorithm
VRP	: Vehicle routing problem
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
MOPSO	: Multi-Objective Particle Swarm Optimization
MOGA	: Multi-Objective PGenetic Algorithm

Introduction

This thesis aims to contribute to the body of knowledge on sustainable optimization techniques, offering insights and solutions that can support the transition towards more sustainable and efficient systems in waste management.

In recent years, the pursuit of sustainable development has gained a significant interest in innovative approaches to managing resources and reducing environmental impacts. This thesis explores three interrelated areas: the circular economy, vehicle routing problems (VRP), and multi-objective optimization, with a focus on advanced algorithms like the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and the Gurobi solver.

The concept of the circular economy (CE) has emerged as a transformative strategy to address environmental challenges by promoting resource efficiency and sustainability. Unlike the traditional linear model of resource use, which follows a "take, make, dispose" approach, the circular economy emphasizes regenerative and cyclical flows, extending the products lifecycles and minimizing waste. The first chapter delves into the principles of the circular economy, studying how its integration with modern technologies, such as the Internet of Things (IoT) and smart waste management systems, can revolutionize waste management practices. By leveraging IoT-enabled devices and data analytics, cities and organizations can optimize waste collection, disposal, and recycling processes, thereby enhancing operational efficiency and reducing environmental impacts.

Central to logistics and transportation management is the Vehicle Routing Problem (VRP), a complex combinatorial optimization challenge that involves determining the most efficient routes for a fleet of vehicles to service a set of nodes. Chapter two provides a comprehensive overview of various solution methods for VRP. The integration of IoT in smart waste management systems is also explored, highlighting how advanced optimization techniques like metaheuristics utilization such as NSGA-II can enhance operational efficiency and sustainability.

For the last chapter, in addressing vehicle routing problems with multiple objectives, this thesis presents a bi-objective optimization model aimed at minimizing total travel costs and CO_2 emissions. The model employs advanced optimization techniques, including the Gurobi solver and NSGA-II, to navigate the complex landscape of VRP under various scenarios. These scenarios reflect real-world conditions and constraints such as vehicle capacities, bin loads, travel costs, distances, and time windows. The thesis provides a detailed description of the problem formulation, solution encoding methods, and the implementation of optimization algorithms.

The results section evaluates the performance of the proposed model across different scenarios, comparing the effectiveness and computational efficiency of Gurobi and NSGA-II. The findings demonstrate NSGA-II's capability to provide near-optimal solutions with small gaps compared to the optimal solutions obtained using Gurobi, making it a viable alternative for large-scale and complex optimization problems.

Through the exploration of these interconnected themes,

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. This section explores the integration of principles of the circular economy into supply chains, emphasizing the importance of sustainable sourcing, designing of recyclable products and efficient processes. Additionally, it 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. Smart waste management systems leveraging IoT technology and data analytics provide innovative solutions to optimize waste collection, disposal and recycling processes. This section 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.

Through the exploration of these topics, this chapter aims to provide a comprehensive understanding of the potential of circular economy principles and technological innovations to revolutionize waste management practices and contribute to a more sustainable future.

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]

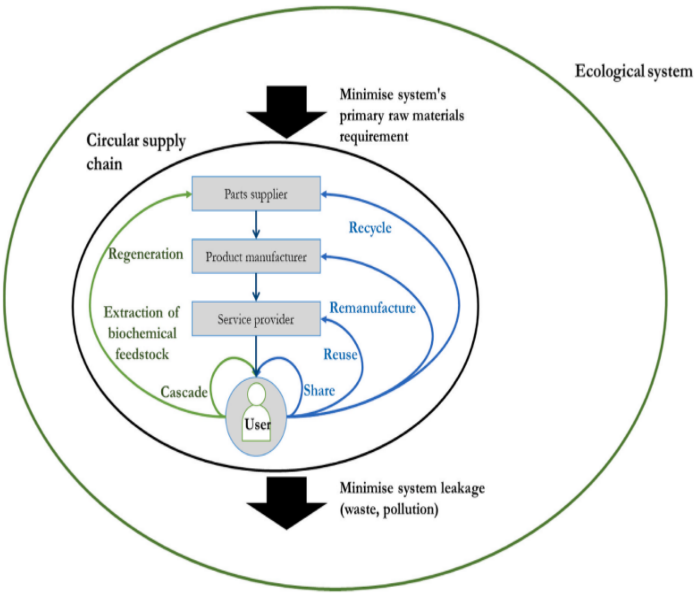

Figure 1.1: Circular Supply Chain as part of the Ecological system [BR15]

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

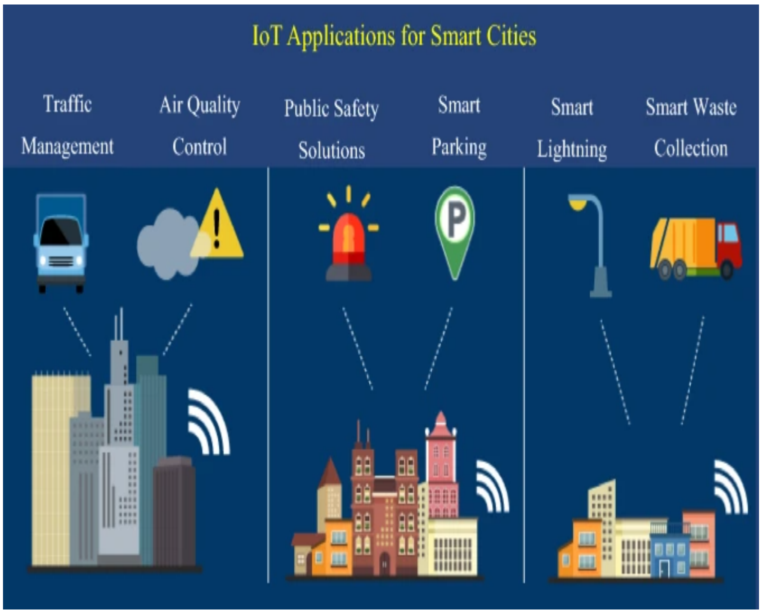

Figure 1.2: IOT application areas for smart cities[RIKA19]

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.

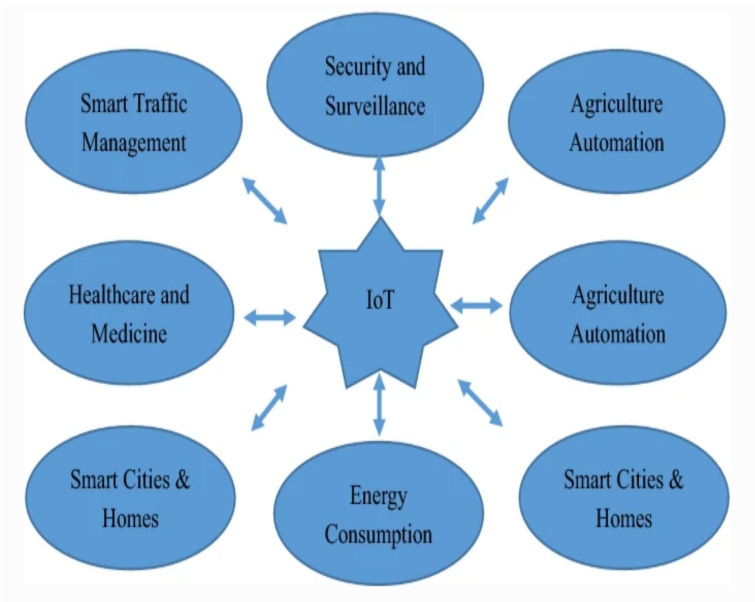

Figure 1.3: Potential application domains of IOT [RIKA19]

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]

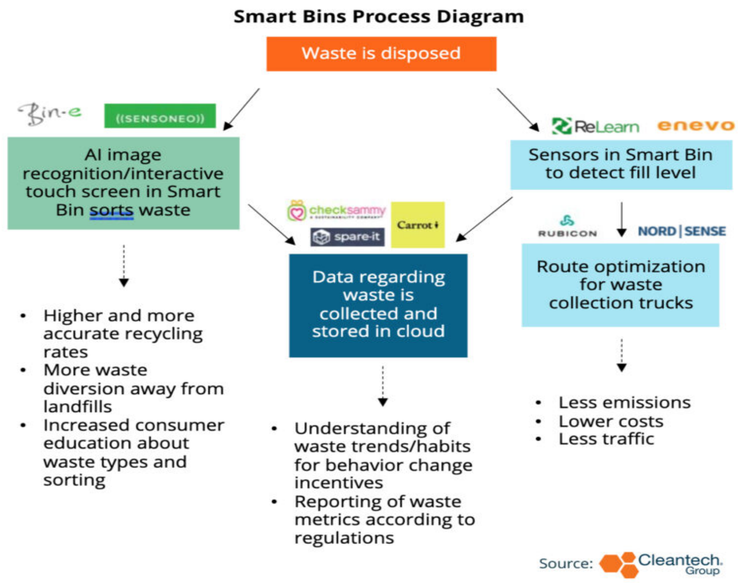

Figure 1.4: Smart Bins Process Diagram [Cle]

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 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] This article 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

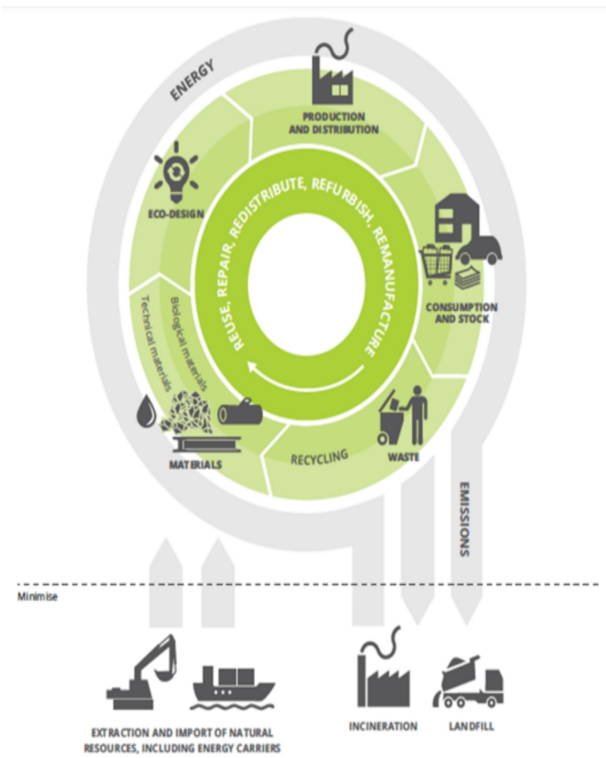

Figure 1.5: The circular economy concept [LSB+17]

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] examines 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

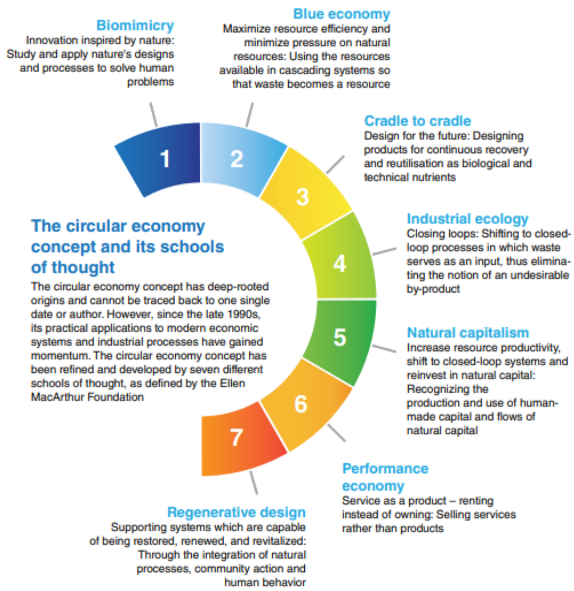

Figure 1.6: CE Concept, and its schools of thought[MN20]

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 optimiz-

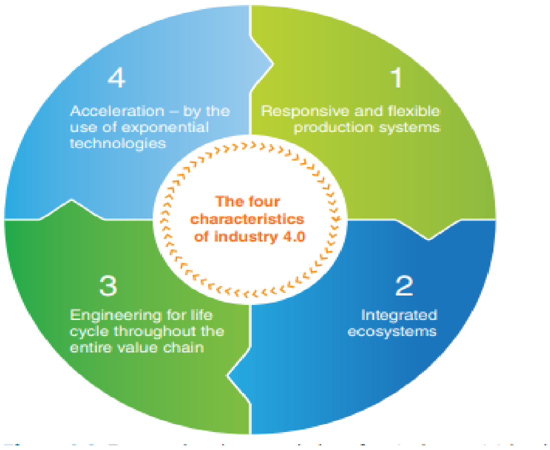

Figure 1.7: 4 main characteristics of an industry 4.0 business environment [MN20]

ing waste management, it was necessary to reevaluate this hierarchy, and asses how waste management strategies align with it's principles.

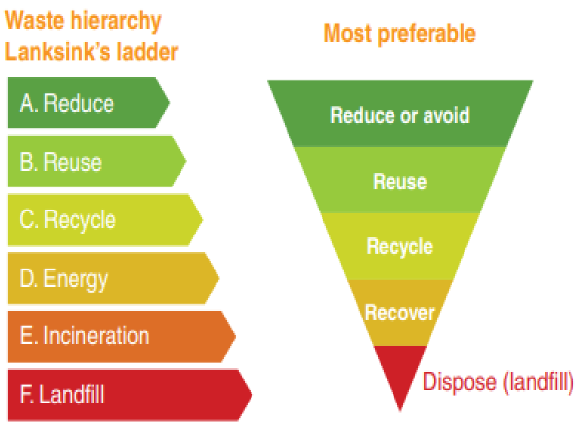

Figure 1.8: Lansink's ladder and Pyramid form of waste hierarchy [MN20]

- **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), 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

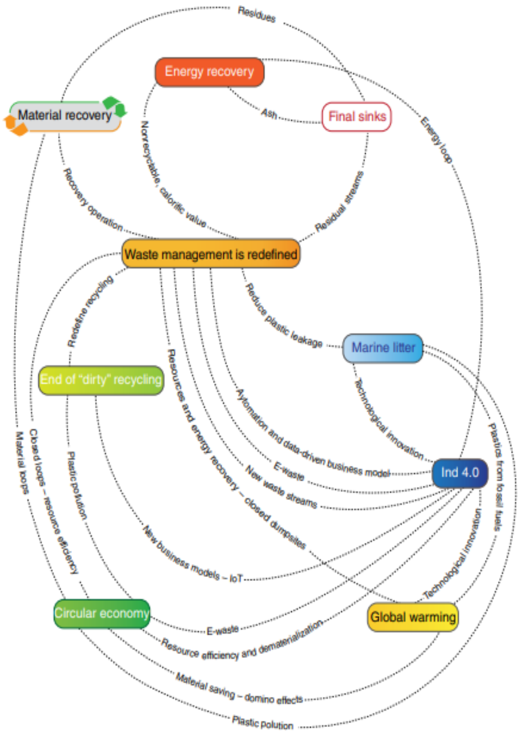

Figure 1.9: A mind map with the interconnections of the five trends [MN20]

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.

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 $\rightarrow$ products $\rightarrow$ waste.	Circular approach: raw materials $\rightarrow$ products $\rightarrow$ 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

Multi-Objective Vehicle Routing Problem and Metaheuristics

Introduction

The Vehicle Routing Problem (VRP) is a fundamental and complex problem in the field of logistics and transportation management. It involves determining the most efficient routes for a fleet of vehicles to service a set of customers with varying demands while adhering to a set of constraints. Given the problem's combinatorial nature and its relevance to real-world applications, VRP has been extensively studied, and numerous solution methods have been developed to address it.

This chapter provides a comprehensive overview of various solution methods for VRP, categorizing them into Exact Methods, Approximate Methods, and Hybrid Methods. An analysis is done on the Non-dominated Sorting Genetic Algorithm II (NSGA-II). NSGA-II is a popular and robust algorithm used for solving multi-objective optimization problems, where multiple objectives need to be optimized simultaneously. This chapter delves into the mechanics of NSGA-II, including its use of genetic operators like selection, crossover, and mutation, as well as its non-dominated sorting and crowding distance mechanisms that ensure a diverse set of high-quality solutions.

Additionally, the chapter explores various applications of VRP in smart waste management, highlighting how advanced optimization techniques like NSGA-II can significantly enhance operational efficiency and sustainability. The integration of Internet of Things (IoT) technology in smart waste management systems further optimizes waste collection and transportation by enabling real-time data collection and dynamic route planning.

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, each with its unique characteristics and complexities, which have been extensively studied and documented in the literature [Lap92]. This paper has aimed 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.

VRP traditionally focuses on minimizing traveling costs. However, real-world applications require considering additional factors such as environmental impacts. [MERG14] This paper proposes a multi-objective VRP model that incorporates a heterogeneous fleet of vehicles with different capacities, costs, and emission factors and their, it aims to minimize total internal costs, CO2 emissions, and emissions of air pollutants.

[KTSA14] Solves a Multi-objective Vehicle Routing Problem with Time Windows, it looks for minimizing the total distance traveled, the total number of vehicles used, and balancing the routes.

[JPS15] Focuses on addressing the VRP in the environmental challenges posed by the logistics and transportation sector. it proposes a multi-objective optimization model that aims to minimize both economic costs and CO2 emissions, highlighting the importance of balancing financial and environmental goals.

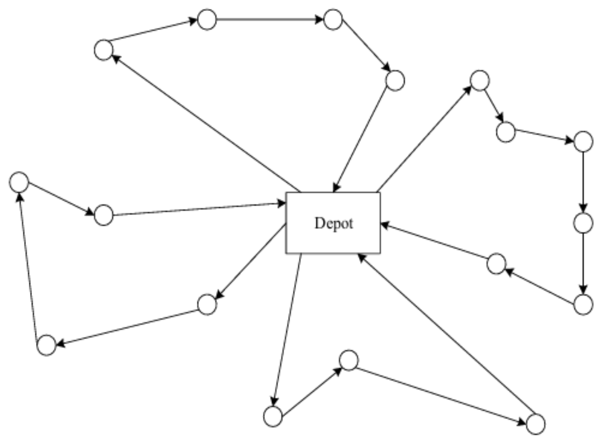

Figure 2.1: Vehicle Routing Problem [ZGYT22]

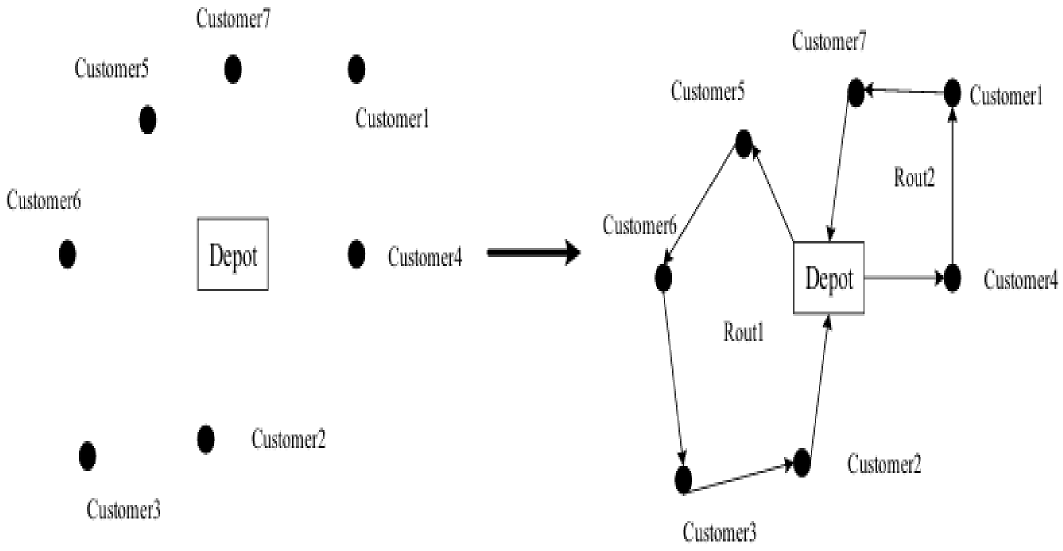

Figure 2.2: Cpacitated Vehicle Routing Problem [ZGYT22]

2.1.1 VRP classification

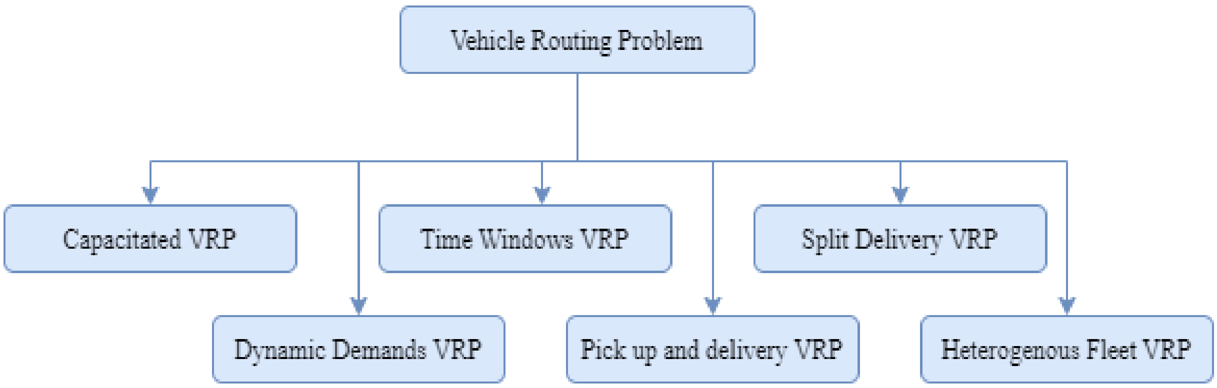

Figure 2.3: VRP Classification

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 necessitate 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]. This 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

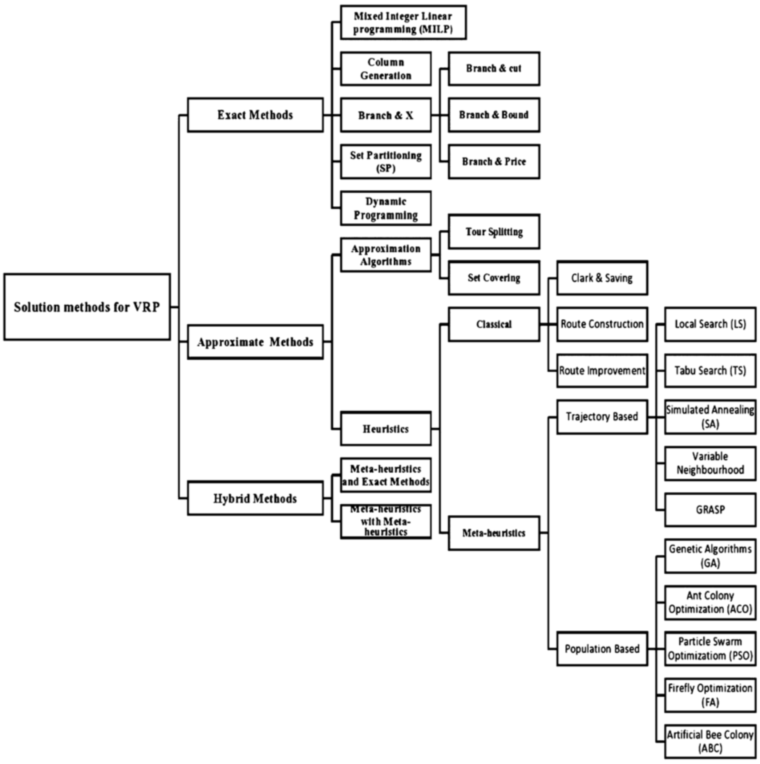

Figure 2.4: Solution Methods [GB20]

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)

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 Multi-objective VRP:

The Multi-Objective Vehicle Routing Problem (MVRP) involves optimizing two or more conflicting objectives simultaneously. Common objectives include minimizing total travel distance, minimizing CO2 emissions, minimizing cost, maximizing profit, and minimizing penalties. These problems are extensions of the classical VRP and incorporate additional real-world constraints like vehicle capacities and time windows [MERG14] some of the common multi-objective models can be summerized as followed:

Minimizing Total Distance and CO2 Emissions:

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

$$\text{Minimize:} \quad \text{Total CO2 Emissions} = \sum_{i=0}^{n} \sum_{j=0}^{n} e_{ij} x_{ij} \tag{2.2}$$

Minimizing Cost and Maximizing Profit

$$\text{Minimize:} \quad \text{Total Cost} = \sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij} x_{ij} \tag{2.3}$$

$$\text{Maximize:} \quad \text{Total Profit} = \sum_{i=0}^{n} p_i y_i - \text{Total Cost} \tag{2.4}$$

Minimizing Cost and Minimizing Penalties

$$\text{Minimize:} \quad \text{Total Cost} = \sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij} x_{ij} \tag{2.5}$$

$$\text{Minimize:} \quad \text{Total Penalties} = \sum_{i=1}^{n} \text{Penalty}_i (1 - y_i) \tag{2.6}$$

2.1.4 MVRP in Smart waste management

For our case, the Multi-objective Vehicle Routing Problem (MVRP) in smart waste management is used to optimize the collection and transportation of waste and optimize the gas emissions, 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 and emissions, 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 [EVR09]. 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 [SP22].

[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).

[KMRM23] Focuses on optimizing waste collection in smart cities using Internet of Things (IoT) technology. It addresses the challenges of waste collection by proposing a model that incorporates real-time data from IoT-based smart bins. Their objective is to minimize the total routing cost and penalties associated with overflowing bins.

[ARY15] presents a comprehensive study on optimizing door-to-door freight transportation. For their multi-objective model aims to balance multiple criteria, such as minimizing travel distance and the number of vehicles used.

2.2 Metaheuristics for VRP in SWM

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.

[LLLG20] Provides a detailed review of the advancements in multi-objective metaheuristics specifically for discrete optimization problems (MODOPs). The paper elaborates on existing multi-objective metaheuristics, their application areas, performance metrics, and test instances. The main focus of this review is to explore the developments and applications of multi-objective metaheuristics in addressing discrete optimization problems, which are optimization problems involving discrete variables and multiple conflicting objectives.The MODOPs are generally used in scheduling problems and allocation and Routing Problems (VRP, TSP).

[JMT02] Another state-of-art focusing on several key meta-heuristics used in multi-objective optimization, it outlines the challenges associated with multi-objective optimization, such as balancing the trade-offs between different objectives and maintaining diversity among solutions. It emphasizes the need for effective meta-heuristic algorithms to address these challenges.

[LSKG13] provides a comprehensive survey of the applications of the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, MOPSO extends Particle Swarm Optimization (PSO) to handle multiple conflicting objectives. In MOO, the goal is to find a set of solutions that represent the trade-offs among objectives, known as the Pareto

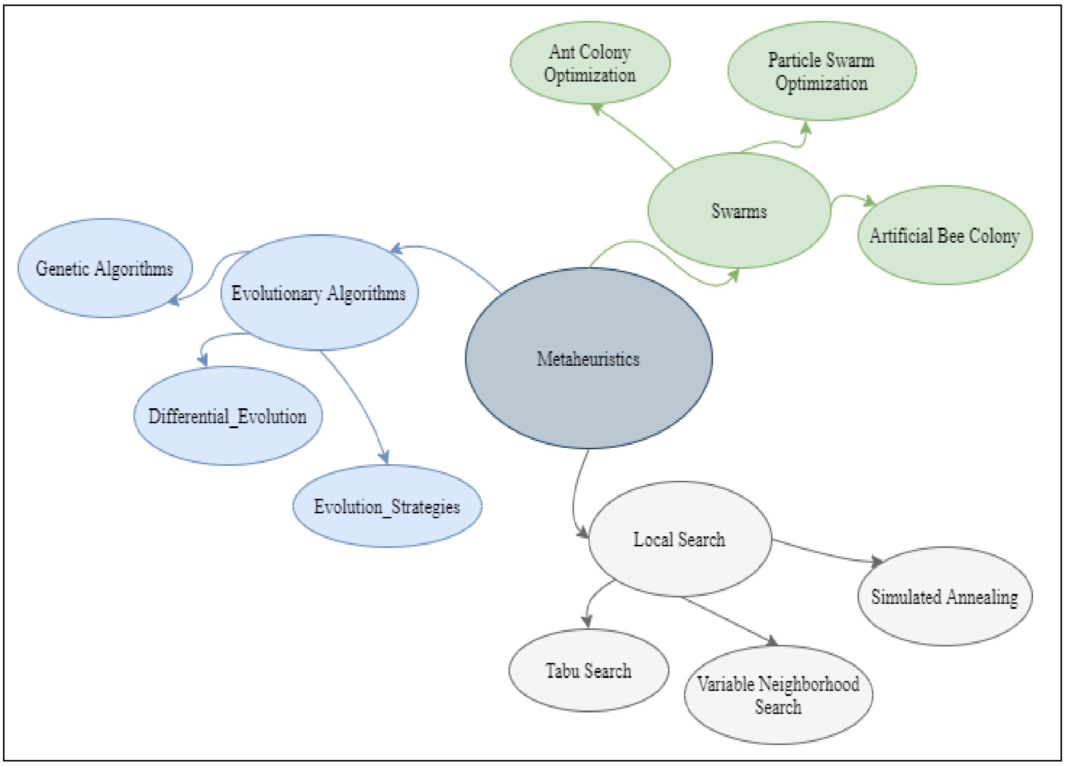

Figure 2.5: Metaheuristics

optimal set. The paper surveys various applications of MOPSO in different domains such as aerospace engineering, biological sciences, chemical engineering, civil engineering, data mining, electrical engineering, and many others. Each application area utilizes MOPSO to address specific multi-objective optimization problems, demonstrating its versatility and effectiveness.

[NSDG+20] Compares the performance of four multi-objective optimization algorithms applied to evacuation planning. The algorithms evaluated are Archive Multi-Objective Simulated Annealing (AMOSA), Multi-Objective Artificial Bee Colony (MOABC), Multi-Objective Standard Particle Swarm Optimization (MSPSO), and Non-Dominated Sorting Genetic Algorithm II (NSGA-II). The study focuses on evacuation planning, a critical component of disaster management aimed at minimizing the impact of natural disasters on urban communities. The study's findings and conclusions contribute to the understanding of how these algorithms can be applied to real-world problems, particularly in disaster management.

[JZM12] Presents a bi-objective optimization approach to solving the Green Vehicle Routing Problem (GVRP) using NSGA-II. The focus of the paper is on developing a model that minimizes both the total travel distance and CO2 emissions generated by the transportation fleet, The study concludes that explicitly considering emissions as a separate optimization objective can lead to significant environmental benefits without compromising on cost efficiency. And NSGA-II algorithm proves to be an effective tool for solving the multi-objective GVRP, providing a practical approach to integrate environmental considerations into logistics planning.

[ZLPS20] this article discusses how MOGA (Multi-objective Genetic Algorithm), a guided random search optimization technique, is particularly suitable for solving multi-objective optimization problems in engineering. The method's capability to explore diverse regions of the solution space makes it possible to optimize multiple variables simultaneously. The article emphasizes the use of Pareto fronts to illustrate MOGA solutions, which represent sets of non-dominated solutions. The objective functions' values corresponding to these solutions form the Pareto front.

2.2.1 Multi-Objective Genetic Algorithm (MOGA)

Genetic algorithms are a type of self-adaptive global search optimization method, distinct from conventional optimization techniques. Unlike traditional methods, GAs operate on a population of potential solutions, evolving each individual in parallel. The final optimal solution is part of the evolved population after a series of generations. The evolution of the population is driven by genetic operators—selection, crossover, and mutation—which are crucial for the performance of the GA [GSY00]. the basic approaches of GA are:

1. Determine the Coding Structure: Define how to represent solutions.
2. Determine the Fitness Function: establish the objective functions.
3. Determine the Selection Strategy: Choose a method for selecting individuals for reproduction.
4. Select Control Parameters: Set parameters such as population size, crossover rate, and mutation rate.
5. Design Genetic Operators: Develop the mechanisms for selection, crossover, and mutation.
6. Determine the Termination Criterion: Define the condition under which the algorithm stops (e.g., a maximum number of generations or a satisfactory fitness level).

Multi-Objective Genetic Algorithm (MOGA) is a subset of evolutionary algorithms, it is an optimization technique based on the principles of natural selection and genetics. It is used to solve problems involving multiple, often conflicting, objectives. MOGA stands out for its ability to explore a diverse solution space, ensuring a wide range of optimal solutions. It uses Pareto fronts to represent solutions, with the Pareto optimal set containing non-dominated solutions, meaning no other solution is superior across all objectives. Unlike traditional methods, MOGA effectively avoids local minima or maxima, finding the global optimum instead. It can optimize multiple parameters or objective functions simultaneously, making it particularly suitable for complex engineering challenges [ZLPS20].

In the context of genetic algorithms, finding the Pareto front involves evolving a population of solutions such that the population converges towards the Pareto front. The Pareto front includes the solutions that are non-dominated, this means that in the set, no other solution is better in all objectives simultaneously, reflecting the trade-offs between objectives [MI95].

[EYM+20] Focuses on utilizing MOGA to enhance energy efficiency and reduce GHG emissions in rice cultivation. The MOGA model shows a significant potential for reducing GHG emissions compared to current farming practices.

[Deb99] provides a detailed study of the features that can cause difficulties for multi-objective genetic algorithms (MOGAs) in converging to the true Pareto-optimal front, such as multi-modality (multiple local optima), deception, and the presence of convex, non-convex, or discrete Pareto-optimal fronts.

[Hos17] Addresses optimization challenges in a two-stage production system. The first stage fabricating parts and the second stage involves assembling these parts into final products. The focus is on minimizing both the makespan (the total time required to complete all jobs) and the sum of earliness and tardiness. Multi-objective Genetic Algorithm (MOGA) to tackle it in two phases: first, determining the sequence of product assembly, and second, scheduling the fabrication of parts. The MOGA utilizes a non-dominance rule and fitness value for selecting the new population in each iteration.

[AA14] This article compares three evolutionary algorithms—Multi-Objective Genetic Algorithm (MOGA), Non-Dominated Sorting Genetic Algorithm II (NSGA-II), and Multi-Objective Particle Swarm Optimization (MOPSO)—in the context of optimizing regression test suites(Collections of test cases used to verify that software still functions correctly after changes have been made). The study concludes that MOGA outperforms NSGA-II and MOPSO in terms of minimizing the size and execution time of regression test suites. however, it has a drawback in terms of safety, as it tends to reduce the fault detection rate more than NSGA-II.

Non-Dominated Sorting Genetic Algorithm NSGA-II

NSGA-II (Non-dominated Sorting Genetic Algorithm II) is considered a part of the broader class of Multi-Objective Genetic Algorithms (MOGAs). MOGAs are designed to solve optimization problems involving multiple conflicting objectives, and NSGA-II is a specific implementation within this class that has gained significant popularity due to its efficiency and effectiveness. [ZDT00]

[MWM+16] Discusses the application of the NSGA-II algorithm to optimize the Vehicle Routing Problem with Demand Responsive Transport (VRPDRT). It proposes a multi-objective approach, integrating five different objective functions into three aggregated objectives. The NSGA-II algorithm is employed to find a set of non-dominated solutions, and it outperforms random solution generation methods, providing better optimization for both cost and service quality objectives.

[SAAHK+22] Presents a comprehensive study on optimizing waste management systems (WMS) within smart cities using a multi-objective approach. Several meta-heuristic algorithms, including NSGA-II, to solve the optimization problems. NSGA-II is used to balance the trade-offs between minimizing operational costs and maximizing the revenue from waste recovery.

[HAMR+23] explores the design of an efficient and integrated system for managing solid waste using a combination of allocation and routing optimization. The model looks to minimize the total travel cost, the travel time and the Co2 emissions. The results from the application of NSGA-II demonstrated its effectiveness in solving the allocation-routing optimization problem for integrated solid waste management. The algorithm provided near-optimal solutions with minimal gaps compared to the optimal solutions obtained from exact solvers like Gurobi, making it a viable alternative for complex and large-scale problems

2.2.2 MOGA and NSGA-II

Evolutionary algorithms are defined as population-based stochastic direct search algorithms that mimic the process of natural evolution [BBBMM14], their key elements are:

1. Population: A set of potential solutions (individuals).
2. Fitness or objective Function: A measure of how good each solution is.
3. Selection: The process of choosing individuals based on their fitness to produce offspring.

4. Variation Operators: Includes mutation (random alterations) and recombination (combining parts of two or more solutions).

5. Replacement: The process of forming a new generation from the current population and the offspring.

There are also multiple types of Evolutionary Algorithms such as: Genetic Algorithms (GAs), Evolution Strategies (ES), Evolutionary Programming (EP), Genetic Programming (GP) and Swarm Intelligence Methods. MOGA and NSGA-II are both algorithms that employ evolutionary strategies to explore and exploit the search space, aiming to find a diverse set of Pareto-optimal solutions. However, they have some slight differences explained int the following table [CC99] [VVL00] [DAPM00]

Feature/Aspect	**NSGA-II**	**MOGA**
Algorithm Type	Evolutionary Algorithm	Evolutionary Algorithm
Primary Use	Multi-objective Optimization	Multi-objective Optimization
Non-Dominated Sorting	Yes, employs non-dominated sorting	Yes, employs non-dominated sorting
Diversity Preservation	Uses crowding distance to maintain diversity	Uses sharing function or other techniques to maintain diversity
Pareto Front	Generates Pareto front using elitist strategy	Generates Pareto front using ranking and selection
Selection Mechanism	Binary tournament selection based on rank and crowding distance	Can use various selection mechanisms based on rank and fitness
Ranking Process	Ranks individuals using non-dominated ranking	Ranks individuals using non-dominated ranking
Fitness Assignment	Assigns fitness based on rank and crowding distance	Assigns fitness based on Pareto dominance and other criteria
Elitism	Strong elitism, always retains best solutions	May use elitism, but approach can vary
Complexity	More computationally complex due to sorting and crowding calculations	Less computationally intensive than NSGA-II in some variations
Convergence	Good convergence properties, well-studied	Good convergence, effectiveness can depend on implementation
Application Scenarios	Widely used in academia and industry for various multi-objective problems	Also widely used, often compared against NSGA-II
Typical Use Cases	Routing Problems, resource allocation, scheduling	Routing Problems, manufacturing, scheduling
Strengths	Robust performance, well-maintained diversity, clear methodology	Flexible, can be adapted for specific problem domains
Weaknesses	Computationally expensive for large populations and many objectives	May require tuning of parameters for best performance

Table 2.1: Comparison between NSGA-II and MOGA

Pareto Front NSGA-II generates the Pareto front using an elitist strategy, which guarantees that the best solutions are retained across generations, ensuring that high-quality solutions are not lost. MOGA, on the other hand, generates the Pareto front using a ranking and selection process, which can vary in implementation but aims to rank solutions effectively to identify the Pareto front.

Selection Mechanism In NSGA-II, binary tournament selection based on rank and crowding distance is used to select individuals for reproduction, which ensures that both dominance and diversity are considered. MOGA, however, can use various selection mechanisms based on rank and fitness, providing flexibility in how individuals are chosen for the next generation.

Elitism Elitism is a strategy in evolutionary algorithms that involves preserving the best solutions found in the current generation so they are not lost in subsequent generations. NSGA-II employs strong elitism by always retaining the best solutions to ensure they are not lost in subsequent generations, which is crucial for maintaining solution quality. MOGA may use elitism, but the approach can vary, offering flexibility in how the algorithm ensures the best solutions are preserved without necessarily always retaining them.

Conclusion

This chapter has provided an in-depth exploration of various optimization techniques applied to the Vehicle Routing Problem (VRP), a pivotal challenge in logistics and transportation. We have categorized solution methods into Exact Methods, Approximate Methods, and Hybrid Methods, each offering unique advantages and trade-offs.

A significant focus of this chapter was on the Non-dominated Sorting Genetic Algorithm II (NSGA-II), a robust technique for multi-objective optimization. NSGA-II effectively balances conflicting objectives by maintaining a diverse set of high-quality solutions, approximating the Pareto front. This approach is particularly advantageous in scenarios where trade-offs between multiple objectives, such as cost and emissions, must be optimized simultaneously.

The application of VRP optimization in smart waste management systems exemplifies the practical benefits of advanced optimization techniques. By integrating Internet of Things (IoT) technology, these systems achieve dynamic and efficient route planning, significantly reducing operational costs and environmental impact. The use of NSGA-II in this context demonstrates its capability to handle complex, real-world problems, providing near-optimal solutions with minimal computational overhead compared to traditional exact solvers like Gurobi.

Overall, the advancements in optimization techniques for VRP, particularly through the use of metaheuristics like NSGA-II, highlight the ongoing evolution of problem-solving approaches in logistics. These methods not only improve operational efficiency and sustainability but also pave the way for innovative applications in various domains. This chapter underscores the importance of choosing the appropriate optimization strategy based on problem characteristics, computational resources, and specific objectives, ensuring the effective and efficient resolution of VRP challenges.

Chapter 3

A Sustainable Vehicle Routing Problem for circular Economy

Introduction

In this chapter, we present a comprehensive bi-objective optimization model designed to address vehicle routing problems with two objectives. The primary objectives of this model are to minimize the total travel cost and to reduce CO2 emissions across various routing scenarios. To achieve these goals, we integrate advanced optimization techniques such as the Gurobi solver and the Non-dominated Sorting Genetic Algorithm II (NSGA-II).

The vehicle routing problem is formulated with a set of decision variables and constraints that consider vehicle capacities, bin capacities, travel costs, distances, fuel emissions, and time windows. We explore the performance of the proposed model under different scenarios, each characterized by varying numbers of bins and vehicles. The model's parameters, including vehicle capacities, bin loads, travel costs, and time windows, are carefully defined to simulate real-world conditions.

This chapter is structured as follows:
Problem Description: provides an in-depth description of the bi-objective optimization model, including the decision variables, objective functions, and constraints.
Section 3.2 outlines the resolution approaches, detailing the implementation of the Gurobi solver and the NSGA-II algorithm.
Solution Encoding: presents the solution encoding methods used in NSGA-II, along with examples of chromosome construction, crossover, and mutation operations.

Results: evaluate the model through different scenarios and comparing the performance of Gurobi and NSGA-II in terms of objective function values and computational time. We also present the results, highlighting the effectiveness of NSGA-II along with the computational efficiency of both methods.

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 bi-objective 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 cost of total distance traveled, and to minimize the Co2 gas emissions caused by these vehicles.

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 bi-objective 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.
- The traveled distance incurs also emissions proportional to the distance traveled,thus the need for minimizing the CO2 gas emissions.

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
$\mathbf{FE}$	: Fuel Emission Factor
$\mathbf{FC}$	: Fuel Consumption Factor
$\mathbf{E}_i$	: Earliest service time of bin b
$\mathbf{F}_i$	: Latest service time of bin b
$\mathbf{L}_{ij}$	: Travel time from i to j
$\mathbf{S}$	: 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:

$$\begin{aligned} Z1 &= \min\left(\sum_i \sum_j \sum_v C \cdot X_{ijv} \cdot D_{ij}\right) \\ Z2 &= \min\left(\sum_i \sum_j \sum_v \mathrm{FE} \cdot FC \cdot X_{ijv} \cdot D_{ij}\right) \end{aligned} \tag{3.1}$$

The objective functions Z1 and Z2 in 3.1 aim to minimize the total cost of traveling and the total emissions of Co2 respectively 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 and multiplying the Fuel Emissions and consumption factors with the distance, also if that arc is chosen.

Constraints:

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

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

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

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

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

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

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

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

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

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

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 preserved 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 Gurobi Solver

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

Gurobi uses a hierarchical or lexicographic approach for multi-objective models, it prioritizes each objective and optimizes them sequentially based on their priority levels. In each optimization pass, the algorithm seeks the best solution for the current objective while ensuring that the solution quality for higher-priority objectives is not compromised. You can specify the priority of each objective using the setObjectiveN function, or alternatively, by setting the ObjNPriority attribute. These priorities are assigned as integer values, with larger numbers indicating higher priorities.

Bi-Objective Genetic Algorithm

NSGA-II is an extension of the traditional multi-objective Genetic Algorithm (MOGA) tailored for multi-objective optimization problems, where multiple objectives need to be optimized simultaneously. NSGA-II operates by maintaining a population of potential solutions that evolve over generations to approximate the Pareto front, representing the set of optimal trade-offs between objectives.

In NSGA-II, individuals (solutions) are represented using chromosomes, which encode possible solutions in forms suitable for the problem domain, such as binary strings, real-valued vectors, or permutations. The algorithm uses genetic operators like selection, crossover, and mutation to generate new offspring from the current population. Non-dominated sorting and fitness assignment are key aspects of NSGA-II, ensuring that solutions are ranked based on Pareto dominance and diversity is maintained. This approach enables NSGA-II to effectively explore and exploit the search space, providing a diverse set of high-quality solutions that balance multiple objectives.

3.2.2 Solution Encoding

Common Encoding Schemes in NSGA-II:

- **Binary Encoding:** Used when solutions can be naturally represented in binary format. Each gene in the chromosome is represented by a 0 or 1, suitable for problems where variables can only take two distinct states, such as feature selection or knapsack problems.
- **Real-Valued Encoding:** Ideal for problems requiring continuous variables. Each gene is represented by a real number, making this encoding suitable for optimization problems involving parameters with a wide range of values, such as tuning control systems or designing engineering structures.
- **Integer Encoding:** Used when variables can take on a discrete set of integer values. This encoding is suitable for problems like job scheduling or resource allocation, where each gene represents an integer corresponding to a specific choice or category within the problem.
- **Tree Encoding:** Specifically used in genetic programming, where solutions are represented as tree structures. This encoding is suitable for evolving mathematical expressions or decision rules, where each node in the tree represents an operation or operand.

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

Chromosomes Construction

In NSGA-II for a vehicle routing problem, the initialization and evolution of chromosomes is 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 chromosomes, The figure **??** represents a population of two chromosomes. Each chromosome represents a potential solution to the routing problem.

To construct each chromosome:

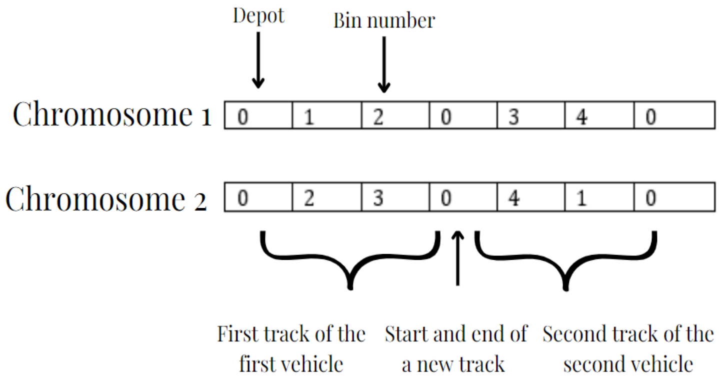

Figure 3.1: Chromosomes Representation

1. We initialize the chromosome with 0 to indicate that the start is from the depot
2. We start by generating random indices from 1 to B.
3. These indices are then used to create one individual
4. This process is then repeated to generate a list of individuals
5. We verify the constraints after building the chromosome, wherever the constraint is not verified, a 0 is added.
6. If the last element is not the depot, we will add a 0 to indicate the vehicles arrival.

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

Crossover Operations

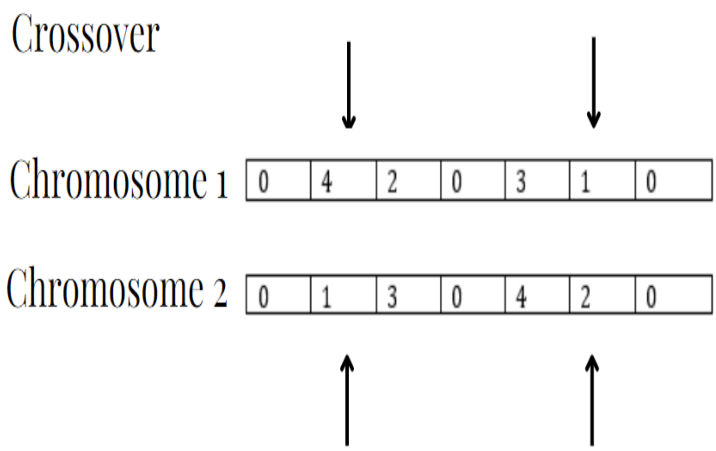

Figure 3.2: Crossover

Crossover operations in genetic algorithms and are used to combine the features of two parent chromosomes to create new offsprings. The goal is to inherit the best characteristics from both parents, thus generating potentially better solutions.

In this method, the crossover happens as follows:

1. In the parents chromosomes (parent 1 and 2), two crossover points (start and end) are randomly selected ensuring that they are in ascending order.
2. We take the elements between the two points start and end, and copy them in the offsprings (1 and 2 respectively to the parents).
3. we take the remaining elements from parent2 and insert them in the offspring 1. Do the same thing for offspring 2 with parent 1.

The figure 3.2 explains this operation, by following these steps, the offspring will include a segment from Parent 1, completed by non-repeated elements from Parent 2, maintaining the diversity of elements and adhering to the constraints of the problem. This is crucial for maintaining the feasibility of solution.

Mutation

In the context of NSGA-II, the mutation operation involves creating a new sequence 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 functions (total cost and emissions).

The insert mutation operator modifies an individual's permutation by relocating an element to a new position within the sequence. This operation helps in exploring new permutations while maintaining the feasibility of solutions. The mutation happens as follows:

1. Select an element randomly from the chromosome.
2. Remove the selected element from its current position.
3. Insert the element at a new randomly chosen position within the chromosome.

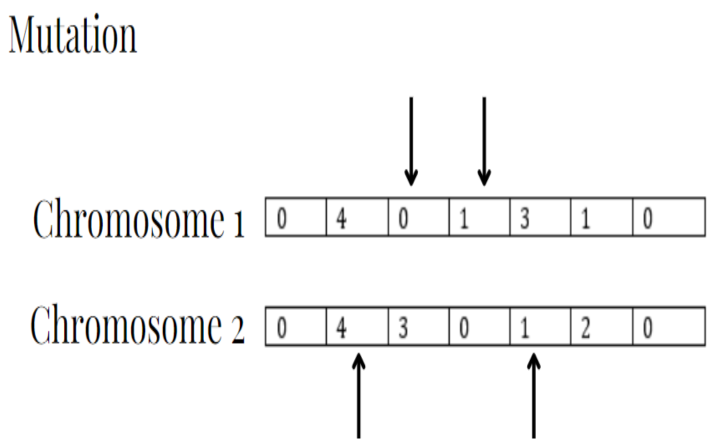

Figure 3.3: Mutation

3.2.3 NSGA-II ALGORITHM

The provided figure 3.4 illustrates the algorithm of NSGA-II. The algorithm begins with the initialization of parameters such as crossover rate, mutation rate, population size and

```
Algorithm :

Data: Crossover rate C, Mutation rate M, Population size N, Number of generations G

Population: Set of individuals with random positions and objective function values

Result: Set of Pareto-optimal solutions
Function NSGA-II (CR, MR, N, G)
Initialize Population: Initialize a population of N individuals with random positions.
Evaluate Population: Calculate the objective functions of each individual in the population.
While Termination Condition Not met:
    Do
        Selection: Select parents from the population.
        Crossover: For each pair of parents, if a random number r< CR, perform crossover to
        generate offspring.
        Mutation: For each offspring, if a random number r< MR, perform mutation to introduce
        genetic diversity.
        Evaluate Offspring: Calculate the fitness of the offspring
        Combine Populations : Combine parents and offspring populations.
        Select New Population: Select N best individuals based on fitness values to form the new
        population.
    END Do
End While
Return Best Solution Found
```

Figure 3.4: NSGA-II Algorithm

number of generations. We start by initializing the population of chromosomes that is randomly generated. We then evaluate the objective functions of each chromosome.

If the termination condition is not met (number of generations) we will select the parents for each crossover of each chromosome, then perform the operations of crossover and mutation, then we evaluate the population again after each update.

For the selection process, NSGA-II performs the following steps for Pareto front selection:

1. The population is sorted into different fronts based on Pareto dominance. The first front consists of individuals that are not dominated by any other individuals in the population. The second front consists of individuals dominated only by those in the first front, and this process continues for subsequent fronts

2. Each individual is ranked based on their fitness values, with those in the first front having the best fitness values

3. A crowding distance is calculated for each individual, it is a measure of how close an individual is to its neighbors in the objective space. Individuals with a higher crowding distance are preferred, as they contribute to maintaining diversity by occupying less crowded regions of the solution space.

4. The new population is formed by selecting individuals from the sorted fronts, starting with the first front and moving to subsequent fronts until the desired population size is reached. Within each front, individuals are selected based on their crowding distance to ensure a diverse set of solutions

The final result is going to be the best individual found in the population after all the generations. This approach allows NSGA-II to effectively explore the trade-offs between conflicting objectives, providing a comprehensive set of high-quality solutions.

DEAP Library in Python

[FDRG+12] This article on the DEAP (Distributed Evolutionary Algorithms in Python) which is a library in python designed to facilitate the rapid prototyping and testing of evolutionary algorithms. DEAP aims to make algorithms explicit and data structures transparent. It incorporates tools and data structures to easily implement genetic algorithms, genetic programmings, evolution strategies, and particle swarm optimization. It is developed at Université Laval since 2009. This library has been used on this model for more efficiency and accuracy, the Pareto front operation is pre-defined in the library as well as the crowding distance calculations.

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)

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

The proposed multi-objective model was evaluated using three different scenarios, each with a varying number of bins and one depot. The NSGA-II algorithm demonstrated strong performance across both objectives 3.1, showing a gap between 0% and 5% compared to the optimal solutions obtained using the Gurobi solver. The first scenario of 4 bins and a depot, a gap of 0 was obtained, the second scenario of 9 bins and a depot, the gap was around 2% for both objectives , the third scenario of 14 bins and depot, the gap was 5% with bigger computation time in Gurobi 3.4.

Scenario	Gurobi		NSGA-II		GAP	
	F1	F2	F1	F2	F1	F2
Scenario 1	844.3	1504.2	844.3	1504.2	0%	0%
Scenario 2	1413.25	2517.84	1445.13	2574.64	2%	2%
Scenario 3	2011.75	3584.13	2136.89	3807.09	5%	5%

Table 3.3: Comparison of Gurobi and NSGA-II across different scenarios.

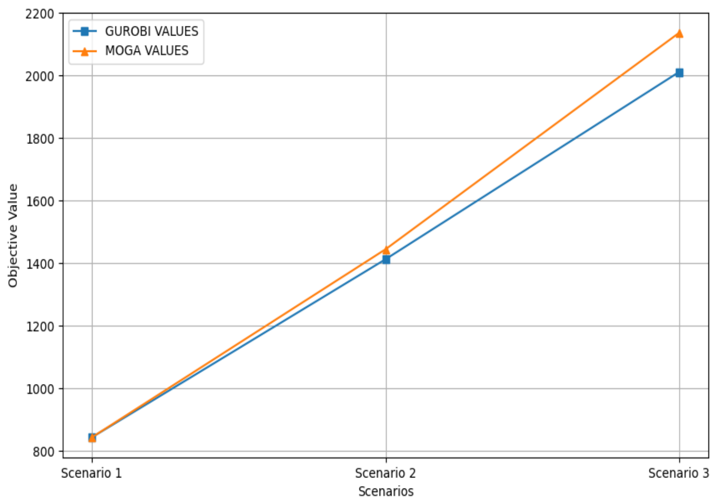

Figure 3.5: Comparison of solutions using Gurobi and NSGA-II for the first objective

Computational Time

Scenario	Gurobi Time (s)	NSGA-II Time (s)
Scenario 1	0.06	0.08
Scenario 2	0.14	0.09
Scenario 3	9.68	0.10

Table 3.4: Comparison of computation times for Gurobi and NSGA-II across different scenarios.

NSGA-II demonstrated remarkable performance across all scenarios, it achieved near-optimal solutions with small gaps compared to the optimal solutions obtained using Gurobi. The results indicate that NSGA-II is particularly effective for smaller problem instances and is slightly competitive for larger instances with a moderate increase in the gap. This makes NSGA-II viable as an alternative to exact solvers like Gurobi, especially when considering computational efficiency and scalability.

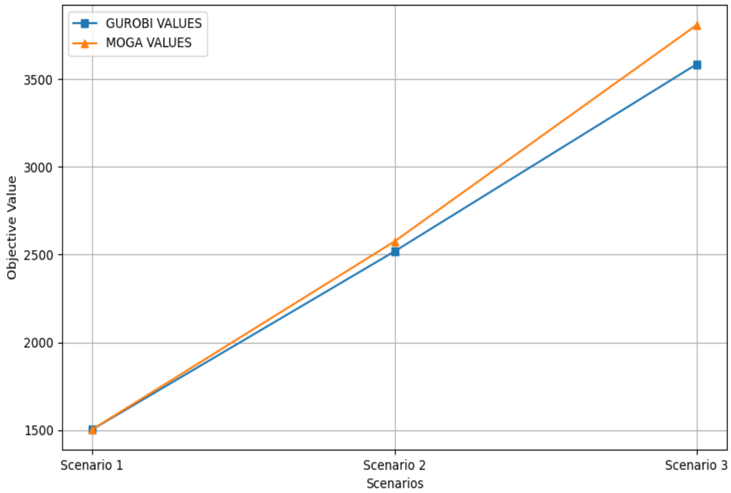

Figure 3.6: Comparison of solutions using Gurobi and NSGA-II for the second objective

Conclusion

In this chapter, we presented a robust Bi-objective optimization model for solving vehicle routing problems with two objectives, minimizing travel costs and CO2 emissions. The model incorporated key constraints such as vehicle and bin capacities, travel times, and time windows, ensuring realistic and practical solutions. We employed two powerful optimization approaches: the Gurobi solver and the Non-dominated Sorting Genetic Algorithm II (NSGA-II). Through comprehensive evaluations across different scenarios, NSGA-II demonstrated strong performance, achieving near-optimal solutions with minimal gaps when compared to the exact solutions provided by Gurobi. Moreover, the computational time analysis revealed that NSGA-II is particularly advantageous for larger problem instances, offering significant computational efficiency and scalability. While Gurobi provided exact solutions, it required considerably more computational time for larger scenarios. In contrast, NSGA-II maintained competitive performance with much lower computational time, making it a viable and practical alternative for real-world applications.

Moreover, this chapter highlights the potential of NSGA-II in solving complex multi-objective optimization problems. Its ability to provide high-quality, diverse solutions while maintaining computational efficiency makes it an excellent choice for practitioners and researchers dealing with large-scale waste collection vehicle routing problems.

General Conclusion

This thesis has explored and integrated optimization techniques within the concept of vehicle routing problems (VRP), with a special focus on contributing to the principles of the circular economy. Through the detailed examination of three key chapters, we have provided valuable insights into how optimization models and algorithms can significantly enhance waste management practices and overall operational efficiency in logistics.

The first chapter delved into the principles of the circular economy, emphasizing the shift from a traditional linear model of resource consumption to a regenerative and cyclical framework. By integrating technological innovations such as the Internet of Things (IoT), we have shown how smart waste management systems can optimize resource use, reduce waste generation, and promote sustainable practices. This approach not only contributes to environmental sustainability but also supports the efficient management of resources, aligning with the goals of the circular economy.

In the second chapter, we examined various optimization techniques for solving the Multi-objective VRP, categorizing them into Exact Methods, Approximate Methods, and Hybrid Methods. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) was highlighted as a particularly robust method for multi-objective optimization. By balancing objectives of cost and emissions, NSGA-II proved effective in generating high-quality solutions. The application of VRP optimization in smart waste management demonstrated how advanced techniques could lead to dynamic and efficient route planning, thus reducing operational costs and environmental impact.

The third chapter presented a comprehensive bi-objective optimization model aimed at minimizing travel costs and CO2 emissions in vehicle routing problems. By incorporating constraints such as vehicle and bin capacities, travel times, and time windows, the model ensured practical and realistic solutions. The comparative analysis between the Gurobi solver and NSGA-II highlighted the strengths of each approach. While Gurobi provided exact solutions, it was computationally intensive for larger scenarios. In contrast, NSGA-II offered near-optimal solutions with significantly lower computational time, making it a viable alternative for large-scale applications.

Overall, this thesis underscores the importance of combining circular economy principles with advanced optimization techniques to address complex logistical challenges. By leveraging models like NSGA-II, we contribute to more sustainable and efficient waste management practices. This integration not only helps in conserving resources and reducing environmental impact but also paves the way for innovative applications in various industrial domains. The insights gained from this research highlight the potential of multi-objective optimization in promoting sustainable development and enhancing operational efficiency in real-world scenarios. Through this work, we have demonstrated the transformative power of integrating technological innovation and circular economy principles, ultimately contributing to a more resilient and resource-efficient future.

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