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# OPTIMIZING WASTE MANAGEMENT ROUTES USING HEURISTIC FOR THE VEHICLE ROUTING PROBLEM: A GIS-BASED APPROACH

Publicly defended on 25/06/2025 in front of the jury composed of :

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# Dedication

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## Abstract

This thesis explores the application of biologically inspired optimization techniques to the problem of urban waste collection routing, focusing on the BLOB algorithm a Physarum-based metaheuristic modeled on the adaptive foraging behavior of *Physarum polycephalum*. Building on prior research involving Simulated Annealing and Traveling Salesman Problem (TSP) formulations, the work aims to address both the classical TSP and the more complex Vehicle Routing Problem (VRP) under realistic operational constraints. The research is conducted in two phases: (1) benchmarking the performance of the BLOB algorithm against established methods (Simulated Annealing and Lingo Solver) on three representative waste collection routes, and (2) extending the analysis to a full-scale VRP scenario comprising 150 collection points, heterogeneous vehicle capacities, and a centralized depot. Performance is evaluated using metrics such as total distance traveled, execution time, and adherence to capacity limits. GIS-based spatial validation is employed to visualize and substantiate results within the urban context of Tlemcen, Algeria. The findings demonstrate that the BLOB algorithm offers a viable and computationally efficient alternative to conventional heuristics, achieving competitive route optimization while supporting the operational and environmental goals of municipal waste management systems.

**Keywords:** GIS, ArcGIS Pro, Vehicle Routing Problem, Traveling Salesman Problem, Waste Collection, Network Analysis, Spatial Optimization, Tlemcen.

## ملخص

تستكشف هذه الأطروحة تطبيق تقنيات التحسين المستوحاة بيولوجيًا على مشكلة توجيه جمع النفايات في المناطق الحضرية، مع التركيز على خوارزمية BLOB وهي خوارزمية ميتاهورستية قائمة على الفيزيائية على غرار سلوك البحث التكيفي للفيزيائي متعدد الرؤوس. واستناداً إلى الأبحاث السابقة التي تتضمن صيغاً لمحاكاة التلدين ومشكلة البائع المتنقل (TSP)، يهدف العمل إلى معالجة كل من مشكلة التلدين التقليدي ومشكلة توجيه المركبات (VRP) الأكثر تعقيداً في ظل قيود تشغيلية واقعية. وقد تم إجراء البحث على مرحلتين: (1) قياس أداء خوارزمية BLOB مقابل الطرق المتبعة (محاكاة التلدين وحلّ Lingo Solver) على ثلاثة مسارات تمثيلية لجمع النفايات، و(2) توسيع نطاق التحليل ليشمل سيناريو كامل النطاق لمشكلة التوجيه بالمركبات (VRP) الذي يضم 150 نقطة تجميع، وسعات مركبات غير متجانسة، ومستودع مركزي. يتم تقييم الأداء باستخدام مقاييس مثل إجمالي المسافة المقطوعة ووقت التنفيذ والالتزام بحدود السعة. يتم استخدام التحقق المكاني القائم على نظم المعلومات الجغرافية لتصور النتائج وإثباتها في السياق الحضري لمدينة تلمسان بالجزائر. تُظهر النتائج أن خوارزمية BLOB تقدم بديلاً عمليًا وفعالًا من الناحية الحسابية عن الاستدلال التقليدي، مما يحقق تحسينًا تنافسيًا للمسار مع دعم الأهداف التشغيلية والبيئية لأنظمة إدارة النفايات البلدية.

**الكلمات المفتاحية**: نظم المعلومات الجغرافية، ArcGIS Pro، مشكلة توجيه المركبات، مشكلة البائع المتجول، جمع النفايات، تحليل الشبكات، التحسين المكاني، تلمسان.

## Résumé

Cette thèse explore l'application de techniques d'optimisation d'inspiration biologique au problème de l'acheminement des déchets urbains. Elle se concentre sur l'algorithme BLOB, une métaheuristique basée sur Physarum et modélisée sur le comportement adaptatif de recherche de nourriture de Physarum polycephalum. S'appuyant sur des recherches antérieures impliquant le recuit simulé et des formulations du problème du voyageur de commerce (TSP), ce travail vise à traiter à la fois le TSP classique et le problème plus complexe de l'acheminement des véhicules (VRP) sous des contraintes opérationnelles réalistes. La recherche se déroule en deux phases : (1) l'analyse comparative des performances de l'algorithme BLOB par rapport aux méthodes établies (recuit simulé et solveur Lingo) sur trois itinéraires de collecte représentatifs ; et (2) l'extension de l'analyse à un scénario VRP grandeur nature comprenant 150 points de collecte, des capacités de véhicules hétérogènes et un dépôt centralisé. Les performances sont évaluées à l'aide de paramètres tels que la distance totale parcourue, le temps d'exécution et le respect des limites de capacité. La validation spatiale basée sur les SIG est utilisée pour visualiser et étayer les résultats dans le contexte urbain de Tlemcen, en Algérie. Les résultats démontrent que l'algorithme BLOB offre une alternative viable et performante aux heuristiques conventionnelles, permettant une optimisation compétitive des itinéraires tout en soutenant les objectifs opérationnels et environnementaux des systèmes municipaux de gestion des déchets.

**Mots-clés :**SIG, ArcGIS Pro, Problème de tournées de véhicules, Problème du voyageur de commerce, Collecte des déchets, Analyse de réseau, Optimisation spatiale, Tlemcen

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# GLOSSARY

| | |
|---|---|
| **VRP** | Vehicle Routing Problem |
| **CVRP** | Capacitated Vehicle Routing Problem |
| **DVRP** | Dynamic Vehicle Routing Problem |
| **SVRP** | Stochastic Vehicle Routing Problem |
| **VRPTW** | Vehicle Routing Problem with Time Windows |
| **TSP** | Traveling Salesman Problem |
| **MH** | Metaheuristic |
| **SA** | Simulated Annealing |
| **ACO** | Ant Colony Optimization |
| **MST** | Minimum Spanning Tree |
| **SA** | Sensor Angle |
| **RA** | Rotation Angle |
| **API** | Application Programming Interface |
| **OSRM** | Open Source Routing Machine |
| **SMA** | Slime Mold Algorithm |
| **TPSMA** | Two-Way Parallel Slime Mold Algorithm |
| **TSPLIB** | Traveling Salesman Problem Library |

## General Introduction

Waste management stands as one of the critical environmental and operational challenges confronting societies in the 21st century. Rapid urbanization and evolving patterns of consumption have placed considerable strain on the ability of cities to manage waste effectively. The need to collect, transport, and dispose of waste in ways that are not only efficient but also sustainable and socially equitable has become increasingly urgent. Beyond environmental concerns, effective waste management plays a vital role in safeguarding public health, enhancing the quality of urban life, and supporting economic development.

In the North African context, and more specifically in Algeria, these challenges are further intensified. Urban expansion, insufficient infrastructure, and inefficient waste collection systems contribute to the frequent accumulation of municipal solid waste, particularly in densely populated areas. This accumulation often leads to health risks and environmental degradation. Traditional methods of waste collection, which tend to rely on static, route-based systems and manual labor, are not always equipped to handle the rising volume of waste or to adapt to the spatial and temporal variations in waste generation.

To confront these challenges, researchers and urban planners have increasingly adopted advanced computational techniques for optimizing waste collection routes. Of particular interest are problems such as the Traveling Salesman Problem (TSP) and the Vehicle Routing Problem (VRP), which aim to minimize operational costs such as distance traveled, time, or fuel consumption while servicing a network of locations. However, the introduction of real-world constraints, such as vehicle capacities, time windows, and road conditions, adds considerable complexity to these problems.

In response to this complexity, a variety of heuristic and metaheuristic methods have been developed to find near-optimal solutions within acceptable timeframes. While heuristic approaches often yield quick and practical results, metaheuristics provide greater flexibility and the ability to explore wider solution spaces. Among these, biologically inspired algorithms have gained attention, particularly those modeled after the foraging behavior of *Physarum polycephalum*, also known as the slime mold. The so-called Blob Physarum model offers a promising avenue for solving routing problems due to its capacity for adaptive and decentralized decision-making.

Chapter Three of this thesis examines the application of TSP and VRP formulations using a range of optimization strategies, from conventional methods to bio-inspired algorithms. The chapter evaluates each approach in terms of efficiency, scalability, and their practical applicability to waste collection systems.

Building upon this theoretical foundation, Chapter Four presents a case study focused on the city of Tlemcen, Algeria. Here, the VRP is implemented using the Network Analyst extension in ArcGIS Pro, integrating spatial data, road networks, and operational constraints. The case study illustrates how GIS-based routing models can significantly improve the performance of municipal waste collection. The findings offer meaningful insights into how advanced spatial analysis tools and metaheuristic algorithms can contribute to addressing the logistical challenges of urban infrastructure in Algerian cities and potentially across similar contexts.

# CHAPTER 1:
# Waste Management Optimization

## 1.1 Introduction:

Effective waste management plays an essential role in shaping sustainable cities and protecting the environment. As urban areas grow and industries expand, the volume of waste keeps rising putting added pressure on local governments to improve how they collect, dispose of, and recycle waste. To meet these demands, cities need smart, data-driven strategies that boost efficiency while minimizing harm to the planet.

In many developed countries, waste management has made strong progress thanks to circular economy models, sophisticated recycling programs, and waste-to-energy technologies. These innovations have helped cut down on landfill use and improve the recovery of valuable resources. In contrast, Northern African nations still face major hurdles, including unreliable collection systems, tight budgets, and underdeveloped infrastructure. While countries like Algeria, Egypt, Morocco, and Tunisia have launched national plans and regional partnerships, they continue to grapple with challenges in logistics, policy enforcement, and recycling capabilities.

This chapter takes a closer look at how waste management systems can be improved, particularly in the areas of collection, route planning, and decision-making tools. It explores how technologies like Geographic Information Systems (GIS), artificial intelligence (AI), and the Internet of Things (IoT) can make operations more efficient, reduce expenses, and support long-term sustainability. By embracing these modern tools, municipalities can move toward waste systems that are not only smarter and more cost-effective but also better for the environment. [1]

## 1.2 Waste management:

Waste management is a critical field within environmental governance and sustainable development, concerned with the systematic control of the generation, collection, storage, transportation, processing, and disposal of waste. As urban populations and consumption rates continue to rise globally, the volume and complexity of waste have escalated, placing increasing pressure on both developed and developing countries to implement effective waste management strategies [2] The environmental, social, and economic implications of poorly managed waste have elevated the topic to the forefront of international policy agendas.

Defined broadly, waste management encompasses a range of activities designed to mitigate the negative impacts of waste on human health and the environment. These activities include not only disposal but also prevention, minimization, reuse, recycling, and recovery of energy and materials [3].The accepted guiding framework for these activities is the waste hierarchy, which emphasizes waste avoidance as the most preferred option and landfill disposal as the least desirable. This hierarchy reflects the evolving recognition of waste as a resource rather than a burden, and it underpins many national and regional waste policies, especially within the context of the circular economy [4].

Global trends reveal stark contrasts in waste generation and management practices. High-income countries produce significantly more waste per capita but often have access to advanced infrastructure and regulatory systems that enable relatively effective collection, sorting, and recovery. In contrast, low- and middle-income countries frequently face challenges such as informal waste economies, limited institutional capacity, and insufficient funding, which contribute to practices such as open dumping and uncontrolled burning [3].These practices pose serious threats to public health, natural ecosystems, and urban resilience.

The environmental consequences of ineffective waste management are substantial. Decomposing organic waste in landfills emits methane, a potent greenhouse gas, while the open burning of mixed waste contributes to air pollution and human respiratory illnesses. Furthermore, improperly managed hazardous and electronic waste can contaminate soil and water sources, endangering both human and ecological health [2] .Addressing these issues requires integrated solutions that combine technological innovation, policy reform, public participation, and international cooperation.

Given its multidimensional nature, waste management is no longer viewed solely as a technical or municipal responsibility. It has evolved into a strategic priority that intersects with climate change mitigation, resource conservation, urban planning, and economic development. As such, the development of efficient, equitable, and environmentally sound waste management systems is essential for achieving global sustainability goals and fostering long-term resilience in urban and rural communities alike [5] .

## 1.3 Waste Management in North Africa

### 1.3.1 Overview of Waste Generation and Management Challenges

Solid waste management in North Africa presents growing concerns due to rising population densities, rapid urbanization, and limited infrastructure. Countries such as Algeria, Egypt, Morocco, and Tunisia have implemented varied approaches; however, they share a common set of structural challenges including inefficient waste collection systems, financial limitations, and the predominance of informal waste actors. The persistence of these challenges has led to worsening environmental degradation, escalating pollution levels, and increasing public health risks. [6]

Waste generation rates across North African nations vary significantly depending on levels of urbanization, economic activity, and demographic density. Urban areas typically exhibit higher per capita waste generation, ranging from 0.6 to 1.5 kilograms per person per day. This increase is largely driven by commercial and residential consumption patterns. In terms of composition, municipal solid waste in the region is predominantly organic, accompanied by significant fractions of plastic, paper, and textiles, with noticeable differences observed between rural and urban settings. [6]

The accelerated pace of urban growth in North Africa has placed immense pressure on municipal waste management systems. The expansion of urban settlements has resulted in increased volumes of uncollected waste, illegal dumping, and the overextension of existing waste services. This burden is particularly acute in informal settlements and low-income areas, where access to formal collection systems is limited. Additionally, urbanization has driven up demand for single-use plastics and disposable goods, leading to greater accumulation of non-biodegradable waste. [6]

Despite multiple government-led reforms and investments, several key issues continue to hinder effective waste management across the region:

**Deficient Waste Data and Monitoring Systems:** The lack of reliable data regarding waste generation and composition limits policy planning and operational efficiency. [6]

**Insufficient Financial Resources:** Municipalities recover only an estimated 30–40% of operational costs through local taxation and service fees, curbing their ability to invest in infrastructure. [6]

**Weak Legal Enforcement:** Regulatory frameworks exist but are often outdated, under-enforced, or fragmented across institutions, leading to continued illegal dumping and inadequate collection coverage. [6]

**Informal Sector Dependency:** A considerable share of collection and recycling is managed by informal workers, who operate outside legal frameworks and without social protection. [6]

**Underdeveloped Recycling Capacity:** Existing recycling initiatives are constrained by limited technical capacity, minimal investment, and a lack of integration into national waste strategies [6]

**Table 1: Annual Municipal Solid Waste (MSW) Generation in MENA (Middle East and North Africa) Region Countries (2019–2020) [6].**

| Country | Population | Average MSW Generation (kg/capita/day) | Total Waste Generation (million tons/year) |
|---|---|---|---|
| Egypt | 99,413,317 | 0.82 | 29.75 |
| Tunisia | 11,516,189 | 0.60 | 2.52 |
| Jordan | 10,458,413 | 0.90 | 3.44 |
| Iraq | 40,194,216 | 0.87 | 12.76 |
| Algeria | 41,657,488 | 0.90 | 13.68 |
| Lebanon | 6,100,075 | 0.60 | 1.34 |
| Libya | 6,754,507 | 0.77 | 1.90 |
| Syria | 19,454,263 | 0.50 | 3.55 |
| Saudi Arabia | 33,091,113 | 1.80 | 18.13 |
| Oman | 4,613,241 | 1.50 | 2.53 |
| Qatar | 2,363,569 | 1.80 | 1.29 |

| Country | Population | Average MSW Generation (kg/capita/day) | Total Waste Generation (million tons/year) |
|---|---|---|---|
| United Arab Emirates | 9,701,315 | 1.70 | 5.31 |
| Kuwait | 2,916,467 | 1.50 | 1.60 |
| Bahrain | 1,442,659 | 2.70 | 0.79 |
| Yemen | 28,667,230 | 0.60 | 6.28 |
| Morocco | 34,314,130 | 0.80 | 10.02 |

*Table 1 provides an overview of municipal solid waste (MSW) generation in MENA countries (2019–2020), showing differences in population size, per capita waste generation, and total annual waste. High-income countries like Bahrain and Saudi Arabia have high per capita waste rates, while populous nations such as Egypt and Algeria contribute the most to total waste volume. The data reflects regional disparities and highlights the need for country-specific waste management strategies.*

### 1.3.2 Legal and Policy Frameworks for Waste Management

Waste policy frameworks in North Africa are shaped by a combination of national regulations, regional development agendas, and international environmental agreements. Although each country has adopted its own regulatory framework, the effectiveness of these systems is often undermined by weak enforcement mechanisms, limited financial resources, and minimal private sector involvement. [7]

**Algeria**
Algeria has introduced regulations addressing industrial and hazardous waste, including provisions for Extended Producer Responsibility (EPR), which place the burden of waste management on producers. However, institutional fragmentation and the absence of an updated industrial waste registry have impeded the full enforcement of these regulations. [7]

**Tunisia**
Tunisia pioneered environmental policy reform in the region with its 1996 Law 96-41, which established the "polluter pays" principle. Despite its legal strength, the absence of cost recovery mechanisms and limited municipal budgets continue to weaken its implementation. Waste collection and treatment infrastructure remain underdeveloped. [7]

**Morocco**
In 2008, Morocco launched the National Program for Municipal Waste (PNDM), aiming to achieve 90% waste collection coverage by 2020 and 100% by 2030. With an estimated investment of USD 4 billion, the program is primarily financed by municipalities (73%), the central government (9%), and international donors (7%). While substantial progress has been made, the management of hazardous and industrial waste remains insufficient, with much of it disposed of in uncontrolled dumpsites. [7]

**Egypt**

Egypt maintains a centralized waste management system. However, the quality of service varies by income level: affluent neighborhoods benefit from structured, door-to-door collection, while low-income areas rely on informal systems. The Inter-Ministerial Committee on Waste Management, formed in 2009, has attempted to modernize waste strategies and adopt integrated solid waste management (ISWM) models, but the implementation remains inconsistent. [7]

North African countries also participate in international frameworks that shape national waste strategies:

**Basel Convention (1989):** Prohibits transboundary movement of hazardous waste and reduces the risk of illegal dumping in low-income nations. [7]

**Mediterranean Action Plan (UNEP):** Supports marine litter reduction and coastal waste management improvements. [7]

**African Union's Agenda 2063:** Encourages sustainable waste practices, including the expansion of WTE and recycling infrastructure. [7]

Despite these commitments, national systems face institutional and financial bottlenecks. The operationalization of laws often remains symbolic, as enforcement mechanisms are either weak or fragmented.

To address these systemic gaps, policy reforms should focus on:

1. **Improved Institutional Coordination:** Establishing stronger inter-agency collaboration between local authorities, ministries, and regulatory bodies. [7]
2. **Sustainable Financing Tools:** Introducing eco-taxes and standardized service fees to fund collection, treatment, and recycling infrastructure. [7]
3. **Private Sector Engagement:** Promoting public-private partnerships (PPPs) and offering incentives for investment in waste treatment and valorization projects. [7]

**Table 2: Comparative Overview of National Waste Management Policies in Selected North African Countries [7].**

| Country | Key Policy | Year | Main Features | Implementation Challenges |
|---|---|---|---|---|
| Algeria | EPR | ~2001 | Industrial waste regulation | Weak enforcement, no waste registry |
| Tunisia | Law 96-41 | 1996 | Polluter-pays principle | No cost-recovery system |
| Morocco | PNDM | 2008 | 90% collection target, USD 4B budget | Industrial waste underregulated |
| Egypt | ISWM Plan | 2009 | Centralized oversight, Inter-Ministerial Committee | Uneven collection, informal reliance |

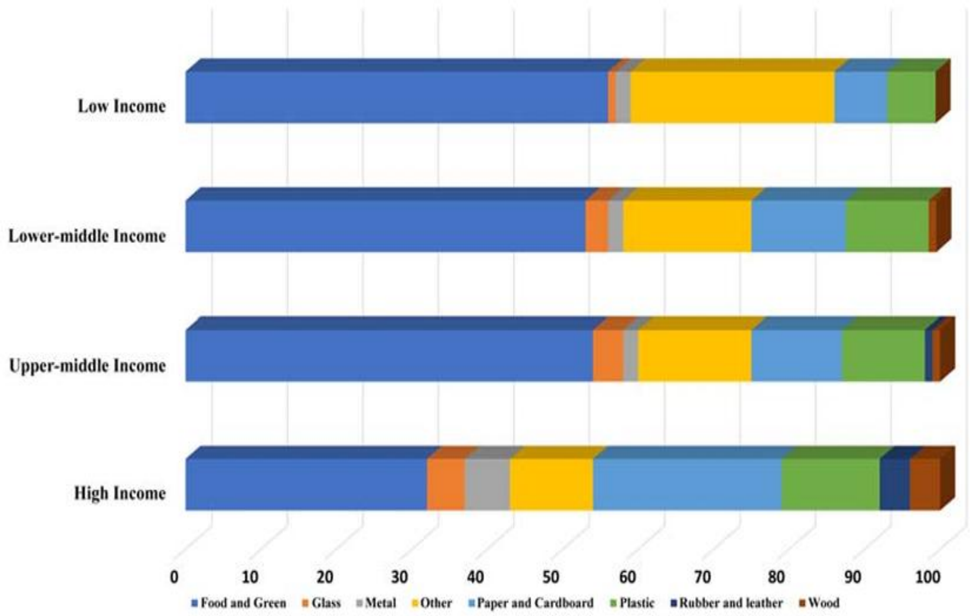


**Figure 1 : Composition of municipal solid waste by income group. [8]**

*The figure 1 illustrates : Higher-income countries generate more recyclable and non-biodegradable waste, while lower-income regions produce a higher share of organic waste*

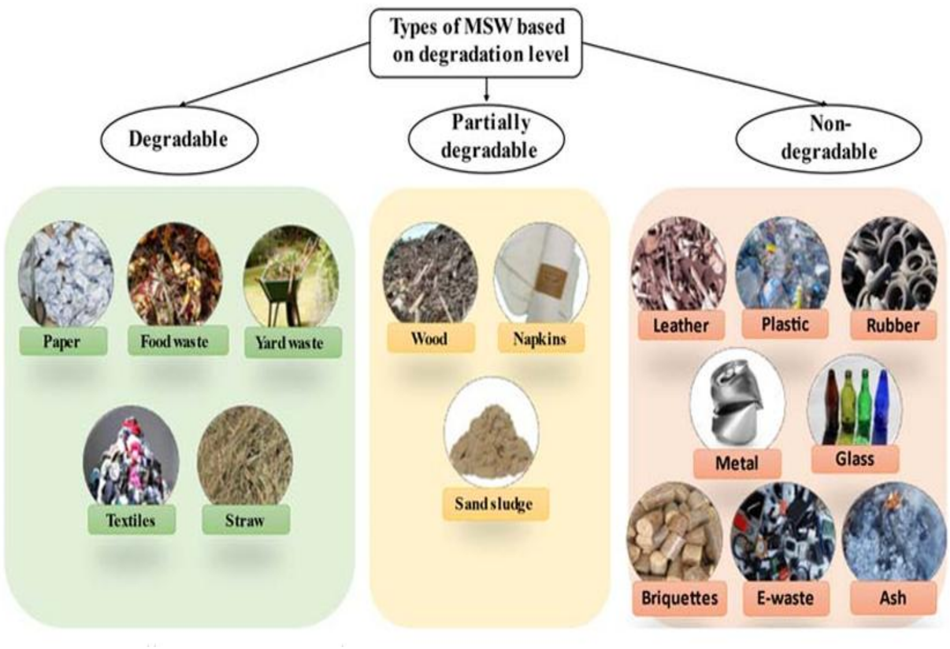


**Figure 2: Classification of municipal solid waste by degradation potential. [8]**

*Figure 2 illustrates how waste composition varies significantly with income level, providing insights into the recycling and treatment challenges faced by countries in the MENA region*

## 1.4 Transition from Landfilling to Advanced Waste Treatment Technologies

### 1.4.1 Treatment Technologies

In response to environmental concerns, limited land availability, and evolving regulations, many developed countries have shifted away from traditional landfill-based waste disposal. This transition has been driven by the adoption of advanced treatment solutions such as Waste-to-Energy (WTE), Mechanical-Biological Treatment (MBT), and modern recycling systems.

One striking example of the consequences of inadequate waste infrastructure is the Thilafushi dumpsite in the Maldives, where vast accumulations of plastic waste illustrate the urgency of adopting sustainable alternatives. Such scenarios underscore the importance of transitioning to circular systems that prioritize resource recovery and environmental protection. [9]

**Figure 3: Massive accumulation of plastic waste at the Thilafushi waste disposal site in the Maldives. [9]**

*A vivid example of the consequences of inadequate waste segregation and insufficient recycling infrastructure is illustrated in Figure 3, where the large-scale accumulation of plastic waste at open dumpsites like Thilafushi highlights the environmental urgency of transitioning toward more sustainable and circular waste management systems.Future Innovations and Policy Trends*

### 1.4.2 Future Innovations and Policy Trends

The future of waste treatment in developed nations is increasingly focused on enhancing sustainability and embracing advanced technologies. Key developments are expected to include more ambitious landfill diversion goals, building on the success of current European Union directives that have already driven substantial reductions in landfill use. One emerging trend is the application of artificial intelligence in recycling operations, where AI-powered sorting systems improve the precision and speed of material separation, thereby boosting overall recycling efficiency. In parallel, innovations in bio-conversion technologies are poised to accelerate, particularly in converting organic waste into biofuels and other renewable energy sources. These advancements support overarching environmental objectives centered on energy recovery and resource conservation, moving away from conventional disposal methods. Evolving policy frameworks continue to promote a circular economy model, encouraging a shift from linear waste practices toward systems designed to maximize resource recovery and minimize residual waste generation. [1] [9]

## 1.5 Recycling Systems and Waste Sorting Mechanisms

Recycling continues to serve as a cornerstone of sustainable waste management in developed countries. These nations have established robust systems for the collection, separation, and processing of materials such as plastics, paper, metals, and glass. In places like Sweden, recycling is deeply embedded in daily life and even contributes to the economy, with sorted recyclables often exported for further refinement. A key element in the effectiveness of these programs is the integration of efficient sorting mechanisms. Waste is sorted at the source ypically through color-coded household bins and further refined in specialized facilities equipped with automated technologies that classify materials based on their physical and chemical properties. This high degree of accuracy helps ensure that recovered materials meet quality standards necessary for reuse. Economically, recycling stimulates job creation and generates revenue through the sale of processed materials. Environmentally, it eases pressure on landfills, reduces pollution, and supports the broader goals of a circular economy by promoting resource conservation and long-term sustainability. [10]

## 1.6 Waste-to-Energy (WTE) Technologies in Developed Nations

### 1.6.1 Incineration as a Key Method

In efforts to reduce reliance on landfills and enhance energy recovery, developed countries have increasingly adopted waste-to-energy (WTE) technologies as a central component of waste treatment strategies. Incineration remains the most commonly used method, involving the controlled burning of municipal solid waste to produce electricity and heat. While incineration is effective in reducing waste volume and generating energy, concerns over air pollution have led to the widespread implementation of advanced emission control technologies. Modern facilities are equipped with systems such as flue gas scrubbers and filters that ensure compliance with strict environmental regulations. In addition to incineration, emerging thermal treatment methods like gasification and pyrolysis are gaining traction. These processes operate in oxygen-limited environments, breaking down waste into syngas and biofuels that can be used for cleaner energy production. Compared to traditional combustion, these techniques offer higher energy efficiency and a reduced environmental footprint, aligning with broader goals to decarbonize energy systems and promote sustainable resource management. [10]

## 1.7 The Scandinavian Model: Incineration and Energy Recovery

Scandinavian countries namely Sweden, Denmark, and Norway have established themselves as global leaders in sustainable waste management by strategically incorporating incineration-based waste-to-energy (WTE) systems into their national frameworks. In these nations, WTE serves as a cornerstone of municipal waste policy, enabling the conversion of non-recyclable waste into electricity and heat for district energy networks. This approach has resulted in the near-total elimination of landfilling, with the majority of waste either recycled or incinerated. By redirecting residual waste away from landfills, these countries have significantly cut greenhouse gas emissions while maximizing the energy potential of their waste. To address environmental concerns, Scandinavian WTE facilities are outfitted with state-of-the-art emission control technologies, including flue gas scrubbers, carbon capture systems, and high-efficiency energy recovery units. These safeguards ensure adherence to strict European Union environmental regulations and minimize the environmental impact of incineration. The Scandinavian model exemplifies how energy recovery and environmental stewardship can be effectively integrated within a circular economy, offering a replicable blueprint for sustainable waste management. [10]

## 1.8 Waste Collection and Disposal Methods in North Africa

Waste collection and disposal remain persistent challenges in North African countries, largely due to inadequate infrastructure, financial constraints, and weak regulatory enforcement. A marked disparity exists between urban and rural waste management systems, and the ongoing reliance on open dumping emphasizes the urgent need to upgrade existing disposal practices. [11]

### 1.8.1 Urban Rural Disparities in Collection Services

Municipal solid waste collection services in North Africa are unevenly distributed. Urban areas, particularly affluent districts, generally benefit from structured and regular door-to-door collection systems supported by greater municipal budgets. In contrast, rural and peri-urban regions often lack basic waste services, relying instead on self-disposal methods such as open burning or illegal dumping in public spaces and waterways. Low-income urban neighborhoods are especially underserved, with sporadic collection leading to severe environmental degradation and heightened public health risks [11].

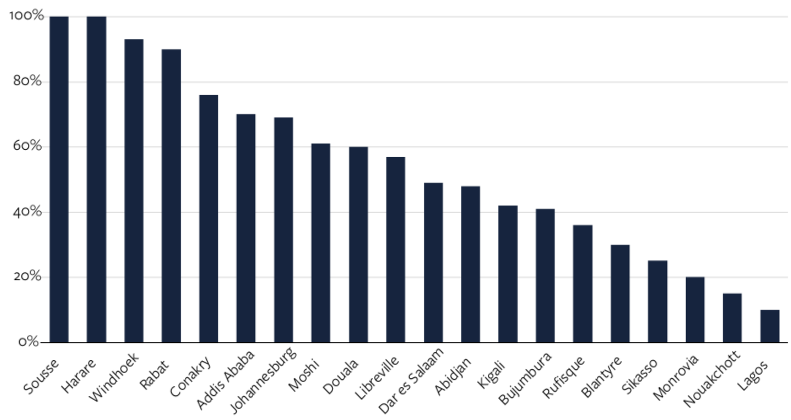


**Figure 4: Comparison of waste collection rates across selected African cities [12]**

*Waste collection coverage remains highly uneven across African cities, with performance ranging from nearly 100% in cities like Sousse, Harare, and Rabat to less than 20% in others such as Monrovia, Nouakchott, and Lagos. This stark disparity highlights persistent infrastructural and governance challenges in many urban systems. As illustrated in Figure 4, these variations underscore the need for more equitable and efficient waste management strategies across the continent.*

**Table 3: Classification of Waste Disposal Methods and Their Environmental Controls in North Africa [11]**

| Disposal Type | Description | Environmental Controls | Example Use in North Africa |
|---|---|---|---|
| **Open Dumping** | Waste disposed without any control or containment | None | Still common in many urban peripheries |
| **Controlled Tipping** | Waste deposited with minimal operational supervision | Limited site control | Intermediate step in upgrading disposal |
| **Basic Sanitary Landfill** | Waste compacted and covered daily with soil | Basic leachate reduction | Used in upgraded municipal disposal sites |
| **Advanced Sanitary Landfill** | Includes leachate collection, methane capture, and environmental monitoring | Full containment & energy recovery | Pilot projects in Algeria and Morocco |

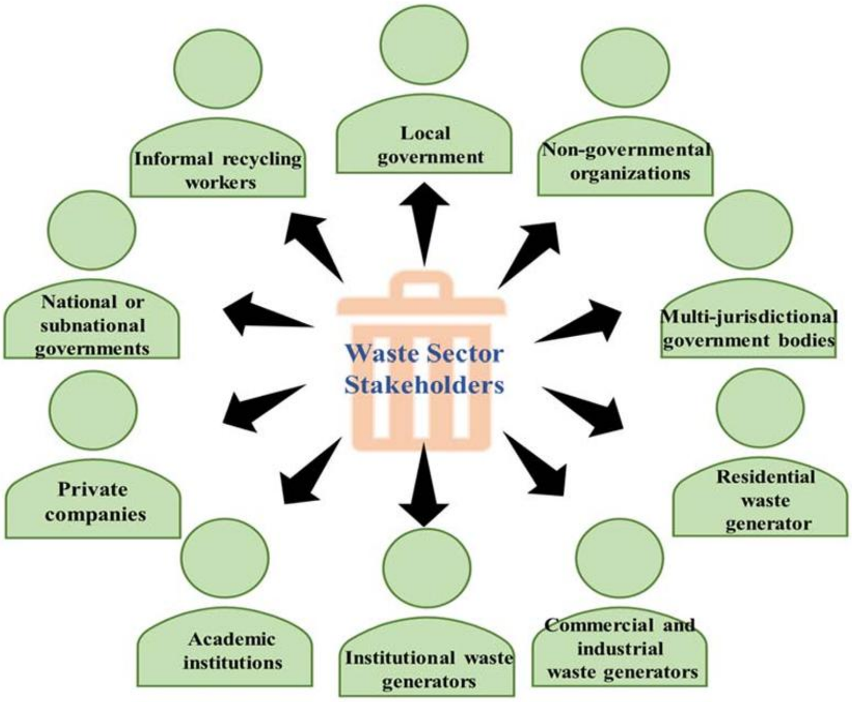


Figure 5: Key stakeholders in the waste management sector [8]

*As shown in Figure 5 , waste management involves a diverse array of stakeholders, from informal workers to multi-level government bodies and private entities. A lack of coordination among these groups often hampers system efficiency*

### 1.8.2 Contributions to Waste Recovery

Informal waste workers play a crucial yet often overlooked role in the recycling ecosystem of North African cities. Operating outside formal waste management systems, they are instrumental in collecting and sorting substantial quantities of recyclable materials such as plastics, metals, paper, and glass from residential neighborhoods, commercial areas, and public waste streams. These recovered materials are then sold to intermediaries or directly to recycling businesses, forming a decentralized but effective value chain. Beyond recyclables, many informal workers also engage in basic composting of organic waste, converting biodegradable materials into compost that is reused in agriculture. While these practices are typically low-tech and lack institutional backing, they nonetheless contribute meaningfully to waste diversion and resource recovery. Despite facing challenges such as inadequate infrastructure and limited legal recognition, informal waste workers significantly ease the pressure on municipal systems and play a key role in promoting circular waste practices in the region. [12]

An exemplary model is the **Zabbaleen** community in Cairo, Egypt, which operates a self-managed recycling system that processes up to 80% of collected waste one of the highest recycling rates globally [12].

Table 4: Overview of Cooperative Waste Management Initiatives in Moroccan Cities. [12]

| City | Intervention Type | Implementing Actor | Key Benefits | Challenges |
|---|---|---|---|---|
| Rabat | Formation of waste picker cooperatives | Municipality & NGOs | Formal contracts, improved wages, safety equipment | Limited scaling, dependence on external funding |
| Casablanca | Public-private waste recovery centers | Municipal + Private Sector | Legal recognition, integration into municipal recycling stream | Need for sustained policy support |

Table 5: Key Features of Zabbaleen Waste Recovery Operations in Cairo. [12]

| Feature | Description |
|---|---|
| Location | Cairo, Egypt |
| Group | Zabbaleen informal waste collectors |
| Coverage | Handles up to 80% of Cairo's waste recovery |
| Process | Door-to-door collection → sorting → recycling or composting |
| Economic Structure | Recyclables sold to local industries; some items reused in artisan crafts |
| Recognition | Limited municipal support; mostly self-organized |
| Environmental Impact | Extremely high recycling efficiency, limited landfill reliance |

### 1.8.3 Case Study: Waste Management in Algeria

Algeria continues to face significant structural challenges in modernizing its waste management system. The country is heavily reliant on landfill disposal, with approximately 89% of municipal waste directed to landfills, and only a small fraction around 8% disposed of in controlled sanitary sites. This high dependence on unregulated dumping reflects deeper issues within the country's infrastructure and regulatory landscape. The recycling rate remains alarmingly low, hovering below 1%, largely due to ineffective waste separation practices and insufficient investment in material processing facilities. Although the Algerian government has introduced ambitious waste reduction targets and implemented bans on the landfilling of certain hazardous materials, enforcement mechanisms are weak and inconsistently applied. As a result, policy frameworks often fail to translate into tangible improvements on the ground. Addressing these systemic weaknesses will require a concerted effort to expand recycling initiatives, strengthen regulatory compliance, and direct substantial resources toward the development of modern waste recovery technologies and infrastructure**.** [12]

## 1.9 Challenges in Waste Collection Logistics

Effective waste collection forms the backbone of any successful municipal solid waste (MSW) management system, yet it remains a persistent challenge in many North African and developing urban centers. Financial limitations, inadequate infrastructure, and poor coordination among institutional actors frequently hinder the reliability and efficiency of collection services. In many cities, waste collection is unevenly distributed, favoring central and affluent districts while marginalizing informal settlements and peripheral areas. The lack of integrated logistical planning often results in inconsistent scheduling, limited vehicle deployment, and inefficient routing. Municipal authorities also face operational hurdles, such as equipment shortages, irregular fleet maintenance, and understaffed waste departments. These systemic issues are further exacerbated by the absence of performance monitoring and data-driven planning, limiting the potential for responsive and cost-effective service delivery. [12] [1]

### 1.9.1 Financial Constraints in Waste Collection

Financial sustainability remains one of the most pressing challenges in the management of waste collection services. In many low-income countries, waste management consumes up to 20% of total municipal budgets, a stark contrast to the 4% typically allocated in high-income nations. This disproportionate burden strains municipal finances, often leaving little room for system improvements. As a result, authorities struggle to maintain or expand vehicle fleets, secure fuel supplies, and provide timely maintenance. These budgetary constraints also limit the ability to offer competitive wages and benefits to sanitation workers, impacting labor retention and service reliability. Compounding these challenges is the widespread inefficiency in cost recovery, with many municipalities facing low waste service fee collection rates. Without adequate revenue streams, even basic operational costs remain unmet, reinforcing a cycle of underfunding and underperformance in urban waste collection systems [12]

### 1.9.2 Inefficiencies in Collection Operations

Operational inefficiencies significantly impact the performance and cost-effectiveness of waste collection services in North African and other developing cities. One of the most prominent issues is the reliance on outdated or inadequate waste collection vehicles, many of which suffer frequent mechanical breakdowns that interrupt service delivery. These interruptions result in inconsistent collection schedules and growing volumes of uncollected waste. Informal settlements and peri-urban zones are particularly underserved due to the inaccessibility of narrow or unpaved roads, which standard waste trucks cannot navigate. Consequently, these areas often experience prolonged waste accumulation and resort to illegal dumping. Studies indicate that the operating efficiency of waste collection vehicles in African cities can fall below 50%, highlighting the urgent need for investment in fleet modernization and route optimization strategies. [11] [13] [8]

### 1.9.3 Geographic and Infrastructure Barriers

The geographical and infrastructural conditions in many urban areas present significant barriers to effective waste collection. In densely populated neighborhoods, particularly informal settlements, the presence of narrow alleys and unpaved roads restricts access for standard waste trucks. Additionally, traffic congestion in central zones not only delays collection times but also increases fuel consumption and operational costs. The absence of conveniently located collection points exacerbates the issue, often leading to uncontrolled dumping in open areas. In response to these challenges, some municipalities have introduced alternative collection models using small-scale transporters or community-based systems. However, these initiatives often remain underfunded and lack the institutional support required for large-scale implementation and sustainability. [8]

## 1.10 Role of route optimization in cost and time reduction

### 1.10.1 Importance of Route Optimization in Waste Collection

Route optimization has emerged as a vital tool for reducing the high operational costs associated with municipal solid waste (MSW) collection. Waste collection alone can represent 50–70% of total waste management expenditures in urban settings. A major contributor to these costs is inefficient routing, which leads to extended travel distances, increased fuel consumption, and excessive vehicle wear and tear. Poorly planned routes also result in longer collection cycles and missed pickups, negatively impacting public health and environmental quality. Implementing optimized routing strategies can significantly reduce these inefficiencies by improving vehicle dispatching and route planning based on demand, geography, and road conditions [11] [8].

### 1.10.2 Cost Reduction Through Route Optimization

The financial advantages of route optimization are well-documented. Efficient routing reduces unnecessary travel distances, resulting in lower fuel consumption—studies suggest savings of 20–30% in some cases. These savings extend beyond fuel; shorter routes reduce vehicle strain, prolonging equipment lifespan and decreasing maintenance costs. Labor costs also benefit, as streamlined routes reduce overtime and the number of collection shifts required. In resource-constrained municipalities, these cumulative savings can be reinvested to expand service coverage or upgrade outdated equipment, further improving operational efficiency and sustainability. [11] [8]

### 1.10.3 Time Efficiency in Waste Collection

Time efficiency is equally important in urban waste management, as delayed collection exacerbates public health risks and contributes to environmental degradation. By implementing intelligent routing systems, municipalities have been able to reduce collection times by up to 40% in some areas. This is especially important in high-density neighborhoods, where timely waste removal is critical to avoid street-level accumulation and illegal dumping. Moreover, regular and predictable collection schedules build public trust and satisfaction, fostering better community cooperation with waste separation and storage practices. [8]

### 1.10.4 Technologies Used in Route Optimization

Recent advances in digital technologies have substantially improved the potential for optimized waste collection. Tools such as Geographic Information Systems (GIS), Artificial Intelligence (AI), and Internet of Things (IoT) sensors allow for dynamic route planning based on real-time data. These technologies enable waste authorities to monitor bin fill levels, traffic conditions, and service frequency requirements to adjust routes accordingly. Such smart systems reduce inefficiencies and enhance overall fleet utilization, offering a scalable model for improving waste management performance in both urban and peri-urban environments. [12]

## 1.11 Geographic Information Systems (GIS)

GIS technology has become a critical asset in the strategic planning and optimization of waste collection services. By mapping variables such as waste generation hotspots, road networks, and traffic patterns, GIS enables planners to design more effective and responsive collection routes. Additionally, GIS tools assist in the strategic placement of waste transfer stations and disposal facilities, minimizing travel distances and service delays. The integration of GIS into municipal operations also supports real-time decision-making, allowing route adjustments based on changing urban conditions or emergent service gaps. In cities where logistical challenges are common, GIS provides a practical and cost-effective solution to enhance system efficiency and coverage. [11]

## 1.12 Artificial Intelligence (AI) and Machine Learning

Artificial Intelligence (AI) and machine learning are emerging as essential tools in optimizing municipal waste collection. These technologies analyze historical waste generation patterns to forecast future accumulation, allowing collection services to adjust frequencies based on real-time demand. As a result, vehicle dispatching becomes more efficient, with fewer redundant trips and reduced operational delays. Additionally, AI supports route flexibility by adapting to traffic patterns and spatial waste distribution fluctuations, enhancing responsiveness in dynamic urban environments. [8]

## 1.13 IoT-Enabled Smart Waste Bins

The integration of Internet of Things (IoT) technology into municipal waste systems, particularly through smart bins, has significantly improved operational efficiency. These bins are equipped with sensors that monitor fill levels in real time and transmit data to waste management systems. This allows for on-demand waste collection, reducing unnecessary truck deployments. IoT systems not only minimize fuel usage and labor hours but also support waste segregation efforts by ensuring timely pickup of recyclable materials, which reduces contamination and supports recycling initiatives. [8]

## 1.14 Challenges in Implementing Route Optimization

Despite the clear benefits of route optimization, its implementation in many developing countries is hindered by structural and financial constraints. A lack of technological infrastructure significantly limits the deployment of advanced systems like Geographic Information Systems (GIS) and AI. Municipal budgets often cannot accommodate the high initial costs of integrating smart technologies. Additionally, data collection challenges such as incomplete or unreliable waste generation records undermine the ability to create predictive routing models. These issues collectively restrict the widespread adoption of optimized collection strategies. [8]

## 1.15 Develop an Optimized Routing Model for Waste Collection

An optimized waste collection routing model is built upon several interdependent technological and analytical components, each contributing to a more efficient, data-driven waste management system. The process begins with data collection and algorithm development, followed by route simulation based on real-time and historical patterns. One foundational element is the use of Geographic Information Systems (GIS), which enable planners to map and analyze spatial variables such as the location of waste bins, volume accumulation rates, and traffic congestion. GIS applications are particularly valuable for navigating topographical barriers and identifying optimal travel paths, with studies showing that GIS-driven route planning can reduce travel distances by up to 30%, resulting in lower fuel consumption and decreased vehicle wear.

Complementing GIS is the deployment of Internet of Things (IoT) technologies, specifically smart bins equipped with fill-level sensors. These sensors provide real-time information on bin status, enabling dynamic scheduling of collections only when bins reach capacity. This approach not only minimizes unnecessary vehicle trips but also reduces fuel expenditures and labor costs. Data suggest that implementing IoT-based systems can cut waste collection costs by 20–40%, while simultaneously enhancing overall service reliability and fleet efficiency.

Artificial Intelligence (AI) and machine learning form the third pillar of an optimized routing model. These technologies analyze past waste generation data to identify trends and forecast future accumulation. As a result, AI-driven models can guide proactive route adjustments, allocate fleets more efficiently, and create adaptive schedules that account for peak waste generation periods. Such predictive capabilities allow for real-time responsiveness to urban dynamics, increasing the efficiency of collection operations by up to 25% and contributing to substantial long-term cost savings. [8] [11]

### 1.15.1 Benefits of an Optimized Routing Model

Implementing an optimized routing model in municipal solid waste collection systems offers wide-ranging operational, economic, and environmental advantages. Strategically planned routes help reduce total travel distances for collection vehicles, which directly cuts down on fuel consumption and associated expenses. Over time, this not only lowers operational budgets but also reduces wear and tear on the fleet, extending vehicle lifespans. Optimized routing also enhances time efficiency, allowing for quicker waste collection and fewer service disruptions. This is particularly valuable in densely populated areas where delays can lead to public complaints or health hazards. In addition to financial and logistical benefits, optimized routing contributes to environmental sustainability by reducing carbon emissions. Faster and more reliable waste removal also plays a role in protecting public health by minimizing the time that waste remains uncollected in residential areas, thus decreasing exposure to pests and pathogens [8].

### 1.15.2 Challenges in Implementing Optimized Routing Models

Despite the clear benefits, several challenges hinder the implementation of optimized routing models, especially in developing regions. A primary barrier is the lack of access to the necessary technological infrastructure, including Geographic Information Systems (GIS), Internet of Things (IoT) tools, and Artificial Intelligence (AI) platforms. These systems require not only financial investment but also skilled personnel to manage and interpret the data they generate. Additionally, the cost of acquiring and maintaining such technologies can be prohibitive for municipalities with limited budgets. Another significant hurdle is the lack of reliable data on waste generation and collection dynamics. Developing accurate and responsive routing models requires real-time input, but many cities struggle with fragmented or outdated records. Some municipalities have begun to overcome these obstacles through partnerships with private firms or development agencies, which provide technical support and funding to facilitate the adoption of smart waste collection technologies [8].

## 1.16 Integrating GIS Tools for Spatial Analysis and Optimization

Geographic Information Systems (GIS) have become indispensable tools in the modernization of urban waste management, enabling spatial analysis, operational planning, and environmental monitoring within a unified digital framework. In the domain of waste collection and transport, GIS facilitates the integration of spatial and logistical data to inform decisions on route planning and resource allocation. By analyzing factors such as population density, waste generation hotspots, and traffic congestion, GIS helps optimize collection paths, improving both service coverage and operational efficiency. Unlike static maps, GIS-driven route planning can adapt to real-time changes in urban infrastructure, making it a dynamic tool for responding to seasonal trends and emergent challenges. As a result, many cities have experienced enhanced service reliability and reduced collection costs.

Beyond routing, GIS also functions as a robust decision-support system, particularly through web-based applications that allow municipalities to monitor fleet movements, track service progress, and evaluate landfill capacity in real time. Some cities have reported efficiency improvements of up to 80% following the implementation of such platforms. GIS is equally critical in forecasting waste generation by correlating demographic trends with historical data, enabling planners to anticipate future service demands and adjust collection schedules proactively.

In terms of infrastructure planning, GIS is instrumental in landfill siting and environmental risk assessment. It supports suitability analyses based on hydrological, geological, and land-use factors, ensuring that selected locations meet safety and zoning requirements. GIS also helps monitor environmental risks such as leachate seepage and methane emissions, reinforcing regulatory compliance and minimizing ecological harm.

Despite these transformative applications, several barriers continue to impede the full-scale implementation of GIS in waste management. High upfront costs for software, hardware, and personnel training are major constraints for many municipalities. Additionally, the shortage of skilled GIS professionals and the reliance on outdated or incomplete spatial datasets limit the technology's effectiveness in several regions. Overcoming these challenges will require sustained investment, inter-agency collaboration, and strategic capacity-building initiatives. [8] [8]

## 1.17 Conclusion

Improving municipal solid waste management is essential for enhancing urban environmental quality, protecting public health, and promoting long-term sustainability. This chapter has examined the persistent challenges that hinder effective waste systems in North Africa, including infrastructural deficits, weak policy enforcement, and continued reliance on unsanitary landfilling.

In response to these challenges, the integration of advanced tools such as route optimization algorithms, heuristic models for vehicle routing, and GIS-based spatial analysis presents a strategic pathway toward more efficient and adaptive waste collection systems. These technologies have demonstrated the capacity to reduce operational costs, expand service coverage, and support environmental resilience.

However, the successful deployment of these innovations requires overcoming entrenched financial and technical barriers. Strengthening institutional capacity, securing investment in digital infrastructure, and fostering cross-sectoral partnerships particularly through public-private collaboration are critical next steps. Future policies should also support training and capacity development in data-driven waste management practices. By pursuing these strategies, cities can transition toward smarter, more resilient, and environmentally responsible waste management systems aligned with circular economy principles and sustainable urban development goals.

# Chapter 2:
# Vehicle Routing Problem and Metaheuristics

## 2.1 Introduction:

The Vehicle Routing Problem (VRP) represents one of the most critical and studied challenges in logistics, transportation, and operations research. Rooted in the foundational work of Dantzig and Ramser in 1959, the VRP extends the classical Traveling Salesman Problem (TSP) by incorporating multiple vehicles and a range of operational constraints, including vehicle capacity, delivery time windows, and service schedules. As cities grow denser and supply chain networks become more complex, optimizing vehicle routes has become essential not only for reducing operational costs but also for improving energy efficiency, minimizing environmental impact, and enhancing customer satisfaction.

This chapter provides a comprehensive overview of the VRP, starting with its mathematical foundations and evolving through its many practical variants such as the Capacitated VRP, VRP with Time Windows, and Stochastic VRP. It also explores the classification of VRP types based on problem characteristics, customer requirements, fleet configurations, and optimization goals. The chapter then delves into the modeling and resolution strategies used to solve VRP instances, including exact, heuristic, and metaheuristic approaches. In particular, it focuses on metaheuristics such as Simulated Annealing and Ant Colony Optimization, highlighting their ability to offer scalable, near-optimal solutions in real-world applications.

A special emphasis is placed on bio-inspired methods, especially those derived from the foraging behavior of the slime mold *Physarum polycephalum*. These methods, including the innovative Blob algorithm, represent a new frontier in solving complex routing problems by mimicking intelligent biological behaviors. This chapter bridges classical theory with emerging biological computing paradigms, offering insights into how nature-inspired intelligence can transform traditional logistics optimization.

## 2.2 Vehicule Routing Problem (VRP) :

The Vehicle Routing Problem (VRP) is a fundamental combinatorial optimization problem in logistics and transportation management. It focuses on designing optimal routes for a fleet of vehicles to deliver goods or services to a set of geographically dispersed customers, with the objective of minimizing costs such as distance traveled, time, and fuel consumption. VRP has widespread application in industries like supply chain distribution, waste collection, public transportation, and e-commerce logistics, where efficient vehicle routing is critical for reducing operational expenses and improving service quality .

Conceptually, the VRP extends the classical Traveling Salesman Problem (TSP) which seeks the shortest possible route for a single traveler visiting multiple locations by incorporating multiple vehicles and a variety of practical constraints. These constraints include vehicle capacities, customer time windows, route length limits, and service requirements. Due to its NP-hard nature, solving VRP optimally becomes computationally infeasible for large instances, prompting the development of heuristic and metaheuristic algorithms that yield high-quality solutions in reasonable computation times .

Numerous VRP variants have been developed to address specific logistical challenges. These include the Capacitated VRP (CVRP), which imposes limits on vehicle load; the VRP with Time Windows (VRPTW), which introduces scheduling constraints; the Dynamic VRP (DVRP), which responds to real-time demand changes; and the Stochastic VRP (SVRP), which accounts for uncertainty in parameters such as demand or travel time. Each of these variants will be discussed in detail in subsequent sections. [14]

## 2.3 Historical Background and Evolution of VRP

The origins of the Vehicle Routing Problem (VRP) can be traced back to the pioneering work of Dantzig and Ramser (1959), who introduced the problem in the context of truck dispatching. Their formulation marked the beginning of systematic research in vehicle routing and set the foundation for decades of subsequent developments . In 1964, Clarke and Wright introduced the Savings Algorithm, which remains one of the earliest and most efficient heuristic approaches for solving routing problems.

During the 1970s and 1980s, research efforts focused on refining exact methods, such as branch-and-bound and integer linear programming. However, as the problem size grew, the computational complexity of these methods became prohibitive. This limitation drove the shift toward heuristic and metaheuristic techniques, including simulated annealing, which allowed for high-quality approximations within acceptable time frames.

The 1990s and early 2000s witnessed a rise in interest in nature-inspired metaheuristics. Notably, Ant Colony Optimization (ACO) and evolutionary algorithms provided scalable approaches to solving large VRP instances. More recently, innovative algorithms such as the Physarum-based Blob Algorithm have been proposed, drawing inspiration from biological systems to model decentralized pathfinding and adaptive behavior .

Today, VRP research continues to evolve in response to modern logistical demands. Real-time data, dynamic routing, stochastic variability, and integration with machine learning models have pushed the boundaries of VRP-solving techniques. These innovations reflect the increasing complexity of transportation systems and the need for intelligent, adaptive optimization strategies. [15]

## 2.4 Characteristics of the Problem

The VRP can be described through several characteristics that influence its complexity and solution methods.

### 2.4.1 Graphical Representation:

The VRP can be modeled using directed, undirected, or mixed graphs. Moreover, problem parameters, such as the travel cost matrix, may or may not adhere to the triangular inequality. In some cases, deliveries can be made either partially or in full, while travel requests and costs may be deterministic or stochastic. [15]

### 2.4.2 Customers:

In a graphical representation, customers are represented as nodes or arcs and are typically categorized as retail customers (depots) or individual customers. Certain VRP instances include multiple depots that may serve as intermediate points. Customers are assigned specific delivery demands, which can be constant or variable, and may need to be fulfilled within predefined time windows, either flexible or strict.Moreover, customers may have assigned priority levels or visit frequency constraints. In certain cases, some customers cannot be served due to fleet limitations. [15]

### 2.4.3 Fleet Attributes:

The vehicle fleet can be **fixed or variable**, depending on the problem constraintsA major constraint is vehicle capacity, which can be **homogeneous**, where all vehicles have the same capacity, or **heterogeneous**, with varying capacities across the fleet. The load capacity may be considered as a single volume or segmented into multiple compartments. Furthermore, constraints related to vehicle availability intervals and synchronization requirements may also be imposed. Some instances also incorporate **cost constraints**, setting maximum travel allowances for each vehicle, which may be uniform or vary across the fleet. [15]

### 2.4.4 Optimization Objectives:

Different variants of the VRP optimize distinct criteria. The most common objectives include minimizing **travel costs, fleet size, or service time**, while ensuring adherence to constraints such as vehicle capacity and availability. In multi-objective formulations, multiple criteria can be optimized simultaneously . [15]

## 2.5 VRP Types

Over the years, extensive research on the VRP has led to the development of various problem variants. These variations address specific logistical and operational challenges encountered in transportation and distribution networks. The most notable VRP extensions include:

### 2.5.1 Capacitated Vehicle Routing Problem (CVRP)

The Capacitated Vehicle Routing Problem (CVRP) is a widely studied extension of the classical Vehicle Routing Problem (VRP), where each vehicle in a fleet must operate under a fixed maximum load capacity. Each customer has a specific demand, typically expressed in units of weight or volume, and the total demand on any given route must not exceed the vehicle's capacity. The primary objective of CVRP is to design cost-efficient routes that satisfy all customer demands while minimizing total travel distance or delivery cost. This variant is especially critical in real-world logistics systems, particularly in industries with volume- or weight-sensitive operations, such as parcel delivery (e.g., FedEx, UPS), retail distribution (e.g., Walmart), and bulk goods transportation (e.g., food, fuel, construction materials). Key operational challenges include maximizing vehicle utilization, optimizing fleet size and route length, and adapting to real-time constraints such as traffic conditions and vehicle availability. [15]

### 2.5.2 Dynamic Vehicle Routing Problem (DVRP)

The Dynamic Vehicle Routing Problem (DVRP) is a real-time extension of the classical Vehicle Routing Problem (VRP), developed to manage dynamic changes during the delivery process, such as new customer requests, traffic disruptions, and fluctuations in vehicle availability. Unlike the static VRP where all input data is known beforehand and routes are pre-planned DVRP requires continuous, adaptive decision-making to update and optimize routes as conditions evolve. Key features include real-time demand updates, traffic-responsive routing, and flexible fleet reassignment. Mathematically, DVRP introduces time-dependent complexity, where the active request set R(t) changes over time, necessitating frequent re-optimization. These dynamics significantly increase computational challenges, complicate fleet coordination, and heighten the risk of service delays. To address these challenges, Montemanni et al. proposed a decomposition approach that treats DVRP as a sequence of static problems, solved iteratively using the Ant Colony System (ACS) algorithm improving responsiveness and flexibility in dynamic logistics contexts. DVRP is vital to the efficiency of modern logistics systems, powering real-time operations in ride-hailing platforms (e.g., Uber, Lyft), food delivery services (e.g., DoorDash, Instacart), and emergency dispatch systems. [15]

### 2.5.3 Stochastic Vehicle Routing Problem (SVRP)

The Stochastic Vehicle Routing Problem (SVRP) is a variant of the VRP where at least one input parameter such as customer demand, travel time, or service duration is uncertain and modeled probabilistically. Unlike the deterministic VRP, which assumes all data is known in advance, the SVRP requires robust route planning that can adapt to variability in real-world conditions. It is especially important in logistics sectors where unpredictable demand or travel conditions are common, such as e-commerce, healthcare, and disaster relief. [15]

### 2.5.4 Vehicle Routing Problem with Time Windows (VRPTW)

The Vehicle Routing Problem with Time Windows (VRPTW) extends the classical VRP by incorporating strict temporal constraints, requiring each customer to be served within a predefined time window **[ai,bi],** such that the vehicle's arrival time **Ti** satisfies **ai ≤ Ti ≤ bi .** These time-based restrictions add significant complexity to the routing process, as they demand precise synchronization across multiple vehicles to maintain service quality. Early arrivals can lead to idle time and increased operational costs, while late arrivals may result in penalties or even service denial. The problem is typically classified according to the severity of these constraints either as “hard” constraints, where late service is not allowed, or “soft” constraints, where tardiness is permitted but penalized. The optimization objectives often include minimizing total travel distance, fleet size, and waiting times, while ensuring adherence to time windows. VRPTW is crucial in sectors where timing is critical, such as same-day delivery services (e.g., Amazon Prime), public transportation scheduling, airport shuttles, and the distribution of perishable goods like fresh or frozen foods. [15]

### 2.5.5 Traveling Salesman Problem (TSP)

The Travelling Salesman Problem (TSP) is a foundational problem in combinatorial optimization that requires a single vehicle to visit each city (or customer) exactly once and return to the starting point, forming a closed, continuous route. It can be viewed as a simplified special case of the Vehicle Routing Problem (VRP), involving only one vehicle and no capacity or time constraints. The problem’s formulation prohibits sub-tours, ensuring that the solution is a single loop rather than multiple disconnected cycles. Despite its apparent simplicity, the TSP is computationally challenging, as the number of possible routes increases factorially with the number of cities. The TSP has been extensively studied due to its theoretical importance and practical relevance, serving as a critical building block for more complex VRP variants. It plays a central role in a wide range of real-world applications, including GPS-based shortest-path routing, robotic path planning in warehouse automation, and CNC machining, where efficient tool paths help minimize production time and material waste. [15]

### 2.5.6 Mathematical Modeling of the Vehicle Routing Problem (VRP) and the Capacitated VRP (CVRP)

The Vehicle Routing Problem (VRP) is typically formulated using a graph-based representation. Let $\mathbf{G=(V,A)}$ be a directed graph, where $\mathbf{V=\{1,...,n\}}$ is the set of vertices (with vertex **1** or **0** representing the depot), and $\mathbf{A=\{(i,j) \mid i,j \in V,\ i \neq j\}}$ is the set of arcs between them. The subset $\mathbf{V'=V\setminus\{1\}}$ refers to all customer locations. Each arc **(i,j)** has an associated non-negative **cost** $\mathbf{c_{ij}}$, representing either the distance or the travel time between nodes.

In this model, a fleet of mmm identical vehicles is based at the depot, each with a fixed capacity **D**. The objective is to design routes that minimize the total travel cost while satisfying the following core conditions:

- Each customer is visited exactly once by one vehicle.
- All routes start and end at the depot.
- No vehicle exceeds its capacity.
- All problem-specific operational constraints are respected.

#### 2.5.6.1 CVRP Formulation and Key Constraints

**Sets and Parameters:**

- **V={0,1,...,n}** set of vertices **(0 = depot).**
- **E={(i,j)}** set of edges with associated **cost cij.**
- **di:** demand of customer **i**, with **d0=0.**
- **Q** or **D**: vehicle capacity.
- **m**: number of vehicles.

**Decision Variables:**

- **xijk=1** if vehicle **k** travels from node **i** to node **j** ; **0** otherwise.
- **xij=1** if any vehicle travels from node **i** to node **j** ; **0** otherwise.
- **ui**: load of the vehicle after visiting node **i**. [15]

**Objective Function:**

Minimize total transportation cost or travel distance:

$$\min \sum_{k=1}^{m} \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} x_{ijk} \text{. [15]}$$

**Constraints:**

**a) Customer Visit Constraints:**

- Each customer is visited exactly once by one vehicle:

$$\sum_{k=1}^{m} \sum_{i=1}^{n} x_{ijk}=1, \quad \forall j \in \{1,\dots,n\} \text{. [15]}$$

$$\sum_{k=1}^{m} \sum_{j=1}^{n} x_{ijk}=1, \quad \forall i \in \{1,\dots,n\} \text{. [15]}$$

**b) Route Continuity (Flow Conservation):**

- Each vehicle entering a customer must also leave:

$$\sum_{j=1}^{n} x_{ijk} = \sum_{j=1}^{n} x_{jlk}, \quad \forall k \in \{1,\dots,m\}, \quad \forall l \in \{1,\dots,n\}\text{. [15]}$$

**c) Capacity Constraint for Each Vehicle:**

- The total demand served by a vehicle must not exceed its capacity:

$$\sum_{i=1}^{n} d_i \sum_{j=1}^{n} x_{ijk} \leq D \qquad , \qquad \forall k \in \{1,\dots,m\} \text{. [15]}$$

**d) Vehicle Availability Constraint:**

- Each vehicle departs from and returns to the depot at most once:

$$\sum_{j=2}^{n} X1jk \leq 1, \forall k \in \{1,\ldots,m\}. \text{ [15]}$$

$$\sum_{i=2}^{n} Xi1k \leq 1, \forall k \in \{1,\ldots,m\}. \text{ [15]}$$

**e) Subtour Elimination:**

- To prevent disjoint cycles:

$$ui - uj + Q \cdot xij \leq Q - 1, \quad \forall i,j \in V, \ i \neq j \text{ [15]}$$

where **u**i tracks the sequence of visits and avoids infeasible loops. [15]

### 2.5.7 Computational Complexity of VRP

The VRP is classified as an **NP-hard problem**, indicating that no known deterministic algorithm can solve it in **polynomial time** .As the number of customers increases, the computational complexity rises exponentially, making exact solutions impractical for large-scale instances. For problems involving **more than 100 customers**, heuristic or metaheuristic techniques are necessary to obtain feasible solutions within a reasonable timeframe. [15]

### 2.5.8 VRP Resolution Methods:

The Vehicle Routing Problem (VRP) encompasses a broad range of variants and complexities. Consequently, researchers have explored multiple approaches to solving these problems. As a member of the NP-hard class of combinatorial optimization problems, the VRP lacks a universal method capable of providing an optimal solution within a reasonable timeframe. [15]

To address this challenge, researchers rely on methods that aim to find near-optimal solutions within an acceptable computational time. These resolution methods are primarily categorized into two main groups: **exact methods** and **approximate methods**. The latter is further divided into two subcategories: **heuristics** and **metaheuristics**. [15] .The following figure illustrates the different resolution methods for the VRP.

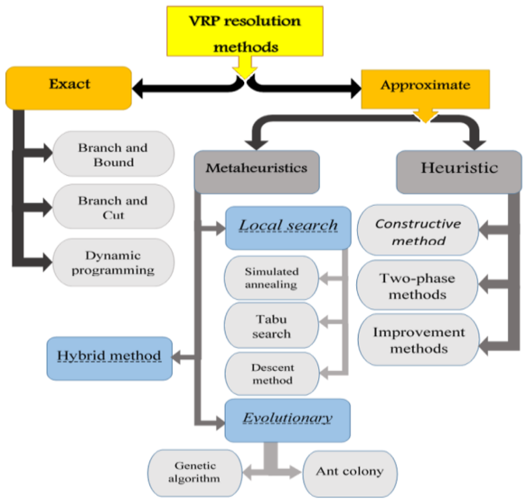


Figure 6: Graphical presentation of the VRP resolution methods. [15]

## 2.6 Metaheuristics:

### 2.6.1 Metaheuristic Approaches for VRP in Logistics Optimization

Solving the Vehicle Routing Problem (VRP) efficiently is a critical task in logistics and operations research, especially for large-scale transportation networks. Because VRP is computationally complex, metaheuristic algorithms have become essential tools for generating high-quality, near-optimal solutions within reasonable time frames.

Among the most effective metaheuristics are **Simulated Annealing**, **Ant Colony Optimization**, and biologically inspired methods like the **Blob Algorithm**. These techniques combine exploration and exploitation strategies, enabling them to navigate complex solution spaces and avoid local optima.

Metaheuristics play a vital role in industries such as **e-commerce logistics** (e.g., Amazon, DHL), **public transportation**, **ride-sharing services** (e.g., Uber), **municipal waste collection**, and **emergency response logistics**. Their adaptability to real-world constraints such as vehicle capacity, delivery time windows, and dynamic demand makes them highly effective for both static and real-time routing problems. [15] [14]

## 2.7 A Comprehensive Overview of Vehicle Routing Problem (VRP) Classification

The Vehicle Routing Problem (VRP) stands as a fundamental concern in logistics and transportation planning, aimed at determining optimal routing strategies for vehicle fleets operating across diverse service points. As the problem has evolved, various VRP extensions have been developed to address complex real-world constraints, including vehicle capacity restrictions, time-sensitive deliveries, single-vehicle routing, dynamic route modifications, and stochastic uncertainties in demand or travel time .

VRP classifications are typically organized along four principal dimensions. The first dimension, **problem characteristics**, considers aspects such as the underlying graph structure and whether constraints are deterministic or stochastic. The second, **customer constraints**, includes service requirements like specific delivery time windows, fluctuating demand levels, and the existence of single or multiple depots. The third dimension addresses **fleet constraints**, distinguishing between homogeneous and heterogeneous vehicle fleets and their capacity limitations. Finally, the **optimization objectives** focus on minimizing operational costs, reducing the number of vehicles used, or improving the efficiency of service times.

Following this taxonomy, researchers have identified and extensively studied several specific variants of the VRP that model these practical considerations more precisely. [15] [14]

## 2.8 Stochastic Vehicle Routing Problem (SVRP)

The mathematical modeling of the Stochastic Vehicle Routing Problem (SVRP) incorporates random variables to represent uncertain parameters such as customer demand, travel time, or service duration. A common formulation involves modeling customer demand as a probabilistic variable: [15] [14]

$$\mathbf{Di \sim P(\mu,\sigma)} \text{ [15]}$$

where:

- **Di** is the random demand at customer **i**,
- **μi** is the expected demand,
- **σi** is the standard deviation, capturing the variability.

Due to the stochastic nature of the input data in the Stochastic Vehicle Routing Problem (SVRP), traditional deterministic models are insufficient. As a result, solution approaches commonly incorporate stochastic programming methods, such as two-stage or chance-constrained optimization, to account for uncertainty in demand or travel time. Monte Carlo simulation is frequently applied to evaluate the robustness of candidate solutions across various realizations. The primary objective remains to minimize expected operational costs while ensuring feasibility under uncertainty. Key challenges include the need for contingency plans in cases of unpredictable demand, maintaining adequate vehicle capacity, and designing flexible routing strategies. SVRP is particularly applicable in environments such as pharmaceutical supply chains, humanitarian logistics, and dynamic retail distribution networks, where variability and responsiveness are critical .

### 2.8.1 Discussion of Exact, Heuristic, and Metaheuristic Approaches

Solving the Vehicle Routing Problem (VRP) requires a range of computational approaches tailored to the size and complexity of the problem, which are typically categorized into exact, heuristic, and metaheuristic methods . **Exact methods** offer mathematically guaranteed optimal solutions by exhaustively exploring the solution space. However, their computational complexity makes them impractical for large-scale instances with many customers or constraints. Techniques such as *Branch and Bound* and *Integer Linear Programming (ILP)* solved via optimization solvers like CPLEX or Gurobi are commonly used exact approaches. In contrast, **heuristic methods** are rule-based and provide good-quality solutions within a reasonable time, especially for large problems where exact methods are infeasible. These include the *Nearest Neighbor algorithm*, which builds routes by selecting the closest unvisited location, and the *Savings Algorithm*, which merges routes based on potential cost reductions. While heuristics are efficient, they are not guaranteed to find optimal solutions. To improve both exploration and solution quality, **metaheuristic techniques** have been developed. These advanced methods employ intelligent search strategies to avoid local optima and explore a broader solution space. Notable examples include *Tabu Search*, which uses memory structures to prevent cycling; *Simulated Annealing*, which occasionally accepts worse solutions to escape local minima; *Genetic Algorithms*, which simulate evolution through selection, crossover, and mutation; and *Ant Colony Optimization (ACO)*, a bio-inspired algorithm where artificial agents emulate ant foraging behavior to discover efficient routes [9, 15]. Each approach has its strengths: while exact methods ensure optimality for small instances, heuristics offer speed and simplicity, and metaheuristics provide a robust balance between computational efficiency and solution quality, making them highly suitable for solving complex, real-world VRP applications. [15]

## 2.9 Blob

Bio-inspired computing focuses on deriving computational models from complex biological systems involved in cognition and understanding.Recent work has centered on cellular computational models, which are inspired by the structures and processes of living cells, such as bacterial colonies and viral systems. Physarum computing is one such example in this field that has attracted a great deal of attention from researchers. [16]

Bio-inspired computing: You design computation models after biological systems, particularly those that are complex and cognitive or for understanding. Research has recently focused on cellular computational structures that draw upon the physical organizations of biological cells, such as bacterial colonies and viral phenomena. One example that has received a lot of attention from researchers in this field is Physarum computing. [16]

Physarum polycephalum, commonly known as Physarum, is a plasmodial slime mold that belongs to the fungus group "Myxomycetes." This organism has become increasingly well known since Nakagaki's landmark 2000 experiments showed that the slime can find the shortest path through.

Physarum is a reaction-diffusion system that is contained within a dynamic elastic membrane composed of an actin–myosin cytoskeleton. In the exploration phase of its early growth, Physarum forages, leading to a lacy, intertwined pattern. Then it is extended through a dynamic proximity graph during the exploitation phase to cover nutrient sources and it bases a structure similar to a Voronoi diagram. Physarum motion is especially useful in solving graph optimization problems, because of this feature of continually exerting adaptations according to changing environment. [16] [17]

Researchers are exploring Physarum-based solutions for NP-hard problem-solving founded on the organism's potential for decision-making, information processing, and complex social behavior. Physarum solves disagreements between alternatives through comparison of their relative values and integrates information about rewards to make adaptive and accurate decisions. It also possesses the capacity to remember and learn, both short- and long-term, enabling it to anticipate and adapt to periodic events. [17] [16]

Beyond these capabilities, Physarum also serves as a model for unconventional computing. The concept of the “Physarum machine” involves using Physarum in programmable computing systems. The "Physarum chip" project, which ran from 2013 to 2016, was designed to explore Physarum’s potential to solve tasks related to graph optimization and logical computations. Additionally, the EU-funded "Physarum Sensor" project built upon the PhyChip initiative by exploring how Physarum polycephalum could function as a living biosensor [18]capable of translating its biological responses into electrical signals These biosensors have promising applications in fields such as environmental monitoring and healthcare. [17] [16]

**Figure 7: Slime Mold. [17]**

### 2.9.1 Bio-inspired Computing :

The field of bio-inspired computing draws on nature's solutions to inspire the development of innovative algorithms and computational techniques. Over the past few decades, this inspiration has fueled the creation of various novel methodologies. Two prominent categories of bio-inspired algorithms are evolutionary algorithms and swarm intelligence algorithms. Evolutionary algorithms draw inspiration from natural selection and the way populations evolve over time. In contrast, swarm intelligence is modeled on the collective behavior seen in animal groups like flocks of birds or swarms of insects where decentralized systems work together to solve complex problems. [16]

Evolutionary algorithms, such as Genetic Algorithms and Artificial Immune Systems, rely on iterative population-based processes that mimic the way species adapt to their environment. These algorithms have shown great potential in tackling complex optimization problems. Meanwhile, swarm intelligence inspired by the collective behavior of simple agents has also proven effective in this field, thanks to well-known techniques like Particle Swarm Optimization and Ant Colony Optimization These approaches demonstrate how simple individual behaviors can result in complex, global problem-solving capabilities. [16]

The field of biology-inspired computing is vast and includes models like artificial neural networks, fuzzy logic, and genetic algorithms, which imitate the behavior of biological processes such as neural systems, immune response, and chromosomal reproduction. However, more recent approaches have begun to explore cellular computational models, which take inspiration from the inner workings and organization of living cells like the cooperative behavior of bacterial colonies or the adaptive strategies of viral systems. [16]

Physarum stands out as a prominent example of a biological model within cellular computing, attracting the attention of numerous researchers due to its unique properties and its ability to model complex processes. [16]

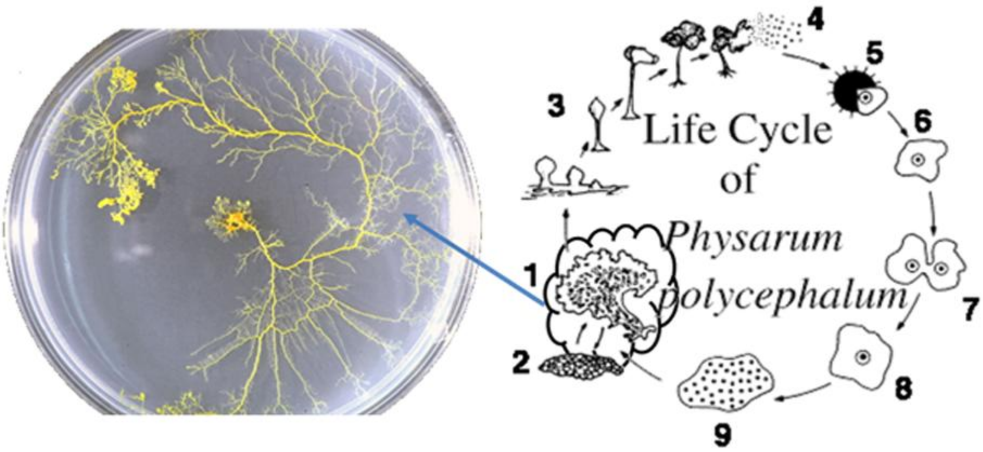


Figure 8: The Physarum tube networks and life cycle [16]

### 2.9.2 Physarum Biological Experiments

Numerous experiments have been carried out to explore the intelligence of Physarum. Researchers aim to create mathematical models based on its behavior to tackle real-world optimization problems. While most studies focus on how Physarum behaves in open spaces like Petri dishes, studying it in more controlled environments is also important to better understand how it makes decisions.. For example, Shirakawa et al. (2015) designed an experiment that discretized the motility of Physarum, forcing its movement to follow a stepwise transition, thus mimicking a two-dimensional cellular automaton. [16]

### 2.9.3 Experimental and Computational Modeling of Physarum polycephalum

Physarum polycephalum, a single-celled slime mold, has demonstrated a surprising ability to solve complex problems, such as finding the shortest path in a maze or simulating efficient transport networks. Early biological experiments revealed its adaptive behavior in real-world environments, sparking interest in its potential for solving computational challenges. Given the limitations of physical experimentation, researchers have also developed a wide range of mathematical and computational models to replicate and extend Physarum’s problem-solving behavior. The table below summarizes both experimental studies and mathematical models that highlight its role in both biological inquiry and bio-inspired computation. [16]

**Table 6: Summary of Experimental Studies and Computational Models of Physarum polycephalum [16]**

| No. | Author | Study/Model Description | #PH | #FS | Environment/Domain | Instrument/Use Case |
|---|---|---|---|---|---|---|
| 1 | Nakagaki et al. (2000) | Physarum solving maze problem | 1 | 1 | Petri dish | Camera – Maze solving |
| 2 | Tero et al. (2010) | Physarum solving minimum spanning tree | 1 | Multi | Petri dish | Camera – Spanning tree approximation |
| 3 | Shirakawa et al. (2015) | Physarum movement based on statistical results | 1 | 0 | CA-like dish | Camera – Movement pattern analysis |
| 4 | Whiting et al. (2014) | Electrical activity under stimuli | 1 | 1 | Petri dish | Electric potential measurement |
| 5 | Reid et al. (2016) | Solving the two-armed bandit problem | 1 | Multi | Petri dish | Camera – Decision-making analysis |
| 6 | Stirrup & Lusseau (2019) | Foraging under competition | 2 | 1 | Petri dish | Camera – Behavioral adaptation |
| 7 | Schumann et al. (2014) | Influence of mass and type in competition | 2 | Multi | Petri dish | Camera – Competitive strategy analysis |
| 8 | Masui et al. (2018) | Allorecognition capacity | 2 | 2 | Petri dish | Camera – Self/other differentiation |
| 9 | Tero et al. (2007) | Hagen–Poiseuille and Kirchhoff Laws (model) | – | – | Mathematical Model | Maze and transport network simulation |
| 10 | Adamatzky (2009a) | Reaction–Diffusion Model | – | – | Graph/logic systems | Maze solving and logic gate design |
| 11 | Gunji et al. (2008) | Cellular Automaton | – | – | Maze, network optimization | Steiner/spanning trees, network approximation |
| 12 | Jones (2011) | Vacant Particle-Based Model | – | – | Network modeling | Network formation simulation |

| No. | Author | Study/Model Description | #PH | #FS | Environment/Domain | Instrument/Use Case |
|---|---|---|---|---|---|---|
| 13 | Liu et al. (2017b) | Multi-agent System | – | – | Maze/optimization | Metaheuristic development |
| 14 | Ntinas et al. (2017a) | Memristor Circuit | – | – | Circuit simulation | Maze and transport network modeling |
| 15 | Tsompanas et al. (2016) | Cellular Automaton + Reaction–Diffusion | – | – | Maze and transport | Dynamic spatial modeling |
| 16 | Awad et al. (2019b) | Hexagonal CA + Reaction–Diffusion | – | – | Wireless sensor networks | Optimization algorithm testing |

*This table presents key biological experiments and mathematical models exploring the problem-solving behavior of Physarum polycephalum, highlighting both empirical observations and algorithmic simulations across various domains.*

### 2.9.4 Physarum Network Construction

Tero et al. (2010) conducted a biological experiment to model *Physarum polycephalum*'s network-building behavior using the Tokyo railway system as a reference (Figure 4 ). A single *Physarum* organism, representing Tokyo, connected multiple food sources symbolizing other cities. The resulting network closely resembled a minimum spanning tree, showcasing the organism's natural ability to form efficient, decentralized transport networks. [16]

### 2.9.5 Environmental Influence on Physarum's Shape

Jones and Adamatzky (2014) showed that *Physarum*'s growth can be shaped by environmental stimuli. By adjusting growth parameters, the organism could shift between convex and concave formations. Using chemo-attractants and light as guides, *Physarum* was able to approximate shapes based on external points, revealing its potential for morphological computation. [16]

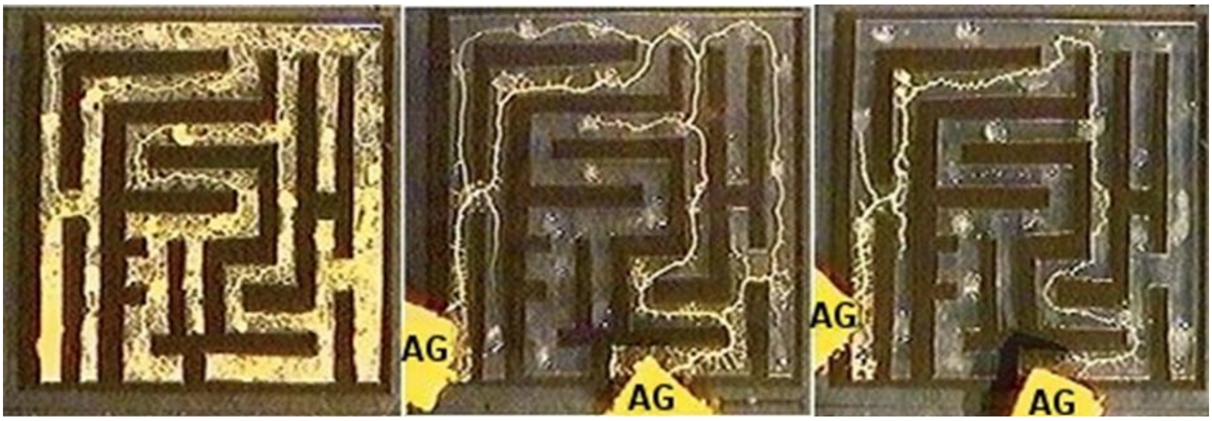


**Figure 9: Maze-solving by Physarum polycephalum [16].**

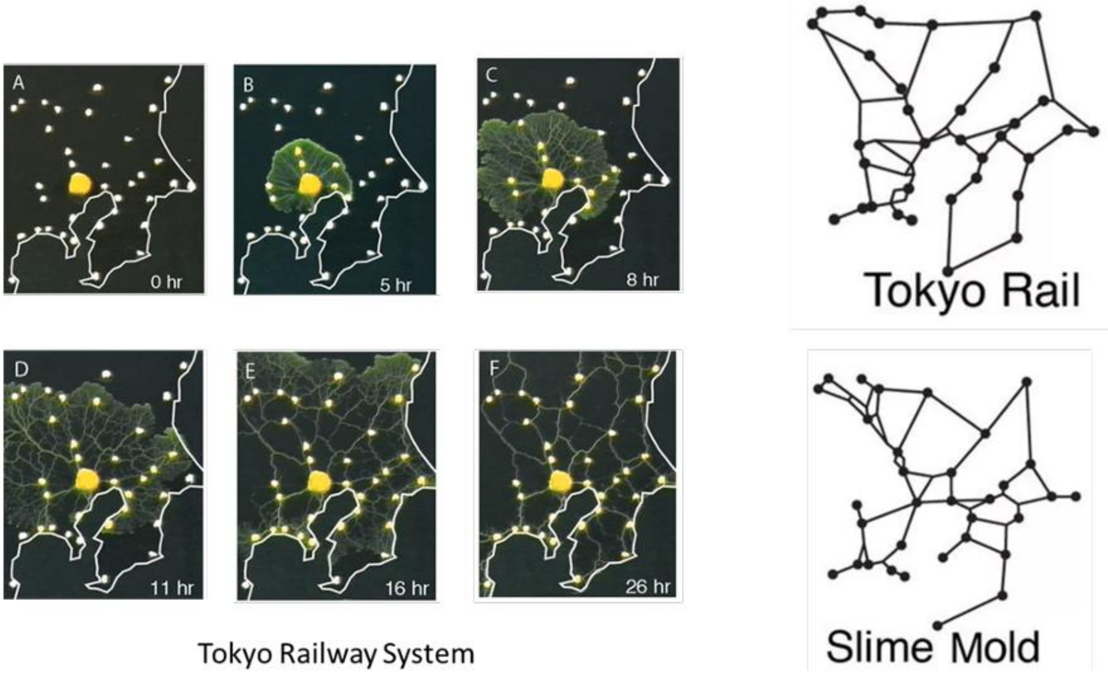


Figure 10: Tokyo rail network formation with Physarum polycephalum [16]

### 2.9.6 Physarum Response to Environmental Stimuli

Physarum’s behavior is strongly influenced by its environment. In a study by Jones and Adamatzky (2014), they explored how altering the growth parameters of Physarum could shift its shape between convex and concave forms in response to environmental cues. Their findings introduced new mechanisms of morphological computation driven by external stimuli. Specifically, they showed how Physarum could use chemo-attractant signals and light to approximate both the external and internal shapes of a set of points. [16]

### 2.9.7 Physarum Living Cellular Automata

Shirakawa et al. (2015) designed an experimental setup to simulate Physarum within a two-dimensional cellular automaton, where its motility was discretized into stepwise transitions. They analyzed the movement of a single Physarum without any food source, developing several models based on statistical data to better understand its step-by-step behavior. [16]

### 2.9.8 Physarum Electrical Activity

Whiting et al. (2014) and Traversa et al. (2013) conducted experiments to measure the electrical activity of Physarum when exposed to stimuli, such as a food source. The study aimed to observe how Physarum's electrical activity patterns change when exposed to attractants and repellents, demonstrating its ability to learn and adapt to periodic environmental changes. In addition, research by Gale et al. (2014) found that the protoplasmic tubes of Physarum display current-voltage characteristics that align with those of ideal memristor systems. [16]

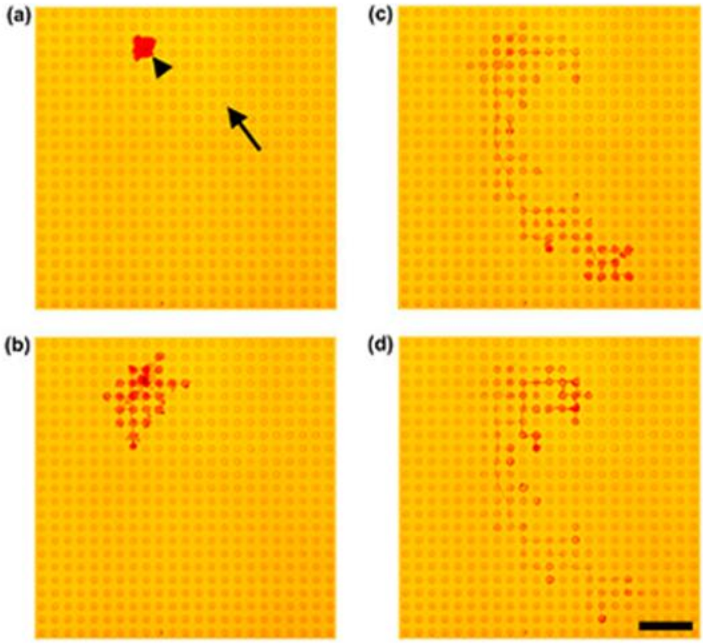


Figure 11: Physarum living cellular automatons [16]

### 2.9.9 Physarum Solving the Two-Armed Bandit Problem

The two-armed bandit problem is typically used to study decision-making in organisms with brains, yet Physarum, a brainless organism, was shown to be capable of solving this problem. In this experiment, *Physarum* was given two options: one offering higher-quality or more food (the high-quality arm) and the other with fewer or lower-quality resources (the low-quality arm). The results showed that *Physarum* consistently chose the high-quality arm, highlighting its decision-making ability. This ability to compare different options and adjust its choices based on the quantity and quality of the reward offers valuable insights into the fundamental principles of decision-making and information processing in *Physarum*. [16]

### 2.9.10 Current Studies on Mould's Capabilities

In the early 2000s, Japanese professor Toshiyuki Nakagaki made an exciting discovery through a series of experiments: slime molds can find the shortest path between two exits in a maze, successfully avoiding longer routes. This breakthrough earned Nakagaki widespread recognition, including a Nobel Prize. The key insight was that slime molds don't move randomly. Instead, they follow a simple but effective pattern. When they explore an area without finding food or moisture, they avoid retracing their steps. This behavior is guided by the slime trail they leave behind, acting as an "external memory." When the mold encounters its own slime, it recognizes the need to take a different route, preventing backtracking and helping it find the most efficient path faster.Further studies have shown that, in controlled environments, slime moulds can replicate the layout of complex networks, such as Tokyo's railway system, as well as highways in Canada, the UK, and Spain. These experiments have spurred interest in simulating these behaviors computationally, particularly in relation to the Travelling Salesman Problem. However, the development of these models remains challenging due to the numerous variables, including the slime's density, thickness, speed, and time constraints, that influence the mould's foraging decisions. [17]

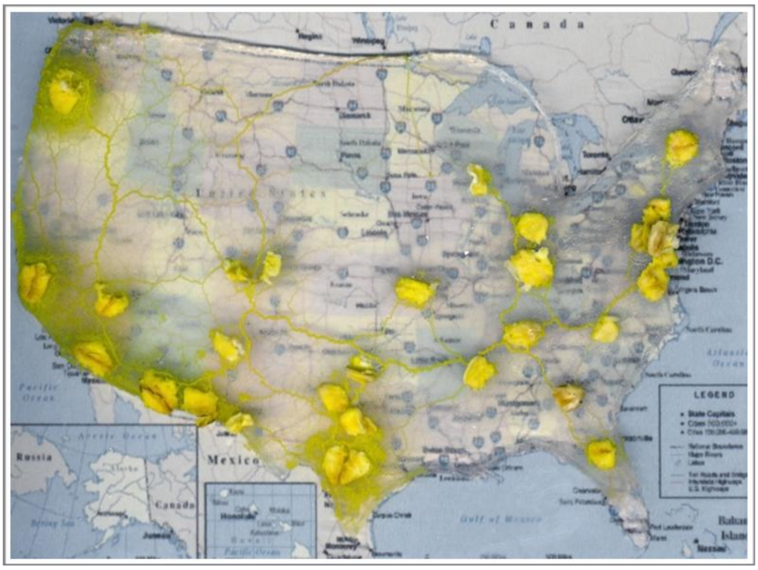


**Figure 12: Slime mould recreating an optimised model of the U.S. inter state system [17]**

### 2.9.11 Blob Algorithm in the Vehicle Routing Problem (VRP)

The Vehicle Routing Problem (VRP) is a well-known NP-complete combinatorial optimization problem, where the goal is to minimize the total distance traveled by a fleet of vehicles as they visit a set of cities starting and ending at a depot. Different methods, such as exact algorithms, heuristics, and bio-inspired approaches like ant colony optimization and particle swarm optimization, have been applied to solve the Vehicle Routing Problem (VRP).In this context, a unique approach inspired by biological systems is the Blob algorithm, which is a multi-agent model based on *Physarum polycephalum* a slime mold renowned for its problem-solving abilities. [14]

The Blob algorithm takes inspiration from the behavior of *Physarum polycephalum*, a slime mold known for its remarkable ability to optimize routes and create network-like structures. For example, *Physarum* can form an efficient network between food sources, which often mirrors the layout of transportation systems like the Tokyo railway network. The core idea behind the Blob algorithm is that individual agents, each representing a vehicle in the Vehicle Routing Problem (VRP), interact in a way similar to how the slime mold spreads its cells and forms efficient paths toward food. Using this bio-inspired approach, the Blob algorithm solves the VRP by simulating a large population of interacting particles, each representing a vehicle.

These particles spread out from a central depot and navigate through a two-dimensional environment with city locations. [14]

Each vehicle in the VRP is modeled as an agent that explores potential routes based on the slime mold's properties, which include decision-making abilities, such as avoiding redundant paths and optimizing the use of available resources. The Physarum-inspired solver can generate near-optimal solutions for the Vehicle Routing Problem (VRP) by harnessing the network-forming behavior of the slime mold. In this model, the slime's extensions represent possible routes, and the strength of these extensions reflects the quality of the routes. This approach highlights the potential of combining biological behaviors with algorithmic principles to tackle real-world optimization problems, like the VRP. [14]

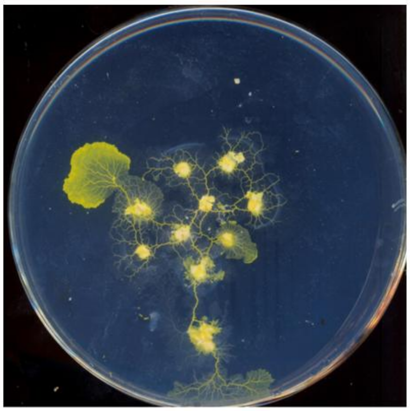

**Figure 13: A network between oat flakes created by Physarum polycephalum. [14]**

### 2.9.12 Bio-Inspired Approaches for TSP

In recent years, biological systems have inspired various heuristic algorithms to approximate solutions to the TSP. One approach takes inspiration from the slime mould *Physarum polycephalum*, a remarkable organism known for creating efficient networks between food sources. Researchers have used this natural behavior to develop algorithms that replicate the organism's response to chemical signals. This process helps approximate solutions to the TSP by adapting a "blob" of virtual material to the problem's constraints. [19]

### 2.9.13 The Shrinking Blob Method

The shrinking blob method utilizes a virtual material composed of simple mobile agents. The process begins by placing the blob of material over a spatial map of the cities. The cities act as attractants, and the blob shrinks over time, conforming to the positions of the cities. As the blob shrinks, it adapts its shape, forming a path that approximates the optimal solution to the TSP. This method is non-heuristic and does not rely on any advanced optimization techniques, instead utilizing the emergent properties of the material. [19]

#### 2.9.13.1 Methodology

- **Initial Setup**: The virtual material is initialized over a spatial map of the cities, covering the convex hull of the city locations. Chemoattractant is projected at each city, with the intensity reduced under the blob's coverage. [19]
- **Shrinkage Process**: The material is gradually reduced by removing its constituent particles. As it shrinks, the cities act as attractants, directing the shape of the blob to align with the optimal tour. [19]
- **Halting the Process**: The shrinking process is automatically stopped when all nodes (cities) are partially uncovered, signaling that a valid tour has been formed. [19]

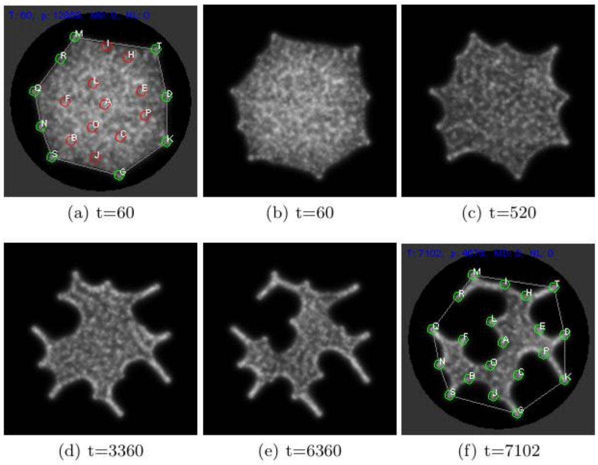


**Figure 14: Visualization of the Shrinking Blob Method for Route Approximation [19]**

Figure 14: illustrates the shrinking blob method. (a) A virtual material sheet is initially placed within the convex hull (gray polygon) of the city points, with nodes marked as circles. The outer nodes are partially uncovered and shown in light gray, while the inner nodes, covered by the material, are in dark gray. (b-e) The sheet gradually shrinks over time, with snapshots at times 60, 520, 3360, and 6360, showing its changing shape. (f) The shrinking process halts automatically once all nodes are partially uncovered at time 7102.

### 2.9.14 Performance and Evaluation

The shrinking blob method, despite its simplicity, provides efficient approximations of the TSP. While it is not guaranteed to find the optimal solution, it generally yields high-quality tours. The method performs similarly to other heuristic algorithms, providing a good balance between computational efficiency and accuracy. [19]

### 2.9.15 The Flow Conductivity Model

The flow conductivity model simulates the adaptation of the tube's radius during the foraging behavior of *Physarum polycephalum*, based on the flow through the system. The radius of these tubes is proportional to the amount of flow they carry, with shorter tubes carrying more flow than longer tubes. The total flow in and out of the tubular system remains constant to conserve the mass of *Physarum polycephalum*. **[15]**

This model can be represented as a graph with N nodes and E edges, where **eij** is the tube connecting nodes **Ni** and **Nj, Dij** is the conductivity of tube eij, **Qij** is the flux through **eij**, and Lij is the length of **eij**. The following formula expresses the flux from node Ni to **Nj** through **[15]**

**eij:**

$$\mathbf{Qij} = \frac{\mathbf{Dij}}{\mathbf{Lij}}\,(\mathbf{pi} - \mathbf{pj})\ . \ [15]$$

Where pi and pj are the pressure values of nodes Ni and Nj, respectively. The mass conservation of *Physarum polycephalum* is modeled by the following equation:

$$\sum_i \frac{D}{L_{ij}}(p_i - p_j) = \begin{cases} -I_0 & if\ j = in \\ I_0 & if\ j = out \\ 0 & otherwise \end{cases} \quad [15]$$

Where **$I_0$** is the flow rate: **$-I_0$** at the source (inflow), and **$I_0$** at the sink (outflow).

Finally, the conductivity D is described by the following equation:

$$\frac{d}{dt}\,\mathbf{Dij} = \mathbf{f(|Qij|) - rDj.}\ [15]$$

Where **r** is a decreasing rate constant of the tube, and **f(|Qij|)** is the growth function of tube . The survived tubes depend on the convergence of **Dij ,** when **Dij** converges to **0**, the corresponding tube **eij** is removed, while only the tubes with high values of **Dij** survive. [15]

#### 2.9.15.1 Agent-Based Model

This model, proposed by Jones in 2009, closely mimics the behavior of *Physarum polycephalum*. In this representation, *Physarum* is modeled by a population of agent-like particles moving on a flat, two-dimensional plane. Each particle is equipped with three sensors that detect the concentration of a local attractant. The particles move based on the attractant concentration: they can move forward, or rotate left or right. Each particle also emits attractant after a successful move. If a particle attempts to move to an already occupied location, it randomly chooses a new direction and does not emit attractant. [15]

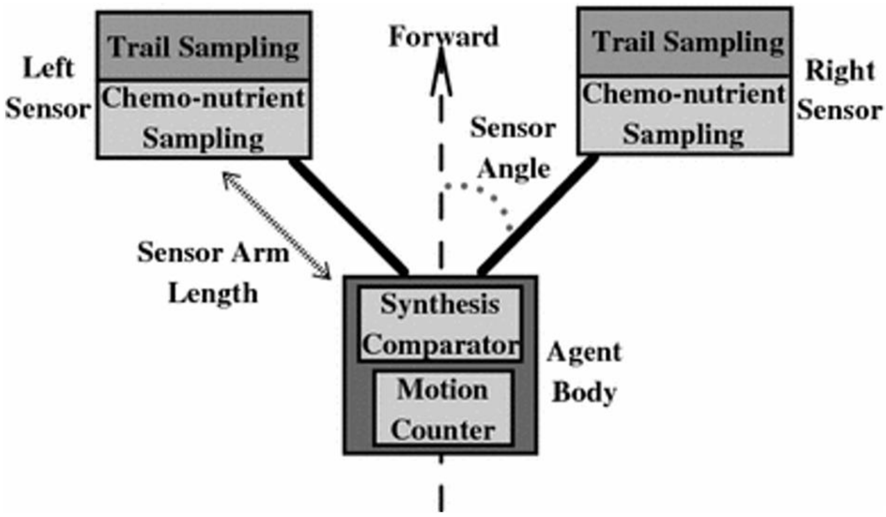


**Figure 15: The architecture and morphology of an agent [16]**

### 2.9.15.2 Flow-Conductivity Model

Developed by Tero et al. (2007, 2008), the flow-conductivity model applies the Hagen-Poiseuille and Kirchhoff's laws to describe the adaptive pathfinding and feedback between flux and conductivity in the protoplasmic tubes of *Physarum*. The model explains how *Physarum* forages and approaches the shortest path problem, emphasizing the likelihood that open-ended tubes (not connected between two food sources) disappear, and that longer tubes are more likely to vanish when multiple tubes connect the same two food sources. The model has been applied to solve dynamic navigation problems, including the design of the Tokyo railway network. [15]

### 2.9.15.3 Cellular Automaton Model

In 2008, Gunji and his team introduced a model based on cellular automata to mimic the intelligent network-building behavior of *Physarum polycephalum*. This model captures key biological traits of the organism and is divided into two main phases: the development phase and the foraging phase. [15]

In the development phase, a simulated cell starts from an initial seed and gradually grows by aggregating components. During the foraging phase, the cell begins to explore its surroundings, mimicking the behavior of *Physarum polycephalum* in its natural vegetative state. [15]

The model uses a grid (planar lattice) where each grid cell can be in one of three states: state 0 (representing the external environment), state 1 (the cell's interior), and state 2 (the cell's boundary). The cell itself is visualized as a cluster of adjacent cells in state 1, surrounded by state 2, while state 0 fills the space outside. The boundary (state 2) simulates the organism's cytoskeletal structure. [15]

As the cell "feeds" on surrounding state-0 areas, it undergoes changes in shape and internal rearrangement. This process imitates how *Physarum* softens parts of its membrane to allow the flow of protoplasm. The consumed state-0 area forms what the model calls a "bubble," which attracts internal flow and guides the movement of cytoskeletal material. This leads to a reorganization of the cell's internal structure. [15]

Initially, this model was used to replicate *Physarum's* movement and apply it to classical optimization problems, such as solving the Steiner Tree Problem. However, Liu et al. later identified a limitation: the use of a single bubble restricted the model's performance. To overcome this, they introduced multiple bubbles into the simulation, significantly improving its efficiency and ability to generate stable, high-quality network structures. [15]

#### 2.9.16 Physarum solver :

The foraging behavior of *Physarum polycephalum*, an extraordinary single-celled organism, has intrigued both scientists and engineers. Its natural ability to solve problems has inspired researchers to create algorithms that mimic its intelligence. One of the latest innovations is the Physarum Solver, which is based on the organism's flow conductivity model. This algorithm has proven to be highly effective, especially when it comes to solving shortest-path problems in weighted graphs, showing remarkable efficiency. [15]

**Input**: L: the cost matrix, s: the start node, e: the destination node

**Output**: the shortest s-e path $S^*$.

$G \leftarrow \infty$ // current conductivity gap

$\underline{G} \leftarrow 10^{-6}$ //a predefined conductivity gap

$itr \leftarrow \mathbf{0}$ //number of iteration

$D_{ij} \leftarrow (\mathbf{0}, \mathbf{1}]$ ($\forall$i, j=1,2….N) // initial conductivity values

$Q_{ij} \leftarrow (\mathbf{0}, \mathbf{1}]$ ($\forall$i, j=1,2….N) // initial flow values

$P \leftarrow \mathbf{0}$ ($\forall$i=1,2….N) // initial pressure vector

**While** *termination criteria not satisfied* **do**

  itr $\leftarrow itr + 1$

  Set $p_e \leftarrow \mathbf{0}$ // the pressure at the ending node **e**

  Calculate the pressure of every node in the network

  Using the equation 2;

$$\sum_i \frac{D}{L_{ij}}(p_i - p_j) = \begin{cases} -I_0 & if\ j = in \\ I_0 & if\ j = out \\ 0 & otherwise \end{cases}$$

  Update the flow values **Q** by using the equation 1;

$$Q_{ij} = \frac{D}{L_{ij}}(p_i - p_j)$$

  Calculate the new conductivity $\overline{\mathbf{D}}$ by the equation 3;

$$\frac{d}{dt} D_{ij} = f(|Q_{ij}|) - rD_{ij}$$

  $G \leftarrow sum(|\overline{D} - D|)$

  $D \leftarrow \overline{D}$

**End while**

**Return** $S^*$

**Figure 16: Physarum solver algorithm. [15]**

*The algorithm begins with a cost matrix **L** and the starting and ending nodes, s and e, as inputs. The output from the algorithm is **S*,** the shortest path obtainable.The algorithm proceeds by repeatedly updating values for the flow **(Q)** and conductivity **(D).** Within each iteration, edges that could component of the shortest path distance from source node to destination node, are gradually expanded and edges which are incapable of contributing to the shortest path, are deleted. When a termination criterion has been met the final flow values are identified, representing the shortest path.* [15].

## 2.10 Simulated Annealing (SA): Theory, Mechanics, and Applications

### 2.10.1 Origin and Fundamental Concept

Simulated Annealing (SA) is a metaheuristic optimization method inspired by the physical process of annealing in metallurgy, where metals are heated and slowly cooled to remove internal stresses and defects. The computational analogy was first formalized by Kirkpatrick, Gelatt, and Vecchi in 1983, who introduced SA as a solution to combinatorial optimization problems by mimicking this thermal relaxation process. The key innovation was the application of the Metropolis algorithm, originally developed for statistical physics by Metropolis and colleagues in 1953, to govern the probabilistic acceptance of worse solutions during the search process. [20] [21]

### 2.10.2 Algorithmic Mechanics and Mathematical Foundation

The SA algorithm iteratively explores the solution space by evaluating a neighboring solution **s′** of the current state **s**, and deciding whether to accept it based on an acceptance probability. If **f(s′) < f(s),** the solution is always accepted. If not, it is accepted with a probability defined by the Metropolis criterion:

$$\mathbf{P(s \rightarrow s')} = \begin{cases} \mathbf{1}, & \mathbf{if\ f(s') < f(s)} \\ e^{-\left(\frac{f(s')-f(s)}{T}\right)}, & if\ f(s') \geq \mathrm{f(s)} \end{cases} \qquad [21]$$

Here, T is the control parameter or “temperature” which gradually decreases following a predefined cooling schedule. This mechanism enables the algorithm to escape local optima, especially in early iterations, and later stabilize around promising regions of the search space.

The theoretical foundation of SA includes a convergence guarantee under specific conditions. Geman and Geman, in 1984, proved that SA converges to the global optimum if the cooling schedule follows a logarithmic decay and if the algorithm is run for an infinite number of steps. Although this guarantee is mostly theoretical, it provides important insight into the design of practical schedules. [21] [22]

### 2.10.3 Strengths and Practical Advantages

Simulated Annealing is valued for its conceptual simplicity and wide applicability. As Van Laarhoven and Aarts emphasized in their foundational work, SA requires no derivative information and can operate effectively on noisy, discontinuous, or high-dimensional objective functions. This makes it especially useful in black-box optimization contexts or for real-world applications where exact models are unavailable.

Moreover, SA is highly adaptable. Practitioners can tailor the neighborhood structure, temperature schedule, and acceptance criteria to fit a wide variety of problem domains. It has been successfully applied in domains ranging from electronic circuit design and job scheduling to facility layout planning and artificial intelligence. The stochastic acceptance of worse solutions gives SA an edge over greedy local search techniques, especially in complex landscapes riddled with local optima. [23] [24]

### 2.10.4 Limitations and Algorithmic Challenges

Despite its strengths, Simulated Annealing faces several challenges. One of the most critical is its sensitivity to parameter settings. Choosing an appropriate initial temperature, cooling rate, and stopping criterion is essential; poor choices may result in premature convergence or excessive runtime. Additionally, while SA is powerful in global exploration, it often suffers from slow convergence when compared to more aggressive heuristics like Tabu Search or Genetic Algorithms.

Another significant limitation is the reliance on neighborhood structures. If the neighborhood function is not well-designed, the search may stagnate or oscillate without meaningful progress. Furthermore, SA's stochastic nature introduces variability across runs, necessitating multiple executions or ensemble strategies to ensure consistent results. [25]

### 2.10.5 Recent Enhancements and Hybrid Models

To overcome these limitations, several modern adaptations have emerged. Adaptive Simulated Annealing (ASA), for instance, introduces feedback mechanisms to adjust the temperature or move strategies based on real-time performance. Hybrid metaheuristics also integrate SA with other methods such as combining SA with Genetic Algorithms to refine elite solutions through local search, or embedding SA within Ant Colony or Particle Swarm frameworks for better exploration.

Parallel Simulated Annealing (PSA) has gained attention with the advent of multicore processors, distributing the computational burden across multiple search threads to reduce time and improve diversity. In multi-objective scenarios, Multi-Objective Simulated Annealing (MOSA) adapts the acceptance rules to consider Pareto dominance rather than scalar fitness, making it suitable for problems with competing objectives.

Emerging approaches also incorporate machine learning into SA. Reinforcement learning agents and surrogate models are being used to dynamically guide neighborhood selection, tune parameters, or predict promising search regions effectively transforming SA into an intelligent and adaptive search framework. [26]

### 2.10.6 Broader Applications Across Disciplines

Simulated Annealing has been widely implemented in numerous application areas. In engineering, it plays a critical role in structural optimization, printed circuit board layout, and mechanical design. In computer science, it is used for software refactoring, feature selection, and network topology optimization. In bioinformatics, it aids in tasks such as DNA sequencing, protein folding, and drug design.

Its role in operations research remains significant as well. SA is used in staff rostering, production scheduling, supply chain configuration, and transportation planning. The algorithm's capacity to adapt to diverse constraints and handle large-scale problem instances makes it especially suitable for combinatorial optimization problems with real-world complexity. [26]

## 2.11 Literature Review of CVRP

The Capacitated Vehicle Routing Problem (CVRP) is a fundamental problem in the area of combinatorial optimization and operational research. It is determining the optimal set of routes for a fleet of given capacity-constrained vehicles that try to fulfill orders from customers and minimize overall transportation cost or distance. Being a natural generalization of the classical Vehicle Routing Problem (VRP), the CVRP has widespread applications in logistics, urban freight transport, and distribution planning.

The history of the CVRP stems back to the pioneering work of Dantzig and Ramser (1959), who formulated the problem as an optimization problem in the logistics of fuel delivery. Their paper laid the foundation for five decades of research on exact algorithms, heuristics, and more recent metaheuristic and hybrid approaches. The scope of CVRP applications has extended significantly over the years, encompassing realistic constraints such as time windows, multi-depot problems, and three-dimensional loading.

This part covers a timeline overview of noteworthy research contributions to the CVRP, categorized into three time frames: the initial work that framed the problem and early mathematical findings; progress in between that incorporated hybrid metaheuristics for complex CVRP variants; and newer studies, which utilize sophisticated bio-inspired algorithms for large-scale and practical applications. Each of the subtopics covers an example study of its respective era, highlighting how the problem definition as well as solution methods have progressed.

### 2.11.1 General Works on CVRP

Over the decades, research on the Capacitated Vehicle Routing Problem (CVRP) has evolved significantly, beginning with the foundational work of George B. Dantzig and John H. Ramser in 1959. Their seminal paper, *The Truck Dispatching Problem*, introduced the concept of optimizing vehicle routes under capacity constraints and is widely considered the origin of the VRP. Despite limited computational power, their linear programming approach laid the groundwork for decades of research in logistics and combinatorial optimization . Building on this foundation, a notable advancement occurred in 2010 with the development of the 3L-CVRP, which integrates three-dimensional loading constraints with traditional capacity and routing requirements. This variant was addressed using a hybrid metaheuristic combining GRASP and Evolutionary Local Search, achieving strong performance on benchmark instances and demonstrating the feasibility of solving more realistic and operationally complex logistics problems. Most recently, in 2024, a novel bio-inspired metaheuristic known as the Discrete Wild Horse Optimizer (DWHO) was proposed. By simulating wild horse behavior and integrating local search mechanisms and decoding strategies, DWHO outperformed several state-of-the-art algorithms on standard benchmarks, showcasing the continued relevance and innovation within CVRP research.

Moreover, recent developments have seen the integration of Geographic Information System (GIS) tools such as ArcGIS into CVRP implementations, enabling spatially-aware route optimization. By leveraging ArcGIS to map road networks, customer locations, and traffic conditions, routing models can be aligned more accurately with real-world constraints. This integration is particularly effective in applications such as national or regional fuel supply logistics, where route efficiency is influenced by geographic dispersion, infrastructure quality, and service point clustering. [27] [28] [29]

### 2.11.2 Simulated Annealing Applied to CVRP

Simulated Annealing (SA) has been progressively applied to the Capacitated Vehicle Routing Problem (CVRP), beginning with early implementations like the one by Harmanani et al. (2011), where a metaheuristic combined random and deterministic neighborhood operators regulated by problem-specific heuristics, such as savings and nearest-neighbor rules. This approach demonstrated strong performance on Solomon benchmarks and confirmed SA's effectiveness for route cost minimization and computational efficiency in CVRP contexts [19]. In 2018, Wei et al. extended SA to the more complex 2D loading variant of CVRP (2L-CVRP), incorporating a dual strategy of temperature cooling/warming cycles and a novel open-space-based heuristic for feasible packing. Enhanced by Trie data structures to accelerate feasibility checks, their SA algorithm outperformed several prior models across traditional benchmarks, underscoring the flexibility of SA in handling both routing and loading constraints [20]. Most recently, in 2024, a customized SA algorithm was applied to fuel distribution logistics in Poland, integrating real-world constraints such as varying fuel demands and road network characteristics. Simulations showed the SA-based approach achieved performance comparable to Mixed Integer Programming models, reinforcing its value in solving large-scale, real-world CVRP instances. [30] [31] [32]

## 2.12 Blob Algorithm Applied to CVRP

Bio-inspired algorithms have been widely applied to tackle the Capacitated Vehicle Routing Problem (CVRP) since the beginning of the 2000s. Some of the earliest applications include metaheuristics such as genetic algorithms, ant colony optimization, and particle swarm optimization, used to tackle various VRP variants, including CVRP, due to their wide applicability and robustness (Potvin, 2008). A comprehensive overview of such algorithms is presented in the book Bio-inspired Algorithms for the Vehicle Routing Problem, where it is shown that nature-inspired computation can be successfully applied to practical issues of routing and logistics (Pereira & Tavares, 2009).

Among them, Physarum-based algorithms from the adaptive intelligence of the slime mold Physarum polycephalum have been found effective in graph-based and pathfinding issues. Masi and Vasile (2013) also introduced the Multidirectional Physarum Solver and utilized it for combinatorial instances such as the Traveling Salesman Problem (TSP) and standard Vehicle Routing Problems (VRPs), demonstrating how it can form and optimize solution paths through a decentralized network-construction process. However, the first written publication that implemented a Physarum-based algorithm for the CVRP appeared later. Versluis (2018) provided a multi-agent system where Physarum's foraging process was used to simulate constructing paths within capacity limits. His work is the first identified use of Physarum-inspired computation specifically designed for CVRP scenarios.

These developments show a clear chronology in introducing biological computing into CVRP research initially through general metaheuristics and subsequently through more specific models such as those based on the adaptive network structure generation behavior of Physarum. [33] [34] [35] [36]

## 2.13 GIS Applications in Logistics and Route Planning:

In the context of urban sustainability, Geographic Information Systems (GIS) have become indispensable tools for optimizing logistics operations, particularly in smart waste management systems. GIS enhances the efficiency, environmental impact, and cost-effectiveness of waste collection by enabling route optimization, spatial analysis, and real-time monitoring. [37]

One notable application is through platforms **like IGiS (Indigenous GIS and Image Processing Software),** which integrates spatial data and advanced network analysis tools to support key aspects of smart waste management: planning, management, and monitoring [37]

**Smart planning** involves using spatial analysis tools such as weighted overlay analysis to evaluate site suitability based on factors like population density, road networks, and service boundaries. This supports informed decision-making in selecting optimal locations for waste collection points or disposal sites [37]

**Route optimization** is another core feature. IGiS leverages network analysis to generate efficient waste collection routes that minimize travel time, fuel usage, and vehicle wear. These optimized routes are dynamically adjusted based on real-time conditions and service needs, reducing operational costs and carbon emissions [37]

**Smart management** is further achieved through the integration of GIS with Internet of Things (IoT) devices. Waste bins equipped with weighing sensors send real-time data to GIS platforms, allowing for timely alerts and efficient scheduling. Vehicle tracking systems provide real-time navigation updates, ensuring that the nearest collection vehicle is dispatched, and helping prioritize urgent areas [37]

Finally, monitoring and analysis functions enable authorities to evaluate the performance of waste management strategies through dashboards, visualizations, and predictive analytics. These tools not only track current operations but also help forecast future waste generation trends. [37]

Overall, the integration of GIS in waste logistics exemplifies how spatial technologies can transform urban service delivery. By enabling data-driven decision-making, improving resource allocation, and engaging the public through interactive platforms, GIS supports a smarter, cleaner, and more sustainable urban environment. [37]

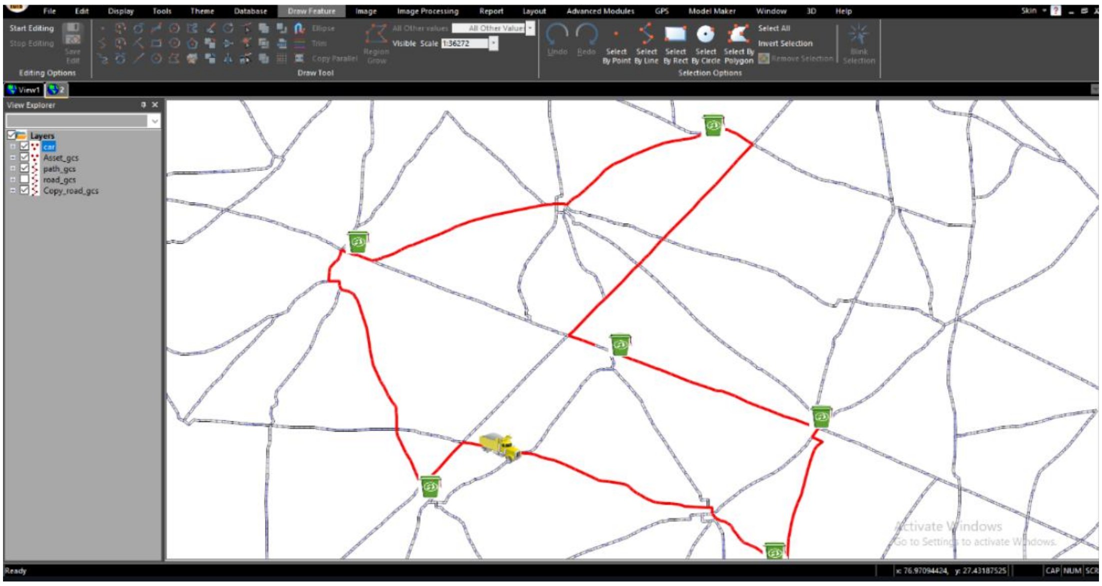

**Figure 17: optimized Waste Collection Routes Visualized in GIS [38]**

## 2.14 Conclusion :

This chapter has examined the Vehicle Routing Problem (VRP) as a foundational issue in the field of logistical optimization, presenting its theoretical underpinnings, practical variants, and the computational methodologies employed to address it. From classical deterministic formulations to dynamic and stochastic extensions, the VRP has demonstrated significant adaptability in tackling diverse real-world challenges, including waste collection, emergency logistics, retail distribution, and urban transportation planning.

While exact solution methods remain valuable for small-scale or structured instances, their applicability is constrained by computational limitations. In contrast, heuristics offer faster, though approximate, solutions, and metaheuristic approaches such as Simulated Annealing, Genetic Algorithms, and Ant Colony Optimization strike an effective balance between solution quality and computational feasibility. Among these, bio-inspired techniques particularly those modeled after the foraging behavior of *Physarum polycephalum* (e.g., the Blob algorithm) i llustrate the potential of unconventional computing in addressing complex, high-dimensional routing problems.

As logistics systems evolve to meet the demands of urbanization, sustainability, and real-time responsiveness, the integration of biologically inspired strategies with advanced algorithmic frameworks offers a promising direction. The study of VRP not only continues to enrich the academic discourse on combinatorial optimization but also plays a crucial role in enhancing operational efficiency, reducing environmental impact, and improving urban service delivery. Future research should prioritize the development of hybrid, adaptive models that combine mathematical rigor with the flexibility and intelligence observed in natural systems.

# CHAPTER 3:
# Implementation and Analysis of TSP and VRP

## 3.1 Introduction:

Route optimization plays a critical role in modern logistics, transportation, and urban service delivery systems. As the demand for faster, more efficient, and cost-effective operations continues to grow, organizations are increasingly required to optimize travel paths, resource allocation, and fleet deployment. Effective routing not only helps reduce delivery times and fuel consumption, but also contributes to broader goals such as minimizing operational costs and promoting environmental sustainability. In this context, mathematical optimization problems like the Travelling Salesman Problem (TSP) and the Vehicle Routing Problem (VRP) have become fundamental to both academic research and practical logistics applications.

The Travelling Salesman Problem (TSP) is a classic combinatorial optimization problem in which the objective is to determine the shortest possible route that allows a single agent (vehicle) to visit a set of locations exactly once before returning to the starting point. Despite its simple conceptual formulation, the TSP is an NP-hard problem, and its computational complexity increases exponentially with the number of locations.

The Vehicle Routing Problem (VRP) extends the TSP framework by incorporating multiple vehicles, a central depot, vehicle capacity limits, and specific service demands at each location. The goal of VRP is to construct a set of routes that collectively cover all service points while minimizing the total travel distance and satisfying real-world operational constraints. This makes VRP a more realistic and applicable model for problems such as municipal waste collection, parcel delivery, and supply chain logistics.

This chapter presents the modeling, implementation, and comparative analysis of the TSP and VRP using real-world waste collection data from the city of Tlemcen, Algeria. Three metaheuristic algorithms **Simulated Annealing (SA)**, and the **Blob Algorithm** (inspired by the behavior of the Physarum polycephalum organism) were implemented in Python to solve TSP instances across three distinct waste collection circuits. The VRP formulation was then applied to the full dataset of 150 locations, incorporating operational constraints such as vehicle capacities and depot returns.

A comprehensive evaluation was conducted to assess the algorithms across key performance indicators including total distance traveled, computational time, and algorithm stability. The chapter concludes with a comparative discussion of TSP and VRP performance, highlighting the impact of real-world constraints on optimization outcomes and the applicability of metaheuristic techniques for urban logistics planning.

## 3.2 Development Environment:

The implementation and evaluation of metaheuristic algorithms for solving the Travelling Salesman Problem (TSP) and the Capacitated Vehicle Routing Problem (CVRP) were conducted within a well-defined computational environment. This section outlines the hardware specifications, programming language, and development tools employed throughout the project.

### 3.2.1 Hardware and System Specifications :

All experiments were executed on a **Dell laptop** configured as follows:

- **Processor**: Intel® Core™ i7 vPro, 8th Generation
- **RAM**: 4 GB DDR4
- **Storage**: 512 GB Solid State Drive (SSD)
- **Operating System**: Microsoft Windows 11 (64-bit)

This setup provided a stable and responsive platform for implementing and testing algorithms. While the available memory is relatively limited, the SSD significantly improved data access and script execution speeds, ensuring efficient performance for small- to medium-scale problem instances.

### 3.2.2 Programming Language: Python :

The entire development work was carried out using **Python**, specifically **version 3.12 (64-bit)**. Python is an open-source, high-level programming language known for its simplicity, readability, and broad applicability in scientific computing and algorithm development.

Python was chosen for several reasons:

- Its clear and concise syntax, which supports rapid development and easier debugging;
- Extensive libraries and frameworks for numerical computation and data visualization;
- Wide community support and comprehensive documentation;
- Cross-platform compatibility and ease of integration with external tools.

Key libraries used in this study include:

- **NumPy** – for numerical and matrix operations
- **NetworkX** – for modeling and manipulating graphs
- **Matplotlib** – for route plotting and visual analysis
- **SciPy** – for optimization-related functions
- **scikit-opt** – for implementing metaheuristic algorithms such as GA and SA

Python scripts were primarily executed using **IDLE** (Integrated Development and Learning Environment), which comes bundled with Python installations. IDLE provides a lightweight interface suitable for writing, testing, and debugging scripts in real time.

**Figure 18: Programing language Python. [16]**

**Table 7: Overview of Python Environment**

| **Attribute** | **Description** |
| --- | --- |
| Version Used | Python 3.12 (64-bit) |
| Interpreter | IDLE |
| Key Libraries | NumPy, SciPy, NetworkX, Matplotlib, scikit-opt |
| Supported Platforms | Windows, Linux/UNIX, macOS |
| Official Website | www.python.org |

### 3.2.3 Code Editor: Visual Studio Code (VS Code)

While IDLE was used for initial testing, the core development work and algorithm structuring were carried out using **Visual Studio Code (VS Code)**. Developed by **Microsoft**, VS Code is a lightweight yet powerful source code editor that supports a wide range of programming languages and tools.

Reasons for choosing VS Code include:

- **Rich extension support**: Python extensions enable intelligent code completion, linting, debugging, and environment management.
- **Integrated Git**: Version control features facilitate tracking changes and managing project iterations.
- **Built-in terminal**: Allows for direct command-line execution without switching contexts.
- **Cross-platform usability**: Ensures consistent behavior across systems.

These features collectively enhanced the development workflow and made code navigation, testing, and documentation significantly more efficient.

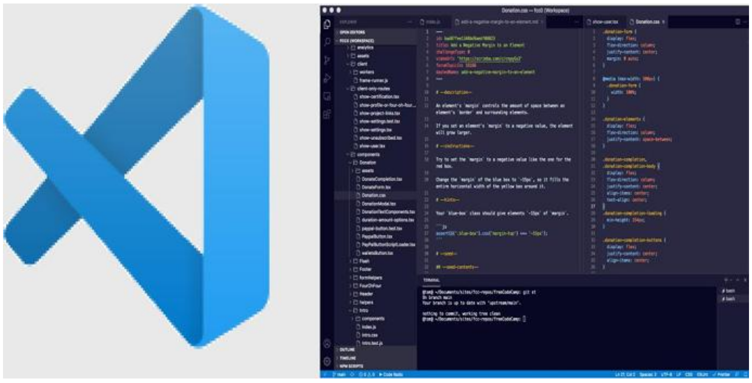

Figure 19: : The text editor Visual Studio Code. [15]

### 3.2.4 Libraries and Frameworks :

Table 8: Libraries and Frameworks Used in Implementation [15]

| Library / Framework | Purpose in Project | Description & Source |
|---|---|---|
| **NetworkX** | Graph modeling, node/edge manipulation, path visualization | Used for building TSP/VRP graphs. Source: NetworkX Documentation |
| **NumPy** | Numerical computation, distance matrices | Efficient handling of vectors, arrays, and mathematical operations. Source: NumPy Documentation |
| **Matplotlib** | Visualization of routes and convergence | Used for plotting TSP/VRP routes and algorithm performance. Source: Matplotlib Documentation |
| **scikit-opt** | Metaheuristic implementation (GA, SA) | Provided prebuilt modules for Simulated Annealing and Genetic Algorithm. Source: scikit-opt GitHub |
| **DEAP** | Advanced evolutionary algorithm design | Offered flexible tools for GA customization. Source: DEAP Documentation |
| **pyvrp** | Solving CVRP with capacity constraints | Used for solving VRP instances with multiple vehicles and depots. Source: pyvrp GitHub |
| **Custom Code** | Heuristics and VRP-specific logic | Additional algorithms coded to fit specific project needs |
| **time, random** | Runtime tracking, stochastic behavior | Built-in Python modules. Source: Python Standard Library |
| **pandas** | Tabular data handling, result tables | Used to structure algorithm results for comparison. Source: pandas Documentation |
| **math** | Geometric calculations | Euclidean distances and angle computation. Source: |

| Library / Framework | Purpose in Project | Description & Source |
|---|---|---|
| | | Python Math Library |

Table 9: Overview of Visual Studio Code

| Attribute | Description |
|---|---|
| Developer | Microsoft |
| Supported Systems | Windows, macOS, Linux |
| Languages Used | TypeScript, JavaScript, HTML, CSS |
| Key Features | Python integration, terminal access, Git support |
| Official Website | code.visualstudio.com |

### 3.2.5 Foundational Study: Mathematical Optimization of Waste Collection in Tlemcen

Efficient waste collection is a cornerstone of sustainable urban management. In the context of Tlemcen, a historic city in northwestern Algeria, the challenges of solid waste collection are exacerbated by dense commercial activity, narrow streets, and the absence of proper waste disposal infrastructure in the city center. A notable foundational study addressed these issues through a quantitative optimization approach, applying the **Multiple Traveling Salesman Problem (m-TSP)** model to improve municipal solid waste collection operations. [39]

#### 3.2.5.1 Overview and Context

The original study focused on the city center of Tlemcen, which comprises high-density commercial zones where hundreds of small shops generate substantial quantities of waste predominantly cardboard (approximately 80%) and plastic or textile materials (approximately 20%). The lack of bins and constrained road accessibility has historically led to the accumulation of curbside waste, adversely impacting public hygiene and the urban aesthetic.

At the time of the study, the Tlemcen municipality operated **21 collection vehicles** across **21 sectors**, collectively responsible for servicing **1502 waste collection points**. Given the complexity and scope of the system, the authors restricted their investigation to **three representative sectors** within the city center. [39]

#### 3.2.5.2 Data Collection and Modeling Approach

To construct an accurate routing model, field data were collected using **GeoTracker**, an Android-based GPS application, which recorded:

- Node coordinates (latitude, longitude, and altitude)
- Travel times and average speeds
- Total distances, including return legs to landfills and depots

Using this data, the researchers developed an **asymmetric distance matrix** for each route. Shortest-path distances between all node pairs were extracted via **Google Maps**, and each sector's routing task was formulated as a **multiple Traveling Salesman Problem (m-TSP)**. [39]

In this context, each waste collection vehicle was modeled as a "salesman" responsible for visiting a set of nodes, beginning at a known depot and ending at a designated landfill site. The problem formulation did not include vehicle capacity or time window constraints, under the assumption that each vehicle could complete its assigned route in a single trip. [39]

#### 3.2.5.3 Optimization Techniques and Computational Tools

Two optimization strategies were employed:

- **Lingo Solver**, a commercial software implementing exact methods for solving small-scale TSP formulations
- **Simulated Annealing (SA)**, a metaheuristic algorithm, custom-implemented in **Java** using the **Eclipse IDE**

While Lingo provided optimal solutions for smaller node sets, it encountered performance limitations with larger instances due to computational constraints. Simulated Annealing, on the other hand, demonstrated robustness across all problem sizes, delivering feasible and near-optimal solutions within acceptable execution times.

#### 3.2.5.4 Results and Performance Analysis

The optimization outcomes for the three studied routes are summarized as follows:

- **Route 01 (42 nodes)**: Simulated Annealing successfully optimized the full route, achieving a **distance reduction of 1.431 km**. Lingo failed beyond 29 nodes.
- **Route 02 (24 nodes)**: Both algorithms produced similar results, with a **marginal gain of 50 meters** per day, translating to approximately **18 km/year**.
- **Route 03 (88 nodes)**: Simulated Annealing achieved a **reduction of 686 meters**, while Lingo was again unable to handle the full problem size.

Cumulatively, the daily distance savings amounted to **2.167 km**, or **788 km annually**. These reductions imply measurable environmental and economic benefits, particularly in terms of **fuel consumption** and **$CO_2$ emission mitigation**. Furthermore, the findings confirmed that even minor improvements in routing can yield substantial long-term gains. [39]

#### 3.2.5.5 Limitations and Future Directions

Despite its valuable contributions, the original study was subject to several limitations:

- It analyzed only 3 of the 21 municipal sectors.
- The vehicle routing was static, lacking adaptability to real-time waste generation patterns.
- No integration of smart technologies (e.g., IoT-enabled bins) was implemented.
- The study stopped short of evaluating the problem at the full **Vehicle Routing Problem (VRP)** level, which would consider multi-vehicle, multi-sector coordination.

Future work proposed by the authors included scaling the optimization to the entire waste collection network, redesigning collection circuits based on distance minimization (rather than empirical routines), reducing the number of active vehicles, and eventually incorporating smart sensors to support **real-time route optimization** within a **Smart Waste Management** framework. [39]

### 3.2.6 Research Objective and Thesis Contribution

The present thesis is directly informed by the aforementioned foundational work. While the initial study introduced important optimization techniques using m-TSP and Simulated Annealing, its scope was limited to a small subset of the urban network and did not explore biologically inspired or more adaptive algorithms.

This research aims to advance the original investigation by applying and evaluating the performance of the **BLOB (Biologically-Inspired Optimization) algorithm** within the same real-world context. The objectives of the thesis are articulated as follows:

1. **To apply the BLOB algorithm to the TSP formulation** of the three previously studied routes, enabling a direct and controlled comparison with existing results obtained through Simulated Annealing and Lingo Solver.
2. **To extend the analysis to the VRP formulation**, encompassing the full-scale municipal collection network with multiple vehicles and sectors, thereby addressing the complexity of real-world operations.
3. **To evaluate the organizational implications** of the optimization results, specifically whether the current empirical routing strategy remains effective or whether a newly optimized structure offers demonstrable improvements in efficiency, cost, and environmental impact.

Through this dual-phase methodology beginning with TSP-based benchmarking and progressing to VRP-level strategic assessment the research contributes both methodologically and practically to the field of urban logistics and municipal waste management.

## 3.3 Travelling Salesman Problem (TSP)

### 3.3.1 Problem Definition:

The Travelling Salesman Problem (TSP) is one of the most fundamental and widely studied problems in the field of combinatorial optimization. Formally, TSP consists of finding the shortest possible route that allows a single agent typically referred to as a "salesman" to visit each city exactly once and return to the point of origin. The objective is to minimize the total travel distance or cost across the entire tour.

From a mathematical standpoint, TSP is defined on a complete weighted graph **G=(V,E),** where **V** represents the set of **n** cities (or nodes) and **E** denotes the edges connecting them, each associated with a cost **Cij** , representing the distance between nodes **i** and **j**. The goal is to find a Hamiltonian circuit of minimum cost. Solving TSP is known to be NP-hard, meaning that the complexity increases exponentially with the number of nodes, making it challenging for exact methods to solve large instances efficiently.

TSP is more than a theoretical problem it has numerous practical applications in logistics, transportation, manufacturing, circuit design, and robotic path planning. In distribution systems, for example, it is crucial to find the shortest route for a delivery vehicle to visit a set of locations before returning to the depot.

In the context of this project, TSP was solved across **three distinct road network instances**, labeled **Road A**, **Road B**, and **Road C**. Each network represents a separate geographic or simulated area with a specific number of nodes and distance constraints. These instances were used to evaluate the performance of various metaheuristic algorithms, with the goal of minimizing total travel distance while ensuring that each location is visited exactly once and the tour returns to the starting node.

The results of solving TSP for these three instances will be analyzed using multiple criteria such as route quality, computation time, and stability across algorithms. The ultimate objective is to determine the most efficient metaheuristic for this class of problem in a practical, real-world-inspired setting. [39]

### 3.3.2 Practical Implementation of the TSP in Urban Waste Collection

Although originally rooted in theoretical computer science, the Travelling Salesman Problem (TSP) has become a fundamental model for addressing a wide range of real-world routing and planning problems. Its structure requiring a complete traversal of a set of nodes with minimal travel cost closely aligns with practical challenges in logistics, urban service delivery, and industrial optimization.

Within the domain of municipal operations, the TSP is particularly relevant to services such as solid waste collection, postal delivery, street cleaning, and field service management. In these contexts, identifying an optimal route enables significant reductions in fuel consumption, operational time, and environmental impact key concerns for both municipal planners and logistics providers.

This study applies the TSP framework to optimize **municipal waste collection in the city center of Tlemcen**. The dataset comprises **150 actual waste collection points**, in addition to a **starting depot and a final landfill**, resulting in **152 total nodes**. Each node is geospatially defined by (X, Y, Z) coordinates, and a complete distance matrix was constructed to represent the pairwise travel distances between all nodes.

For analysis and comparative testing of metaheuristic algorithms, the full set was segmented into three regional clusters **Road A, Road B, and Road C** each representing an individual waste collection circuit. The objective is to determine the most efficient route for a single vehicle assigned to each road, ensuring all collection points are visited exactly once before returning to the depot.

By modeling these circuits as TSP instances and evaluating alternative metaheuristic solutions, the study offers practical insights into optimizing urban waste management systems ultimately contributing to more efficient, cost-effective, and environmentally responsible municipal services. [39]

## 3.4 Resolution Method Description

The Physarum solver algorithm is inspired by the unique way *Physarum polycephalum*, a type of slime mold, searches for food. As it explores its surroundings, the slime mold spreads out in all directions. Once it discovers multiple food sources, it gradually forms efficient pathways known as pipelines between them, naturally optimizing how nutrients are transported across its network.

We use this biological process as a model for tackling waste collection and landfill routing challenges. By applying the Physarum solver, we can determine the flow of connections between each waste collection point (or node). These flow values help us solve complex routing problems like the Traveling Salesman Problem (TSP) and the Capacitated Vehicle Routing Problem (CVRP). In this setup, each collection point acts as a node, while the cost matrix $L_{ij}$ represents the distance or travel time between them.

The figure below illustrates how the flow values are calculated within this waste management context. [15]

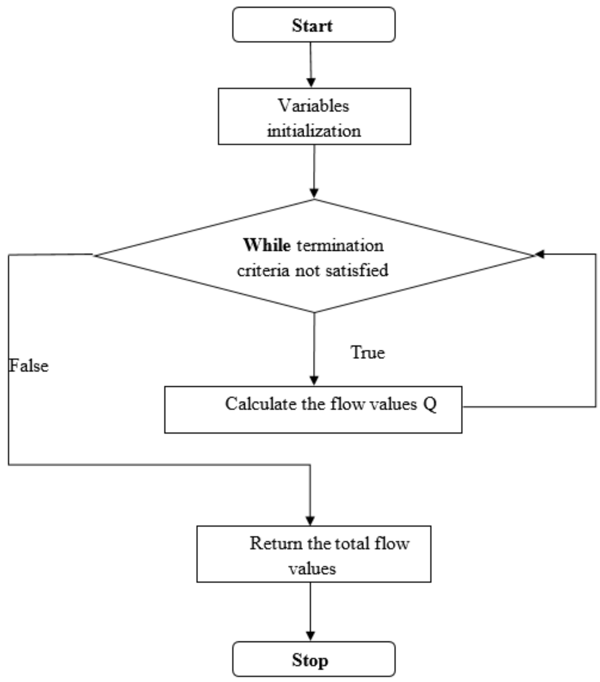


Figure 20: The physarum solver diagram [15]

## 3.5 TSP Resolution with Physarum Solver

The goal of solving the Traveling Salesman Problem (TSP) in the context of waste collection is to find the most efficient route for a single vehicle to visit various waste collection points and then return to the starting location, minimizing the total travel distance. [15]

The main conditions of the TSP are:

- Each waste collection point (or city) should be visited exactly once.
- The vehicle must return to its starting point after visiting all the points.

### 3.5.1 Resolution Steps

**Step 1:** Initialize the parameters of the Physarum solver, including the distance matrix **Dij**, flow values **Qij** initial current **I0**, as well as the designated starting and destination nodes. The cost matrix **Lij** corresponds to the distances between the waste collection points.

**Step 2:** Compute the initial flow values **Qij** using the expression provided in Equation (1).

**Step 3:** Iteratively update the flow values and the conductivity of the network using the formulations given in Equations (2) and (3). This process is repeated until the specified termination criteria are satisfied.

**Step 4:** Upon convergence, determine the routing path starting from a designated origin. The next node **Pnext** is selected based on the maximum flow value emerging from the current node. Once a node is selected, it becomes the new current point for subsequent selections. Each selected node **Pnext** is stored in the list **Lbest** representing the optimal route. The pipeline with the highest flow value between the current node and others is used to guide the selection.

$$Q_{inext} = \max \{|Q_{i1}| , |Q_{i2}| \ldots\ldots\ldots\ldots |Q_{im}|\} \text{ [15]}$$

$$L_{best} = \{i_1, i_2, \ldots\ldots\ldots\ldots i_n\} \text{ [15]}$$

$Q_{inext}$ represents the pipeline with the largest flow value from the current point i to the other points.

This process continues until all collection points are selected, and the complete path $L_{best}$ is determined.

### 3.5.2 CVRP Resolution with Physarum Solver

#### 3.5.2.1 CVRP Parameters

- **N**: Number of waste collection points (customers).
- **T**: The demand (amount of waste) for each collection point.
- **K**: Number of waste collection vehicles.
- **C**: Capacity of each vehicle. [15]

#### 3.5.2.2 CVRP Constraints

- Each waste collection point can only be served by one vehicle.
- The total demand of the waste collection points in one route should not exceed the capacity of the vehicle. [15]

#### 3.5.2.3 Resolution Steps

The process of solving the Capacitated Vehicle Routing Problem (CVRP) using the Physarum solver is similar to solving the TSP, with the added consideration of vehicle capacity.

**Step 1**: Initialize the Physarum solver parameters, including $\mathbf{D_{ij}}$, $\mathbf{Q_{ij}}$, $I_0$, the starting point, and the destination nodes (with the cost matrix $\mathbf{L_{ij}}$, representing the distance between collection points).

**Step 2**: Calculate the flow $\mathbf{Q_{ij}}$, using equation (1).

**Step 3**: Update the flow values and conductivity according to equations (2) and (3), iterating until the termination criteria are met.

**Step 4**: Based on the final flow values, select a starting point. Choose the next collection point **($P_{next}$)** based on the largest flow value from the starting point. For each selection, check if the sum of the demands of the selected points is within the vehicle's capacity. If the sum exceeds the capacity, stop the selection process and form the route **$L_{best}$**.

**Step 5**: Repeat step 4 until a complete path is formed for each waste collection vehicle. [15]

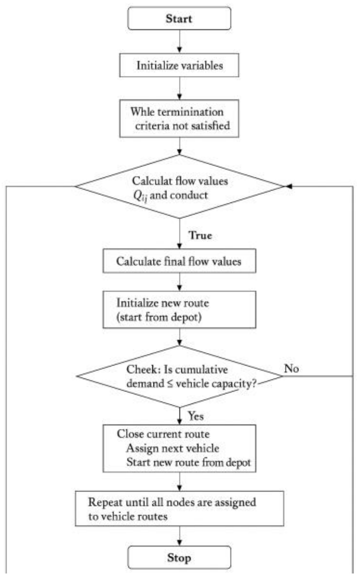


**Figure 21: : Flowchart of the Blob Algorithm for Solving the Capacitated Vehicle Routing Problem (CVRP)**

### 3.5.3 Data and Setup

To conduct a practical evaluation of metaheuristic approaches for solving the **Traveling Salesman Problem (TSP)** and **Capacitated Vehicle Routing Problem (CVRP)**, this study utilizes **real-world data** collected from a municipal waste collection operation in the city center of **Tlemcen, Algeria**. This section outlines the preparation of the dataset, the construction of problem instances, and the computational setup used for algorithm implementation and testing.

### 3.5.4 Data Source and Structure

The dataset consists of **150 real geographic waste collection points**, recorded using the **GPS Tracker mobile application**. Each point includes **X, Y, and Z coordinates**, corresponding to its actual location within the city. A **complete distance matrix** was generated based on **GPS-tracked road travel**, rather than Euclidean distance, to reflect realistic travel paths in the urban environment.

To support comparative benchmarking across different route complexities, the data was segmented into three operational circuits that match real-world routes used by the municipal waste collection teams:

- **Circuit 03 (Road A):** 42 collection points
- **Circuit 08 (Road B):** 23 collection points
- **Circuit 13 (Road C):** 87 collection points

Each circuit was exported as a separate `.csv` file containing the respective distance matrix, and used as an independent instance for solving the TSP. A separate matrix file named `VRPMTRXXX.csv` was prepared for VRP testing, covering the full network of 150 points plus designated depot and landfill nodes.

### 3.5.5 Distance Calculation Method

All distances were computed using **road-based GPS data** rather than theoretical Euclidean geometry. The GPS Tracker app recorded real traversal paths between collection points, and the corresponding pairwise distances were compiled into a complete matrix using pre-processed field data. This method ensures accurate modeling of street-level constraints, such as narrow alleys and one-way roads, which are common in Tlemcen's city center.

### 3.5.6 Software Environment

All algorithm implementations and data processing were conducted in **Python 3.12**. The development environment and libraries used included:

- **NumPy / Pandas** –> matrix operations and data management
- **NetworkX** –> graph-based route modeling
- **Matplotlib** –> visualization of collection routes
- **scikit-opt & DEAP** –>implementations of metaheuristics (Simulated Annealing, etc.)
- **Custom scripts** –> for Physarum-inspired Blob algorithm (TSP and VRP variants)

Scripts were written in **Visual Studio Code**, with preliminary tests conducted in Python's **IDLE**. Execution was performed on a **Dell Core i7 vPro (8th Gen)** PC with **8 GB RAM**, **512 GB SSD**, and **Windows 11**.

### 3.5.7 Algorithm Configuration

This study implements and tests two optimization algorithms each in two variants (TSP and VRP) for solving the waste collection routing problems. These are:

- **Simulated Annealing (SA)**
- **Blob Algorithm (Physarum Solver)**

Parameter settings were selected based on established practices in the literature and refined through controlled trial experiments. The final configurations are presented below:

**Table 10: Parameter Settings and Heuristic Strategies Used for TSP and VRP Models Across Metaheuristic Algorithms**

| Algorithm | Configuration Parameters |
|---|---|
| **Simulated Annealing (TSP)** | Initial Temperature = 1000<br>Cooling Rate = 0.995<br>Max Iterations = 1000<br>Neighborhood: 2-swapInitial<br>Solution: greedy sort by distance from depot |
| **Simulated Annealing (VRP)** | Same as TSP + vehicle constraints:<br>Capacities: [6000, 6000, 10000]kg<br>Depot = Node 0,<br>Landfill = Node 150<br>Route split based on capacity load |
| **Blob Algorithm (TSP)** | Max Iterations = 500<br>Initial Conductivity D=0.5<br>Update Rule: D=0.6D+0.4Q<br>Flow Source/Sink: I0=−1, In=+1 |
| **Blob Algorithm (VRP)** | Greedy heuristic (non-iterative)<br>Capacities: [6000, 6000, 10000] kg<br>Assignment: sorted by waste demand<br>Routing: nearest neighbor within remaining capacity |

### 3.5.8 Results and Visualization

This section presents the comparative results of applying three metaheuristic algorithms **Simulated Annealing (SA)**, and the **Blob Algorithm (Physarum Solver)** to the **Traveling Salesman Problem (TSP)** for three real-world waste collection routes in the city center of Tlemcen: **Road A (Circuit 03)**, **Road B (Circuit 08)**, and **Road C (Circuit 13)**.

Each algorithm was executed on the respective road network using the distance matrices previously generated. The performance was evaluated based on:

- The **initial direct distance**, representing the baseline length without optimization.
- The **optimized total distance** calculated by the algorithm.
- The **gain** achieved (reduction or increase in distance, in meters).
- The **execution time** in resolving the route.
- The resulting **optimized route/path**.

### 3.5.9 Results for Road A (42 Nodes)

**Table 11: TSP Optimisation Results – Road A**

| Algorithm | Optimized Distance (m) | Initial Distance (m) | Gain (m) | Execution Time (s) |
|---|---|---|---|---|
| Blob Algorithm | 30 422.1 | 23 921.0 | –6 501.1 | 0,17 |
| Simulated Annealing | 22 490.0 | 23 921.0 | 1 431.0 | 5,08 |

### 3.5.10 Optimized Paths

- **Simulated Annealing**

0 → 6 → 9 → 7 → 8 → 5 → 4 → 16 → 18 → 33 → 34 → 35 → 36 → 37 → 27 → 28 → 29 → 30 → 31 → 41 → 32 → 17 → 19 → 18 → 21 → 22 → 23 → 24 → 25 → 26 → 38 → 39 → 40 → 3 → 13 → 15 → 14 → 12 → 11 → 10 → 42 → 0

- **Blob Algorithm (Physarum Solver)**

0 → 1 → 2 → 3 → 4 → 5 → 6 → 8 → 9 → 15 → 16 → 17 → 18 → 31 → 32 → 10 → 11 → 23 → 12 → 22 → 30 → 40 → 41 → 39 → 29 → 38 → 27 → 28 → 7 → 21 → 20 → 24 → 25 → 37 → 14 → 34 → 19 → 33 → 13 → 35 → 36 → 26 → 42 → 0

### 3.5.11 Analytical Evaluation of Algorithm Performance on Road A (42 Nodes)

The results for Road A, comprising 42 nodes, highlight differences in performance between two metaheuristic algorithms: Simulated Annealing (SA) and the Blob Algorithm. Both were assessed against a corrected baseline tour of **23 921.0 meters**. Neither algorithm produced an optimized route better than the baseline, reflecting the complexity of the problem and the challenge of achieving global optimality through heuristics alone.

**Simulated Annealing** achieved a final distance of **22 490.0 meters**, improving upon the baseline by **1 431.0 meters**. It produced the best result among the tested methods. SA employs a probabilistic mechanism that accepts worse solutions early in the search to avoid local minima. Combined with a cooling schedule, this approach allows broad exploration of the solution space. The algorithm executed in **5,08 seconds**, indicating moderate computational cost. Its ability to surpass the baseline suggests strong potential for further optimization through parameter tuning, such as adjusting the cooling rate, initial temperature, or neighbor selection.

The **Blob Algorithm (Physarum Solver)** generated a longer route of **30 422.1 meters**, which is **6 501.1 meters** above the baseline. However, it executed significantly faster, completing in just **0,17 seconds**. Its biologically inspired, non-iterative model simulates the adaptive growth of slime mould networks to form paths but lacks mechanisms for global correction. This limits its ability to refine solutions in complex topologies. Despite its lower accuracy, the Blob Algorithm is effective when fast approximations are needed, particularly in real-time or resource-constrained scenarios.

These results demonstrate a trade-off between **accuracy** and **efficiency**. Simulated Annealing offers better-quality routes with moderate time cost, while the Blob Algorithm prioritizes speed at the expense of solution quality. Their contrasting strengths make them suitable for different applications, depending on whether the priority is precision or computational speed.

### 3.5.12 Results for Road B (23 Nodes)

Table 12:TSP Optimisation Results – Road B

| Algorithm | Optimized Distance (m) | Initial Distance (m) | Gain (m) | Execution Time (s) |
|---|---|---|---|---|
| **Blob Algorithm** | 24 156.4 | 20 989.0 | –3 167.4 | 0,17 |
| **Simulated Annealing** | 20 939.0 | 20 989.0 | 50.0 | 0,34 |

### 3.5.13 Optimized Paths

- **Simulated Annealing**

0 → 2 → 3 → 4 → 6 → 5 → 7 → 8 → 9 → 10 → 11 → 12 → 13 → 14 → 15 → 16 → 17 → 18 → 19 → 20 → 21 → 22 → 23 → 0

- **Blob Algorithm (Physarum Solver)**

0 → 1 → 3 → 5 → 2 → 4 → 9 → 10 → 22 → 8 → 19 → 20 → 21 → 17 → 18 → 15 → 14 → 16 → 13 → 11 → 12 → 6 → 7 → 0 → 1 → 23 → 0

### 3.5.14 Analytical Evaluation of Algorithm Performance on Road B (23 Nodes)

The evaluation on Road B, consisting of 24 nodes, reveals a clear contrast between solution quality and computational efficiency across the tested algorithms.

**Simulated Annealing** produced the shortest route, with a total distance of **20 939.0 meters**, resulting in a modest improvement of **50.0 meters** over the baseline value of **20 989.0 meters**. With an execution time of **0,34 seconds**, it demonstrated reliable performance on a smaller instance. The algorithm's ability to explore the solution space stochastically allowed it to generate a reasonably optimized path with limited computational effort. These results reinforce its suitability for small to medium-sized networks where both speed and accuracy are required.

The **Blob Algorithm** yielded a longer route of **24 156.4 meters**, representing a **3 167.4-meter** increase from the baseline. However, it achieved the fastest runtime of approximately **0,17 seconds**, making it the most efficient in terms of speed. Its biologically inspired, decentralized structure enables rapid generation of feasible paths, but lacks refinement mechanisms, leading to lower solution quality. As with previous evaluations, it remains more applicable in time-sensitive or low-resource environments where approximation is prioritized over precision.

In this case, Simulated Annealing again proved more effective for achieving shorter routes, while the Blob Algorithm demonstrated its role as a fast, heuristic estimator rather than a high-precision optimizer.

### 3.5.15 Results for Road C (87 Nodes)

Table 13:TSP Optimisation Results – Road C

| Algorithm | Optimized Distance (m) | Initial Distance (m) | Gain (m) | Execution Time (s) |
|---|---|---|---|---|
| **Blob Algorithm** | 50 980.3 | 27 406.0 | –23 574.3 | 3,68 |
| **Simulated Annealing** | 26 720.0 | 27 406.0 | 686.0 | 4,02 |

### 3.5.16 Optimized Paths

- **Simulated Annealing**

0 → 10 → 8 → 9 → 7 → 6 → 5 → 4 → 14 → 15 → 16 → 17 → 18 → 19 → 20 → 21 → 22 → 23 → 24 → 25 → 26 → 27 → 28 → 29 → 30 → 31 → 35 → 44 → 46 → 47 → 48 → 49 → 50 → 51 → 53 → 54 → 55 → 68 → 56 → 67 → 66 → 65 → 61 → 64 → 60 → 45 → 33 → 34 → 36 → 37 → 38 → 39 → 40 → 41 → 42 → 43 → 69 → 57 → 70 → 71 → 72 → 73 → 74 → 75 → 76 → 77 → 78 → 79 → 82 → 83 → 84 → 87 → 86 → 85 → 81 → 80 → 52 → 58 → 62 → 59 → 61 → 32 → 13 → 12 → 11 → 2 → 3 → 88 → 0

- **Blob Algorithm (Physarum Solver)**

0 → 59 → 9 → 10 → 60 → 44 → 1 → 37 → 38 → 39 → 40 → 41 → 47 → 48 → 51 → 42 → 43 → 58 → 32 → 34 → 33 → 15 → 28 → 35 → 30 → 31 → 16 → 13 → 14 → 27 → 17 → 20 → 19 → 18 → 21 → 22 → 23 → 11 → 12 → 36 → 46 → 49 → 6 → 4 → 3 → 5 → 2 → 61 → 64 → 62 → 73 → 54 → 72 → 67 → 55 → 65 → 66 → 85 → 84 → 82 → 78 → 83 → 80 → 81 → 69 → 52 → 53 → 7 → 8 → 86 → 79 → 57 → 76 → 71 → 74 → 75 → 63 → 77 → 45 → 68 → 29 → 70 → 50 → 26 → 56 → 24 → 25 → 87 → 0

### 3.5.17 Analytical Evaluation of Algorithm Performance on Road C (87 Nodes)

The results for Road C, comprising **87 nodes**, reveal significant contrasts in both **solution quality** and **runtime** across the two algorithms.

**Simulated Annealing** achieved the best solution, with a route length of **26 720.0 meters**, which is **686.0 meters** better than the baseline of **27 406.0 meters**. Although the improvement is modest, this outcome reflects the algorithm's capacity to effectively handle large-scale problems with complex node distributions. Despite the increased problem size, it maintained robust neighborhood exploration and convergence, completing in **4,02 seconds**. This reinforces its applicability to larger instances where a balance between **accuracy** and **computational feasibility** is required.

In comparison, the **Blob Algorithm** produced a longer route of **50 980.3 meters**, which is **23 574.3 meters** above the baseline. It executed slightly faster than Simulated Annealing at **3,68 seconds**, reflecting its non-iterative nature. However, the quality of its solution declined significantly in this larger, more intricate network. While its spatial, biologically driven search mechanism allows for fast approximations, it lacks the **adaptive refinement** and iterative learning required to compete with metaheuristics like SA in high-dimensional scenarios.

These findings highlight the **scalability limitations** of the Blob Algorithm and reaffirm the advantage of **Simulated Annealing** in solving **large and complex routing problems** where **solution quality** is a key concern.

## 3.6 Vehicle Routing Problem (VRP): Modeling, Implementation, and Results

### 3.6.1 **Problem Definition**

The Vehicle Routing Problem (VRP) is a generalization of the Travelling Salesman Problem (TSP), where the objective is to determine optimal routes for a fleet of vehicles serving a set of geographically dispersed locations. Unlike the TSP, which involves a single agent, the VRP accounts for multiple vehicles, each constrained by capacity, and aims to minimize the total travel distance while ensuring all service demands are met.

In this study, the VRP is modeled to reflect the operational setup of municipal solid waste collection in Tlemcen, Algeria. The instance includes **150 waste collection points**, each associated with a real waste quantity (in kilograms) recorded by municipal services. The routing structure incorporates a **fixed depot** (waste collection garage) and a **central landfill** located outside the city center, which serves as the **start and end point** for all vehicle routes.

The problem is subject to the following constraints:

- Each collection point is visited exactly once by one vehicle.
- All vehicles depart from and return to the landfill.
- The vehicle fleet includes three heterogeneous trucks:
    - **Truck 1**: 6000 kg capacity
    - **Truck 2**: 6000 kg
    - **Truck 3**: 10000 kg
- There are no time window or duration constraints.
- Demands are based on real recorded waste amounts per location.

The primary objective is to construct logistically feasible, non-overlapping routes that **minimize total travel distance**, respect vehicle capacity limits, and ensure complete service coverage. This model serves as a realistic benchmark for evaluating multi-vehicle routing algorithms under practical constraints.

### 3.6.2 Data Setup

- **Dataset Description**

The dataset represents a real-world municipal waste collection scenario in the city of Tlemcen. It comprises:

- **150 collection nodes**, each geolocated via **GPS coordinates (X, Y, Z)**
- Corresponding **waste demands (in kilograms)** for each location
- A **150 × 150 distance matrix** based on road-network travel distances (in meters)
- A structured demand vector (CSV format) linking node IDs to waste quantities

Unlike the TSP analysis, where nodes were divided into circuits, the VRP treats all points as part of a single instance. This allows the routing algorithm to assign clusters dynamically, based purely on spatial proximity and vehicle constraints.

- **Depot and Vehicle Configuration**

The **landfill** outside the urban center serves as the **sole depot**, functioning as the origin and destination for all vehicle routes. It is not counted among the 150 collection nodes.

The **vehicle configuration defined in Section 4.5.1 is maintained**, with three trucks of varying capacity. No intermediate depots or transfer points are used, making this a **single-depot capacitated VRP (CVRP)** formulation.

- **Solver Input and Execution**

The VRP solver uses:

- The **pairwise distance matrix** (in meters),
- The **per-node waste demand vector** (in kg),
- The **vehicle capacity constraints**

The solver is responsible for:

- Assigning collection nodes to appropriate vehicles,
- Ensuring no capacity violations occur,
- Constructing efficient, non-overlapping routes that begin and end at the depot,
- Serving all 150 nodes exactly once,
- Minimizing the total travel distance across the fleet

This setup accurately mirrors real operational requirements in municipal waste collection and provides a rigorous environment for evaluating routing optimization algorithms

## 3.7 Comparative Analysis: TSP vs. VRP

The purpose of this section is to compare the results obtained from the Travelling Salesman Problem (TSP) and the Vehicle Routing Problem (VRP) formulations, based on the same set of 150 real-world waste collection points in the city center of Tlemcen. While TSP considers a single vehicle visiting all locations, VRP distributes the workload among multiple vehicles with specific capacity limits, aiming to reduce the total travel distance and improve operational efficiency.

The table below summarizes the total optimized distances obtained from both models for each Truck followed by the cumulative total and percentage increase observed when implementing the VRP approach using Simulated Annealing as the common point of comparison.

**Table 14: SA vs Blob: Per-Truck TSP & VRP Results Summary**

| Truck | Problem Type | SA Distance (m) | Blob Distance (m) | Difference (m) | SA Nodes | Blob Nodes | SA Capacity | Blob Capacity |
|---|---|---|---|---|---|---|---|---|
| Truck 1 | **TSP** (Road A) | 22 490.0 | 30 422.1 | **+7 932.1** | 42 | 42 | – | – |
| Truck 2 | **TSP** (Road B) | 20 939.0 | 24 156.4 | **+3 217.4** | 24 | 24 | – | – |
| Truck 3 | **TSP** (Road C) | 26 720.0 | 50 980.3 | **+24 260.3** | 87 | 87 | – | – |
| Truck 1 | **VRP** | 24 817.3 | 20 510.9 | **–4 306.4** | 46 | 49 | 5 269 / 6 000 kg | 5 644 / 6 000 kg |
| Truck 2 | **VRP** | 22 137.0 | 21 217.4 | **–919.6** | 27 | 48 | 5 989 / 6 000 kg | 5 642 / 6 000 kg |
| Truck 3 | **VRP** | 33 918.4 | 22 905.6 | **–11 012.8** | 76 | 52 | 9 670 / 10 000 kg | 9 642 / 10 000 kg |

### 3.7.1 Unified Analysis of Simulated Annealing and Blob Algorithm: A Comparative Efficacy Study in TSP and VRP

**Table 14** presents a comprehensive comparison between Simulated Annealing (SA) and the Blob Algorithm across two distinct routing configurations Traveling Salesman Problem (TSP) and Vehicle Routing Problem (VRP) applied to three separate truck routes. The comparison uses metrics such as total travel distance, serviced node count, and vehicle load utilization in the VRP context.

- **TSP Configuration (Unconstrained)**

In the classical, unconstrained TSP scenario, SA significantly outperforms the Blob Algorithm across all evaluated cases. Specifically, SA achieves route reductions of **7932.1 m**, **3217.4 m**, and **24260.3 m** for Trucks 1–3, respectively. Because both methods cover the same number of nodes in each scenario, these differences can be solely attributed to the efficacy of SA's probabilistic local search approach. This outcome reinforces SA's well-documented superiority in achieving optimal or near-optimal solutions within unconstrained pathfinding problems.

- **VRP Configuration (Capacity-Constrained)**

When the routing problem is reformulated as a VRP incorporating vehicle capacity constraints, depot returns, and heterogeneous loads the performance results markedly shift. In this context, the Blob Algorithm demonstrates superior efficiency for Trucks 1 and 3, achieving shorter routes by **4306.4** m and **11012.8 m**, respectively. Meanwhile, SA maintains a marginal advantage of 919.6 m in the case of Truck 2. This reversal indicates that **the choice of problem configuration (TSP vs VRP) has a greater impact on performance than the choice of algorithm**. It also highlights that the Blob Algorithm's biologically inspired flow mechanics adapt effectively to the complexities of cap-constrained, multi-vehicle routing.

- **Operational Implications: Load Utilization**

In the VRP experiments, truck load limits were set at 6000 kg for Trucks 1 and 2, and 10000 kg for Truck 3. The Blob Algorithm achieved loads of 5644 kg, 5642 kg, and 9642 kg in the respective truck cases, closely matching the capacity constraints. In contrast, SA exhibited slightly lower utilization levels 5269 kg, 5989 kg, and 9670 kg. These results illustrate that Blob's routing logic is more adept at maximizing capacity usage under operational limitations, thereby reinforcing its applicability in real-world logistics environments.

- **Broader Implications and Strategic Recommendations**

The insights derived from this comparative study convey several critical lessons. First, the transition from TSP to VRP contributes more significantly to routing performance improvement than the selection of SA over Blob. This underscores the necessity of accurate problem modeling, particularly within real-world logistics and municipal service scenarios.

Secondly, while SA remains the most effective choice for unconstrained path optimization, the Blob Algorithm's superior performance under VRP conditions merits considerable attention. Implementing Blob within a VRP framework would benefit organizations requiring capacity compliance and route efficiency such as in waste collection, delivery services, and field operation systems.

Finally, SA continues to provide unparalleled route quality in theoretical and lightly constrained routing problems; however, it is clear that **Bio-inspired heuristics like the Blob Algorithm have the potential to deliver practical advantages** in constraint-rich environments. This supports the need for broader comparative studies involving Genetic Algorithms, Tabu Search, and Ant Colony Optimization, particularly within VRP applications.

### 3.7.2 Directions for Future Work

The analysis confirms that **algorithm effectiveness is inherently tied to the structure of the problem**. In classical TSP formulations, SA stands out due to its optimization accuracy. However, when the problem is recast as VRP, Blob emerges as a powerful alternative, demonstrating competitive or superior performance where practical constraints exist.

**Recommendations:**

- Employ **SA** for unconstrained, optimization-centric routing tasks.
- Utilize the **Blob Algorithm in VRP frameworks** for real-world, capacity-sensitive logistics applications.

**Future Research:**

1. Develop **hybrid metaheuristic models** that integrate SA's solution refinement capabilities with Blob's capacity-aware routing.
2. Conduct benchmarking studies comparing Blob with GA, TS, and ACO in real-world VRP settings.
3. Validate Blob's effectiveness on large-scale and dynamic routing problems using real-world logistics data.

## 3.8 Conclusion

This chapter detailed the design, implementation, and comparative evaluation of two metaheuristic algorithms **Simulated Annealing (SA)** and the **Physarum-inspired Blob Algorithm** applied to both the Traveling Salesman Problem (TSP) and the Vehicle Routing Problem (VRP), using real-world data from **150 municipal waste-collection sites in Tlemcen, Algeria**.

The TSP functioned as a baseline scenario, assuming a single unconstrained vehicle, whereas the VRP model incorporated operational realism by introducing multiple vehicles, capacity constraints, and mandatory depot returns. Unsurprisingly, the imposition of these real-world constraints resulted in a substantial increase in route length by an average of about **124.8%** a consequence of added complexity rather than algorithmic inefficiency.

Within this framework, SA proved to be the clear leader in the unconstrained TSP setting, delivering the shortest routes and serving as an effective reference for performance benchmarking. In contrast, the Blob Algorithm emerged as the superior approach within VRP scenarios, offering competitive routing distances alongside compliance with practical capacity constraints and efficient runtime performance.

These findings underscore the applicability of **bio-inspired metaheuristics** such as the Blob Algorithm when dealing with complex, constraint-rich problems like municipal waste collection. Its notable **scalability**, **solution stability**, and **operational feasibility** recommend it as a viable option for real-world logistics operations in urban environments.

In summary, while SA excels in unconstrained, theoretical optimization, the Blob Algorithm demonstrates remarkable strengths when applied to real-world, capacity-constrained VRP scenarios. This positions the latter as a promising candidate for **future large-scale deployments in waste management and urban route planning**.

# Chapter 4:

## GIS-Based Visualization and Spatial Analysis of Optimized Waste Collection Routes

## 4.1 Introduction :

In this chapter, we take the optimized waste collection routes developed earlier using metaheuristic algorithms and bring them into the real world. While Chapter 3 concentrated on solving the Travelling Salesman Problem (TSP) and Vehicle Routing Problem (VRP) through computational models, our focus now shifts to testing how these solutions hold up in a real urban setting.

To do this, we use Geographic Information Systems (GIS) to visualize and analyze the routes within the actual landscape of Tlemcen. The primary tool for this task is ArcGIS Pro by Esri, chosen for its robust features in spatial data processing, route mapping, and network analysis. Its precision in modeling transportation networks and integrating routing algorithms with detailed maps made it an ideal fit. We also used Google Earth to help ground these routes in reality, verifying that they align with the existing road layout and urban features.

By overlaying the optimized routes, collection points, and depot location onto detailed city maps, this chapter examines how practical and workable these solutions are in the real world. We compare the distances estimated by the algorithms with those measured directly in the GIS environment, helping to determine how well theory translates into practice. This step is crucial to confirm that the routing model is not only mathematically sound but also spatially accurate and suitable for real-life waste collection operations.

## 4.2 Part 1: ArcGIS as a Routing and Spatial Analysis Tool

### 4.2.1 What is ArcGIS?

ArcGIS is a comprehensive Geographic Information System (GIS) software suite developed by Esri, a global leader in geospatial technology and location intelligence. Since its founding in 1969, Esri has been at the forefront of geographic science, promoting what it refers to as "The Science of Where" a philosophy that emphasizes the importance of spatial thinking in understanding and addressing complex real-world problems. [40]

At its core, ArcGIS enables users to capture, manage, analyze, and visualize spatial data. The platform offers a range of tools for creating detailed maps, conducting sophisticated spatial analyses, and representing data in both two-dimensional and three-dimensional formats. [40]Whether used for basic mapping or advanced geospatial modeling, ArcGIS provides the capabilities needed to make informed decisions based on spatial data. [40]

Figure 22 : [40]

### 4.2.2 The Role of ArcGIS in Spatial Decision-Making

ArcGIS plays a critical role in supporting spatial decision-making across several key domains:

#### 4.2.2.1 **Logistics**

In the logistics sector, ArcGIS enhances operational efficiency through tools that support route optimization, fleet tracking, and supply chain management. By integrating spatial data into these processes, organizations can reduce costs, improve delivery times, and enhance overall service performance. [41]

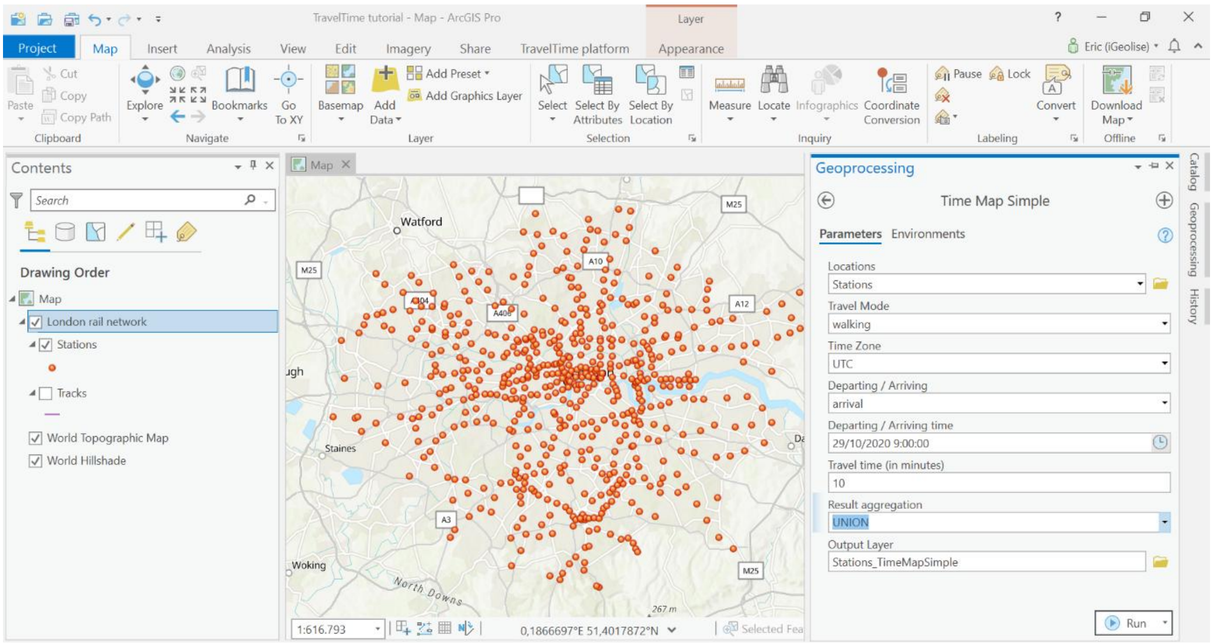


**Figure 23: Application of ArcGIS Pro for Station-Based Travel Time Mapping in Urban Rail Networks. [41]**

#### 4.2.2.2 Urban Planning

For urban planners, ArcGIS provides powerful 3D modeling tools such as those in ArcGIS Urban that facilitate scenario planning and spatial simulations. These tools enable professionals to assess zoning changes, land use proposals, and infrastructure development in a visual and collaborative environment, ultimately contributing to more sustainable and inclusive urban growth. [42]

**Figure 24: 3D Spatial Simulation and Scenario Planning Using ArcGIS Urban for Sustainable City Development [42]**

#### 4.2.2.3 Transportation

ArcGIS supports transportation planning by enabling analysis of traffic flows, infrastructure requirements, and route planning. With the ability to visualize and interpret complex transportation networks, stakeholders can make better-informed decisions about investments, policy-making, and long-term transportation strategies. [43]

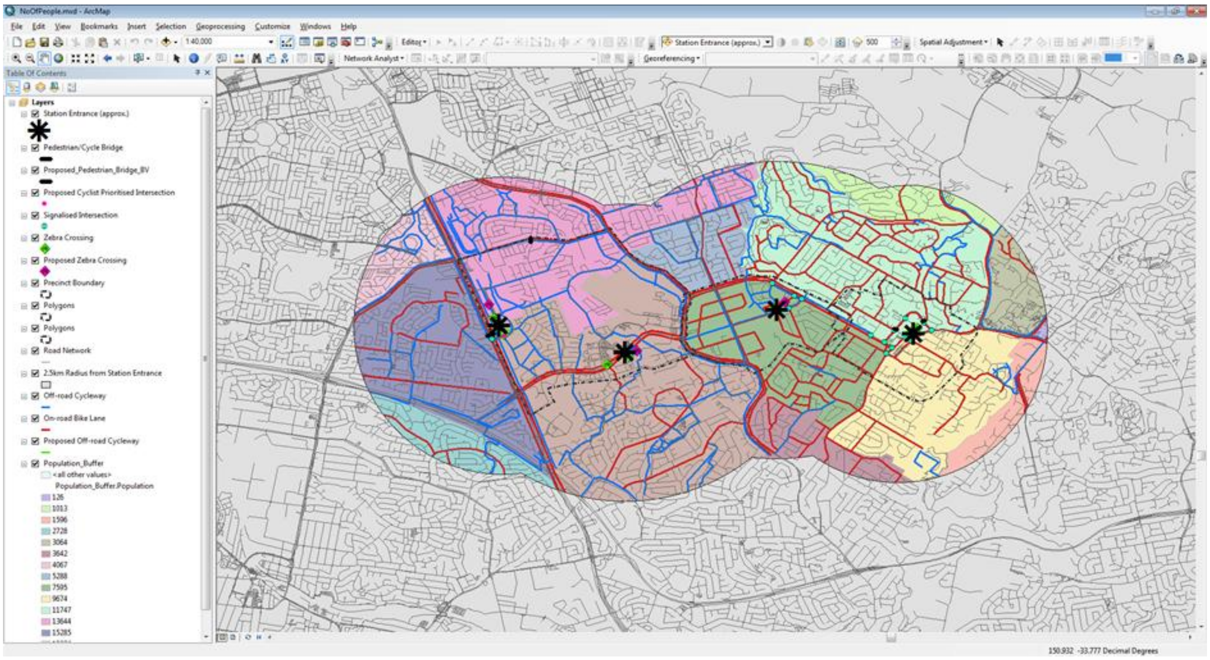


Figure 25: Transportation Network Planning and Accessibility Analysis Using ArcGIs **[43]**

### 4.2.3 Components of ArcGIS

ArcGIS is a robust and comprehensive geographic information system that includes various software components designed to perform a wide range of GIS tasks from desktop-based spatial analysis to cloud-based web mapping. Each component plays a unique role in the overall functionality of the ArcGIS ecosystem. [44]

#### 4.2.3.1 Desktop Tools: ArcMap and ArcGIS Pro

- **ArcMap**
  ArcMap is part of the ArcGIS Desktop suite and was historically the primary interface for visualizing, editing, and analyzing spatial data. It supports vector and raster data processing, cartographic map design, georeferencing, and spatial analysis. Although powerful, ArcMap is now in the process of being phased out by Esri, with support ending in **March 2026**, and users are encouraged to migrate to ArcGIS Pro. [45]

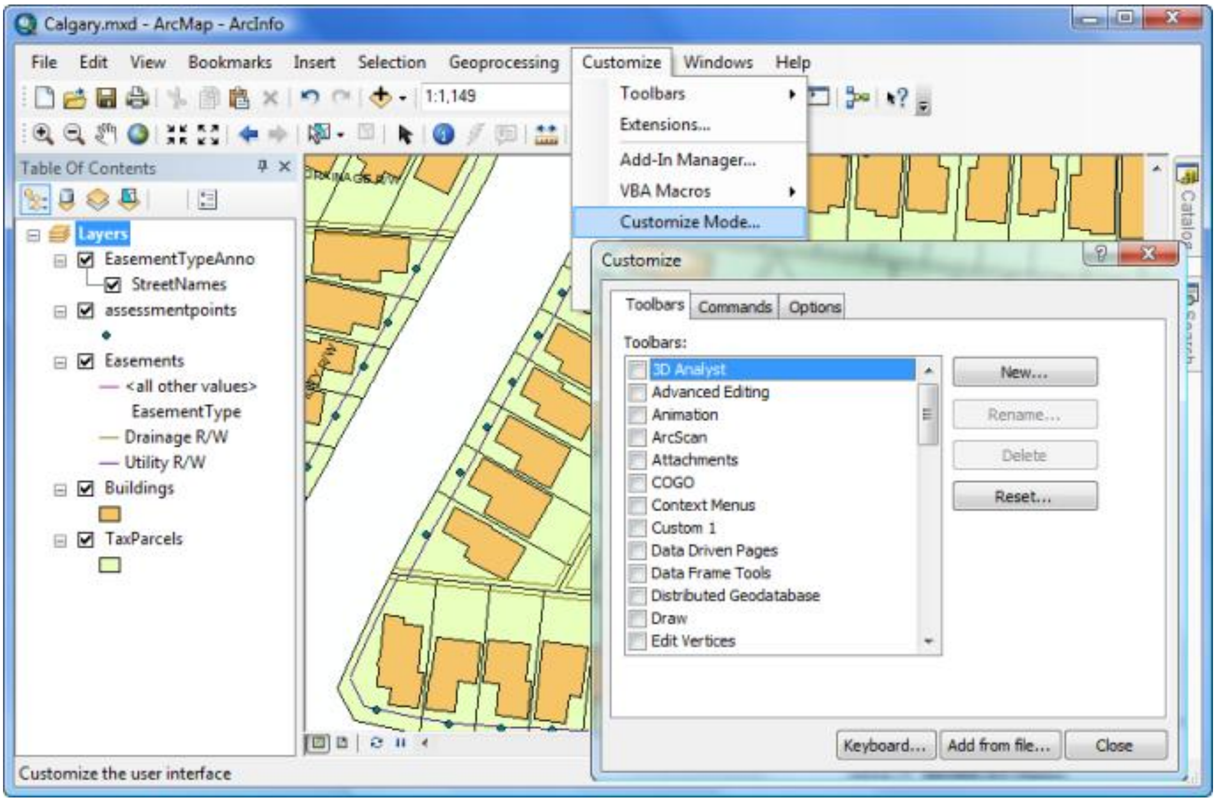


**Figure 26: ArcMap Interface with Customize Toolbar Menu [44]**

- **ArcGIS Pro**
  ArcGIS Pro is the modern 64-bit desktop GIS application designed as the successor to ArcMap. It introduces a more user-friendly ribbon-based interface and supports advanced **2D and 3D visualization**, real-time analytics, and seamless integration with web GIS platforms like ArcGIS Online and Enterprise. It allows simultaneous multi-layout views and includes powerful tools for geoprocessing, Python scripting, and model building. [45]

#### 4.2.3.2 Data Management: ArcCatalog

ArcCatalog is an integral component of the ArcGIS Desktop suite, designed specifically for the management and organization of geographic information system (GIS) datasets. It offers a user-friendly catalog tree interface that facilitates efficient browsing, organization, and maintenance of spatial data. Key functionalities include metadata creation and editing, spatial data preview, and management of file geodatabases. Additionally, ArcCatalog supports the secure transfer of datasets between systems. By centralizing access to GIS resources and streamlining data documentation, ArcCatalog plays a critical role in ensuring data integrity and enhancing overall workflow efficiency in geospatial analysis. [46]

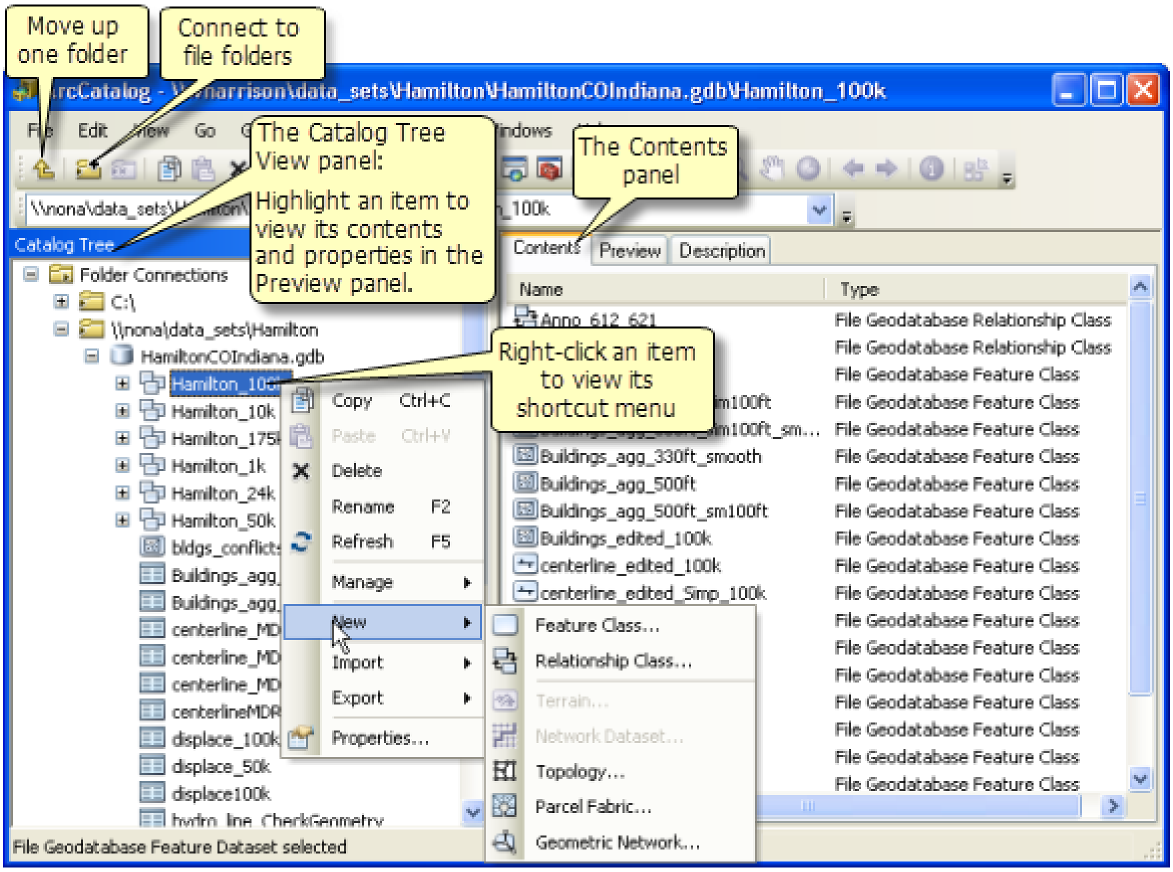


Figure 27: :ArcCatalog Interface Showing Folder Connections and Dataset Management [46]

#### 4.2.3.3 Analytical Tools: ArcToolbox

ArcToolbox is a comprehensive suite of geoprocessing tools embedded within both ArcMap and ArcGIS Pro, designed to support a wide range of spatial analysis and data processing tasks. It provides users with access to an extensive collection of tools organized into specialized categories, including "Analysis Tools," "Spatial Analyst Tools," and "3D Analyst Tools," among others. These toolsets enable functionalities such as spatial analysis, data conversion, data management, and map overlay operations. ArcToolbox also integrates advanced capabilities through scripting with Python and the use of ModelBuilder for visual workflow automation, making it a versatile and powerful component in GIS-based analytical processes. [47]

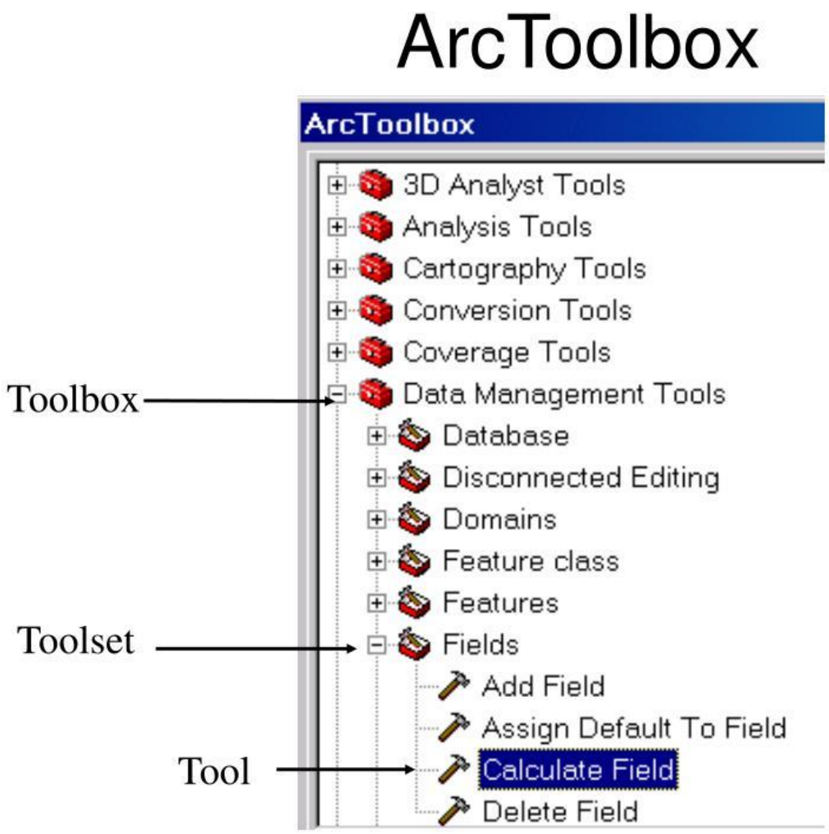


Figure 28: ArcToolbox Interface Showing Toolbox, Toolset, and Individual Tools [47]

#### 4.2.3.4 Web Platforms: ArcGIS Online and ArcGIS Enterprise

**ArcGIS Online :**

ArcGIS Online is Esri's cloud-based platform designed for interactive mapping, spatial analysis, and data sharing. It allows users to create, visualize, and disseminate geographic content through web maps and applications. The platform includes access to a wide range of curated resources such as basemaps, demographic datasets, and spatial analysis tools. With features supporting real-time collaboration, integration with mobile devices, and a user-friendly interface, ArcGIS Online is particularly well-suited for geographically distributed teams and organizations engaged in dynamic, cloud-based GIS workflows. [48]

**ArcGIS Enterprise:**

ArcGIS Enterprise is Esri's on-premises solution for deploying a secure and scalable GIS infrastructure. Comprising core components such as ArcGIS Server and Portal for ArcGIS, it enables organizations to host, manage, analyze, and share geospatial data within controlled environments. ArcGIS Enterprise supports both intranet-based and web-facing deployments, offering robust tools for governance, scalability, security, and high-performance data processing. This makes it an ideal choice for institutions requiring full administrative control over their GIS resources and infrastructure. [48]

#### 4.2.3.5 Extensions: Network Analyst and Spatial Analyst

**Network Analyst**

ArcGIS Network Analyst is an extension that enables advanced network-based spatial analysis, supporting functions such as route optimization, service area delineation, vehicle routing problem (VRP) solutions, and location-allocation modeling. These tools are instrumental in optimizing transportation logistics, enhancing emergency response strategies, and conducting in-depth transportation and accessibility studies. The extension integrates seamlessly with the broader ArcGIS environment, allowing for both interactive and automated workflows tailored to network datasets. [49]

**Spatial Analyst**

ArcGIS Spatial Analyst is a raster-based extension offering a robust set of tools for spatial modeling and analysis. It facilitates tasks such as terrain modeling, hydrological analysis, surface interpolation, suitability assessments, and zonal statistics. The extension is widely applied in disciplines such as environmental management, precision agriculture, urban planning, and natural resource assessment. Its ability to process and analyze raster data supports complex spatial decision-making and modeling scenarios. [49]

**Table 15: Summary of Core ArcGIS Components and Their Functions**

| Component | Function |
|---|---|
| **ArcMap** | Legacy GIS interface for 2D spatial analysis and cartographic mapping. |
| **ArcGIS Pro** | Modern 64-bit GIS desktop app for advanced 2D/3D visualization and analysis. |
| **ArcCatalog** | Data management tool for organizing, previewing, and editing GIS datasets. |
| **ArcToolbox** | Set of geoprocessing tools for analysis, conversion, and spatial modeling. |
| **ArcGIS Online** | Cloud-based GIS for sharing, collaboration, and web map creation. |
| **ArcGIS Enterprise** | On-premise solution for hosting and managing GIS data securely. |
| **Network Analyst** | Extension for route planning, VRP, service areas, and accessibility analysis. |
| **Spatial Analyst** | Raster analysis extension for terrain, suitability, hydrology, etc. |

#### 4.2.3.6 **Data Handling in ArcGIS**

ArcGIS provides a comprehensive environment for the management, transformation, and integration of spatial data. It supports a wide variety of data formats and spatial reference systems, offering robust capabilities essential for efficient geospatial workflows. [48]

- **Spatial Data Types: Raster and Vector**

ArcGIS is built to accommodate two fundamental types of spatial data: raster and vector.

Vector data represent geographic features using points, lines, and polygons, which are well-suited for depicting discrete elements such as infrastructure, administrative boundaries, or land parcels. In contrast, raster data model continuous phenomena through a regular grid of cells. This format is ideal for representing variables such as elevation, temperature, or land cover.

Together, raster and vector data form the foundational structure for both visualization and spatial analysis within ArcGIS, enabling users to explore, model, and interpret geographic patterns and relationships. [48]

- **Commonly Supported Formats: Shapefiles and File Geodatabases**

ArcGIS supports a range of spatial data formats, with shapefiles and file geodatabases among the most widely utilized.

The shapefile is a legacy format consisting of multiple component files that store feature geometry and attribute data. Although still in use, shapefiles have limitations in terms of capacity and functionality. [48]

The file geodatabase, on the other hand, is Esri's recommended storage format. It supports large datasets, complex relationships, topologies, and advanced data types, all within a structured folder-based format. File geodatabases allow for better performance, scalability, and integrity in managing spatial data across projects. [48]

- **Coordinate Systems and Map Projections**

Spatial datasets in ArcGIS must be associated with a coordinate system to ensure accurate placement and alignment across geographic space. ArcGIS supports both geographic coordinate systems (e.g., WGS 1984) and projected coordinate systems (e.g., UTM). [48]

Users can define, convert, and transform spatial reference systems as needed, ensuring that datasets from different sources maintain spatial consistency. Proper use of coordinate systems is essential for preserving the accuracy of spatial measurements, relationships, and overlays. [48]

#### 4.2.3.7 Core Spatial Analysis Features

ArcGIS offers a suite of spatial analysis tools that allow users to explore geographic patterns, measure spatial relationships, and support decision-making across a variety of fields.

- **Geoprocessing Tools: Buffer, Clip, Intersect**

Geoprocessing tools are fundamental to the manipulation and analysis of spatial data within a GIS environment. Among these, the **Buffer** tool generates zones at a specified distance around geographic features, facilitating various types of proximity analysis. The **Clip** tool extracts portions of spatial features based on the boundaries of another dataset, enabling users to focus on specific areas of interest. The **Intersect** tool identifies areas of spatial overlap between multiple datasets, returning only those regions where features coincide. These tools are widely employed in applications such as site suitability analysis, environmental impact assessment, and land-use planning, where spatial precision and analytical depth are critical. [48]

#### 4.2.3.8 Visual Representation: Symbology and Labeling

Effective cartographic communication in ArcGIS relies on customizable symbology and labeling tools. Users can apply visual styles such as colors, patterns, and shapes to represent feature attributes and categories. Labels provide descriptive text based on attribute values, enhancing map readability. [48]

These design tools are essential for producing clear, informative maps that convey spatial information to both technical and non-technical audiences.

#### 4.2.3.9 Working with Attribute Tables and Queries

Each spatial dataset in ArcGIS is linked to an attribute table, which stores descriptive information related to geographic features. Users can perform tasks such as field calculation, table joins, and data sorting.

Querying functions allow users to select features based on attribute values or spatial relationships. These capabilities support data exploration, reporting, and targeted spatial analysis, forming a crucial part of GIS-based decision support. [48]

### 4.2.4 Network Analysis in ArcGIS

ArcGIS includes advanced tools for modeling and analyzing networks, such as transportation routes, utility systems, or service areas. These tools allow users to evaluate connectivity, accessibility, and travel efficiency within defined networks.

#### 4.2.4.1 Role of the Network Analyst Extension

The Network Analyst extension enables users to perform sophisticated network-based spatial analyses. It supports real-world modeling of transportation and service systems by integrating spatial constraints such as travel distance, time, and directional restrictions. This extension is embedded within ArcGIS and supports both manual and automated workflows for network problem solving.

#### 4.2.4.2 Types of Network Problems: Routes, Service Areas, Closest Facility, VRP

ArcGIS Network Analyst supports a range of analytical tools, each designed to address distinct planning and operational objectives. **Route analysis** determines the most efficient path between a series of locations, optimizing travel based on time or distance. **Service Area analysis** delineates regions that are accessible within specified travel thresholds, such as driving time or distance from a given point. **Closest Facility analysis** identifies the nearest facility or resource relative to an incident or demand location. The **Vehicle Routing Problem (VRP)** solver addresses more complex logistical challenges, incorporating multiple vehicles, service locations, and time-based constraints. Collectively, these analytical capabilities are integral to decision-making in domains such as logistics, emergency management, and public service delivery. [48]

#### 4.2.4.3 Network Dataset Requirements

To conduct network analysis, ArcGIS requires a specially constructed network dataset. This dataset includes the geometry of the network (e.g., roads or paths) along with attributes that define movement behavior such as travel times, speed limits, directionality, and access restrictions. Properly configured datasets are critical to ensure realistic and meaningful analysis outcomes. [48]

### 4.2.5 Vehicle Routing Problem (VRP) Tool in ArcGIS

The Vehicle Routing Problem (VRP) tool, accessible through the ArcGIS Network Analyst extension, provides a structured methodology for solving multi-vehicle routing and scheduling problems within a geographic context. Its purpose is to optimize the assignment of service orders to a fleet of vehicles, taking into account both spatial and operational constraints. This functionality is widely applied in domains such as logistics, emergency response, utility maintenance, and service delivery, where the efficient allocation of mobile resources is a central objective. [48]

#### 4.2.5.1 Tool Description and Scope

The VRP tool automates route planning for multiple vehicles originating from one or more depots to fulfill geographically distributed service orders. The tool supports constraint-based modeling, allowing users to define a variety of conditions including time windows for service, vehicle capacities, route durations, and cost parameters such as travel time or distance. [48]

#### 4.2.5.2 Required Inputs

The analysis depends on the preparation of several essential input feature classes, each of which is spatially referenced and organized within a network dataset that incorporates transportation cost attributes. These inputs include **Depots**, which are point features representing the origin and/or destination of vehicle routes; **Orders**, denoting service locations defined by demand quantities and service durations; and **Routes**, which outline the characteristics of the vehicle fleet, including operational constraints such as maximum travel time, service hours, and capacity limits. Additional inputs include **Time Windows**, which impose temporal constraints on when service can be delivered at each order location, and **Breaks** (optional), which account for scheduled pauses in service, such as driver rest periods. Together, these components form the foundation for a robust and realistic routing analysis. [48]

#### 4.2.5.3 Output Characteristics

Upon execution, the VRP tool produces several outputs that support both visualization and decision-making processes. These include route layers that illustrate the optimized paths assigned to each vehicle, tabular summaries detailing key performance metrics such as route costs, service start and end times, total travel time, and distance and sequenced stop orders that adhere to the specified operational constraints. These outputs can be visualized directly within the GIS environment or exported for integration into subsequent spatial analyses or logistical planning workflows. [48]

#### 4.2.5.4 Parameters and Customization

The Vehicle Routing Problem (VRP) solver provides a comprehensive set of configurable parameters, allowing analysts to model a wide spectrum of real-world logistical scenarios. These settings include the prioritization of service orders in accordance with service level agreements, the ability to define permissible violations of time windows (i.e., soft constraints), the specification of impedance attributes such as distance, travel time, or custom cost functions, and the capacity to represent both delivery and pickup operations while maintaining balance constraints. This level of flexibility enables the VRP solver to address a broad range of applications, from straightforward last-mile delivery planning to the coordination of complex, multi-shift fleet operations. [48]

#### 4.2.5.5 Practical Applications

The integration of the Vehicle Routing Problem (VRP) tool within the broader ArcGIS platform enhances its adaptability across various operational scenarios. It is frequently employed in contexts such as optimizing waste collection routes, planning the distribution of medical supplies, and coordinating the dispatch of emergency vehicles in time-sensitive situations. By supporting high-resolution spatial routing within a network-based framework, the VRP tool plays a significant role in reducing operational costs, expanding service coverage, and promoting spatial equity in the delivery of public services. [48]

## 4.3 Part 2: Practical Workflow and GIS-Based Results

### 4.3.1 Step 1: Defining the Study Area Using Google Earth

The geospatial workflow began with identifying and delimiting the area of interest in **Google Earth**. Using the built-in **search function**, the city of **Tlemcen, Algeria** was located. To define the specific study zone for waste collection analysis, the **Polygon tool** was used to manually draw the boundaries of the target area.

Once the polygon was created, it was saved and exported in **KML (Keyhole Markup Language)** format. This format is widely supported by GIS software and serves as the initial input for further processing in ArcGIS Pro.

**Tool Used**: Google Earth , Placemark & KML Export

**Purpose**: Define and export the study area boundary

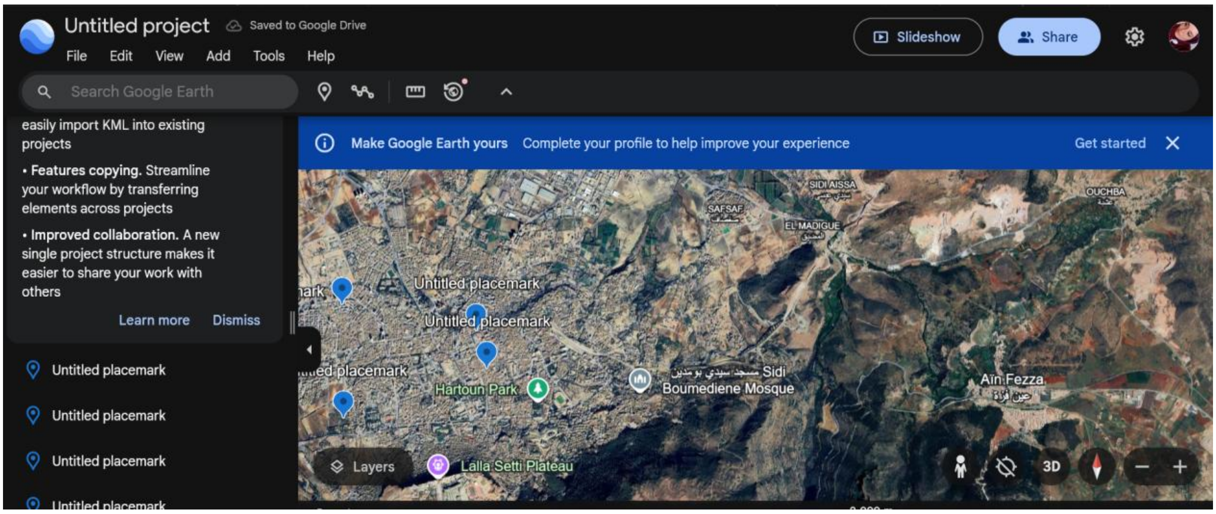


Figure 29: Study area defined in Google Earth using placemarks over the urban area of Tlemcen, Algeria

### 4.3.2 Step 2: Converting KML to Shapefile in ArcGIS Pro

Following the delineation of the study area in Google Earth and the export of its boundaries as a KML file, the next phase involved transforming this data into a format suitable for geospatial analysis within ArcGIS Pro. As KML files are not directly editable or fully compatible with most GIS tools, it was necessary to convert the data into the standard **Shapefile (SHP)** format.

This conversion was accomplished using the **Conversion Tools** available in ArcGIS Pro’s ArcToolbox. Initially, the **“KML to Layer”** tool was utilized to convert the KML file into a geodatabase feature class. Subsequently, the **“Feature Class to Shapefile”** tool was applied to export the feature class into a standalone shapefile. This process ensured that the spatial data could be fully integrated into the GIS environment and used in subsequent analysis and mapping stages.

**Tools and Functions Used:**

- *KML to Layer* , Converts KML input into a feature class stored in a geodatabase.
- *Feature Class to Shapefile* , Extracts a shapefile from the geodatabase for external use.

**Purpose of this Step:**
To convert and standardize the format of spatial data exported from Google Earth, ensuring compatibility with further spatial processing in ArcGIS Pro.

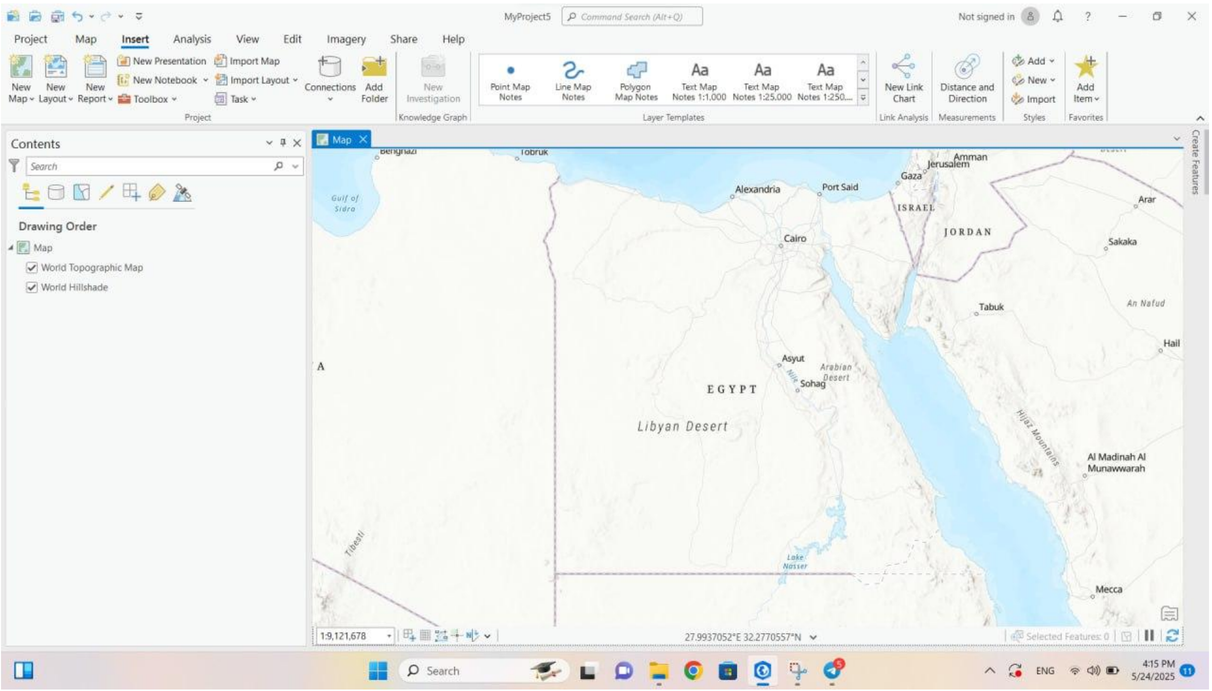


**Figure 30: ArcGIS Pro interface showing the project workspace where spatial data conversion from KML to shapefile was prepared.**

### 4.3.3 Step 3: Extracting the Road Network Using QGIS and QuickOSM

To build the transportation network for the study area, **QGIS 3.36 (Maidenhead)** was employed alongside the **QuickOSM** plugin, which enables direct querying and downloading of OpenStreetMap (OSM) data.

**QGIS (Quantum Geographic Information System)** is a powerful, open-source, cross-platform Geographic Information System that enables users to visualize, edit, analyze, and interpret spatial data. As a freely available alternative to commercial GIS software, QGIS supports a broad array of vector, raster, and database formats, and is widely used in academic research, urban planning, environmental monitoring, and geospatial modeling.

In this project, the **shapefile** representing the study boundary was first loaded into QGIS. Then, using the **QuickOSM** tool, a query was executed with the key set to **"highway"**, allowing the extraction of all road segments within the defined area. This query retrieved various types of roads from OpenStreetMap, including residential streets, primary roads, paths, and service lanes. The resulting road network data was saved and exported as a **line shapefile**, which was subsequently used in **ArcGIS Pro** for further route analysis and integration with the routing algorithms.

**Tools and Functions Used:**

- **QGIS 3.36 (Maidenhead):** Open-source GIS software used for data extraction and pre-processing
- **QuickOSM Plugin:** Enables OSM queries by key-value tags (e.g., “highway”) for live data retrieval
- **Export as Shapefile:** Converts extracted data into a standard GIS format compatible with ArcGIS Pro

**Purpose of this Step:**

To extract accurate and up-to-date road network data from OpenStreetMap and prepare it in shapefile format for integration into ArcGIS Pro, enabling spatial analysis and route optimization.

**Brief Comparison: QGIS vs. ArcGIS Pro**

While **QGIS** is open-source and highly extensible with a rich plugin ecosystem (such as QuicSM), it is best suited for flexible, lightweight data extraction and pre-processing tasks. In contrast, **ArcGIS Pro**, a commercial product developed by Esri, offers advanced geoprocessing, 3D visualization, and enterprise integration tools. In this study, QGIS was leveraged for its ease of access to OSM data, while ArcGIS Pro was used for high-performance spatial analysis and integration with routing algorithms. Together, these tools formed a complementary workflow.


Figure 31: QGIS 3.36

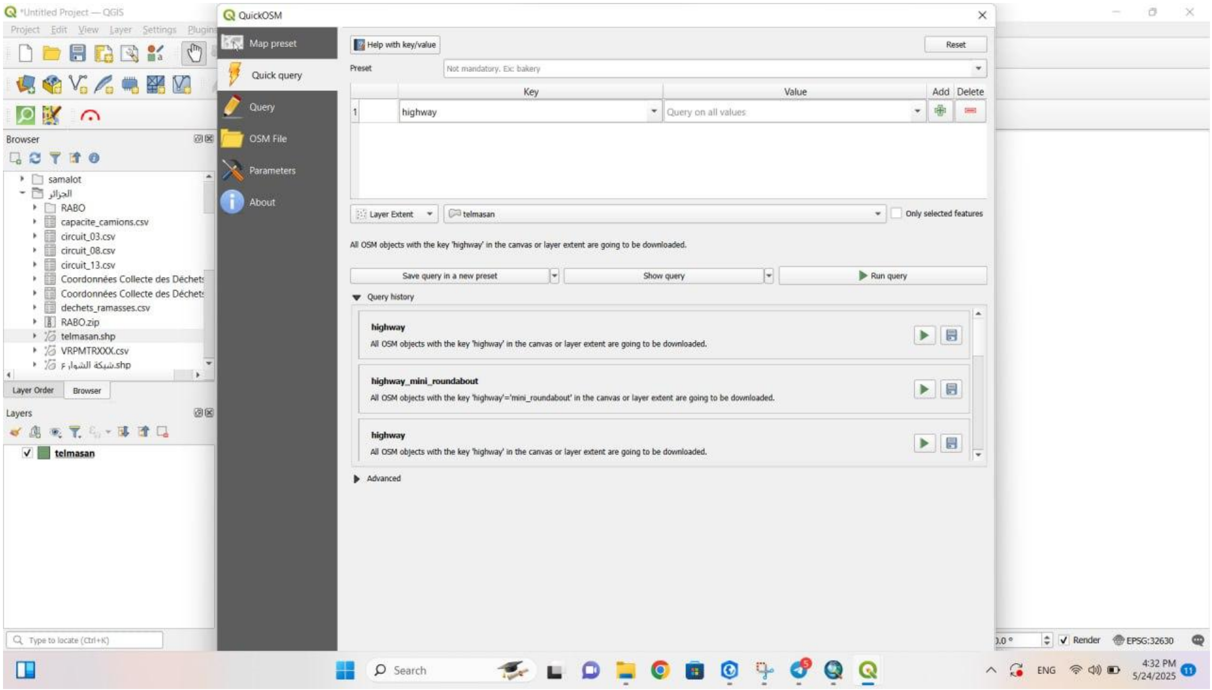

Figure 32: Querying OpenStreetMap Road Data in QGIS Using QuickOSM Plugin

### 4.3.4 Step 4: Preparing the Road Network in ArcGIS Pro and Ensuring Topological Integrity

Once the road network was extracted and exported from QGIS in shapefile format, it was imported into ArcGIS Pro for preprocessing and validation. In order to perform accurate route optimization, it is essential that the transportation network is spatially clean and logically connected. For this purpose, **topology rules** were applied.

In GIS, topology refers to the spatial relationships between features (e.g., connectivity between roads, absence of gaps or overlaps). ArcGIS Pro provides a dedicated **Topology toolbar** that allows users to define rules, validate geometry, and inspect errors.

During this step, the following actions were taken:

- The road network shapefile was added to a **feature dataset** in a **geodatabase**, a requirement for enabling topology.
- A **topology class** was created with rules such as **"Must Not Have Dangles"** and **"Must Not Overlap"** to ensure road segment connectivity and accuracy.
- The **Error Inspector** tool was used to identify and correct any topological errors (e.g., broken lines, open ends), ensuring that the road network is valid for network analysis.

**Purpose of this Step:**
To ensure that the road network is spatially consistent, topologically correct, and suitable for further routing analysis in ArcGIS Pro.

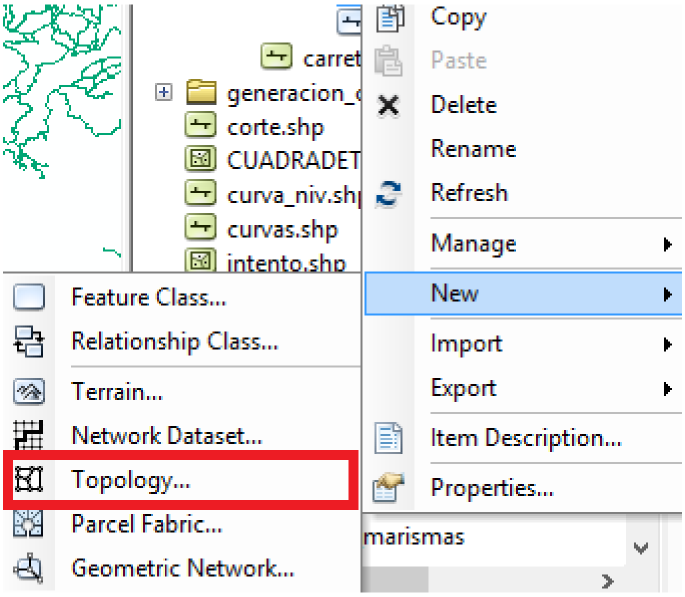


Figure 33: topology tool [38]

### 4.3.5 Step 5: Generating Waste Collection Points from Coordinate Data

To integrate waste collection locations and the depot into the geospatial workflow, a CSV file containing the **geographic coordinates (X, Y, Z)** of each point was used. This data was imported into **ArcGIS Pro** and converted into a point layer using the **"XY Table to Point"** tool.

This tool allows users to transform tabular coordinate data into mappable spatial features by specifying which columns represent the X and Y axes (longitude and latitude). Once the point shapefile was created, it was projected into the same coordinate system as the road network to ensure spatial consistency.

The resulting point layer served as a critical input for the routing model, representing both waste collection locations and the central depot for vehicle dispatch.

**Tools and Functions Used:**

- *XY Table to Point* , Converts tabular coordinates (CSV or Excel) into a GIS-compatible point shapefile.
- *Define Projection* , Ensures all spatial data layers use the same coordinate reference system.

**Purpose of this Step:**
To transform tabular coordinate data of collection sites into spatial point features that can be used for routing and distance calculations within the GIS environment.

**Note:** The coordinate data was prepared externally in a CSV file and imported directly into ArcGIS Pro using the XY Table to Point tool.

### 4.3.6 Step 6: Calculating Road Segment Lengths Using Geometry Tools

After confirming the topological integrity of the road network, the next step was to calculate the length of each road segment. Accurate distance measurement is essential for supporting precise, distance-based routing within ArcGIS Pro.

This was done through the attribute table of the road network shapefile:

- A new field was created to store segment lengths.
- Using the **"Calculate Geometry"** tool, the lengths were computed in meters, referencing the map's projected coordinate system.

For example, one route assigned to **Truck 2** yielded a **Total_Length** of **3876.39 meters**, with a corresponding estimated **travel time of 5.81 minutes**. These figures are essential for verifying route efficiency.

To visually distinguish truck assignments, different route colors were applied:

- **Truck 1: Red**
- **Truck 2: Blue**
- **Truck 3: Green**

**Tools and Functions Used:**

- **Attribute Table:** Manages road segment data.
- **Calculate Geometry:** Computes physical lengths of features.
- **Symbology and Classification:** Visually differentiates routes by truck.

**Objective of This Step:**
To quantify actual road segment distances for accurate and reliable route optimization and analysis.

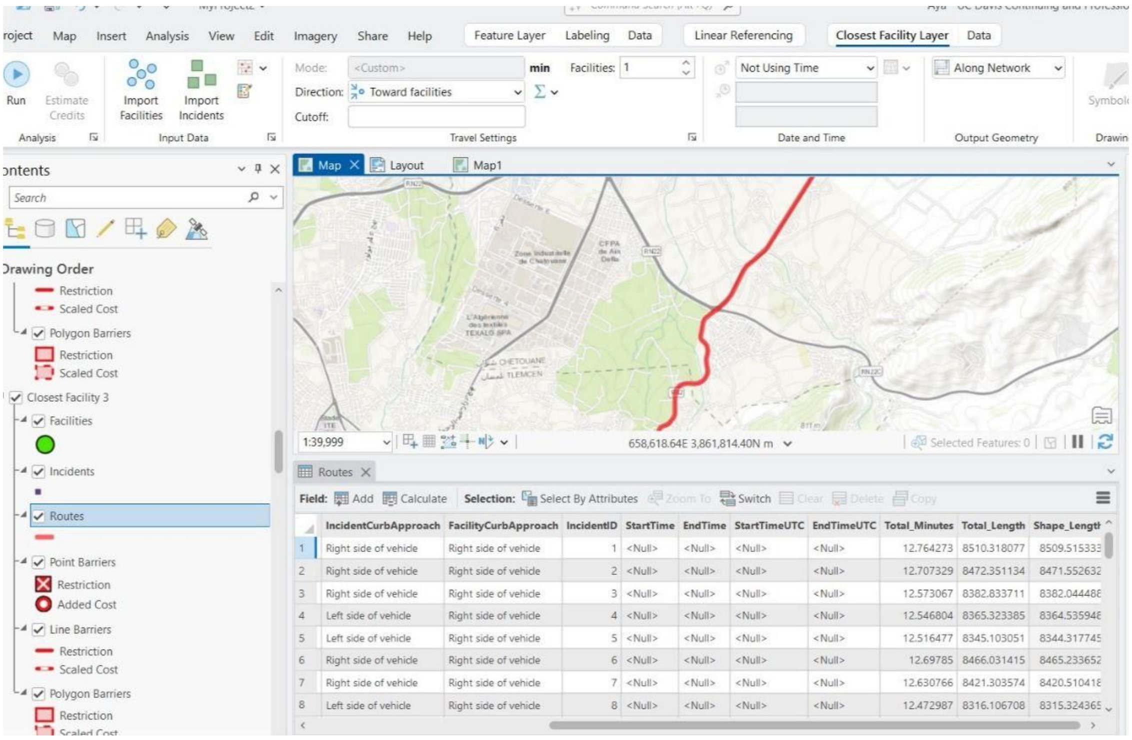


**Figure 34: Closest Facility Analysis in ArcGIS Pro: Route Calculation and Travel Time Assessment**

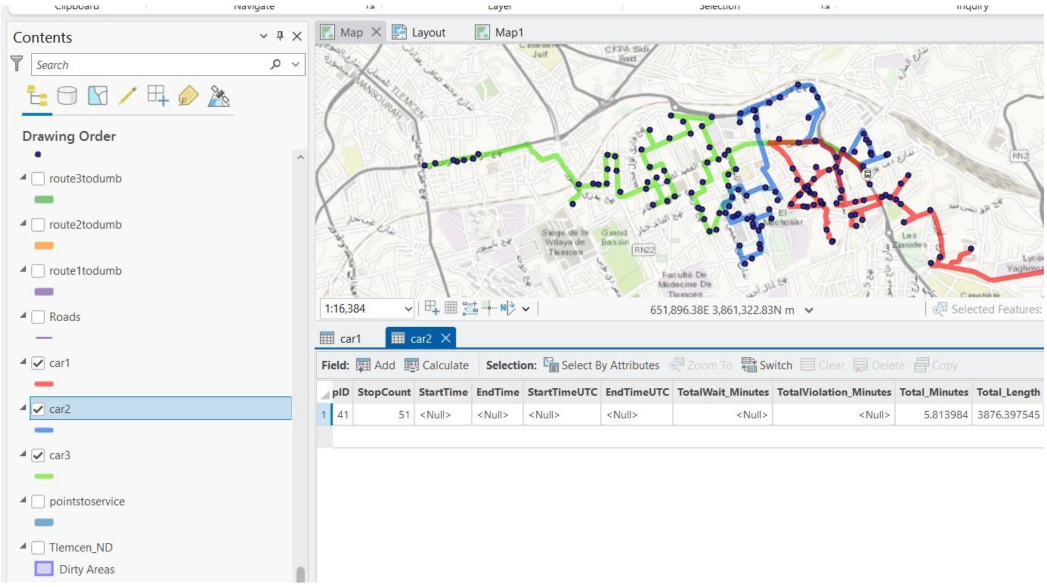


Figure 35: Visualizing Vehicle Routing and Stop Analysis Using ArcGIS Network Analyst

### 4.3.7 Step 7: Applying the Closest Facility Tool for Initial Route Computation

To evaluate connectivity between collection zones and the landfill site, the **Closest Facility** tool from ArcGIS Pro's **Network Analyst** extension was used. This tool calculates the shortest path from multiple origins (waste collection points) to the nearest facility (in this case, the **landfill**), based on travel **distance or time**.

For this analysis, the impedance was set to **time**, allowing route duration to be calculated. The resulting output included a route layer with attributes such as:

- **Total_Length** (e.g., 8516.8 meters)
- **Total_Minutes** (e.g., 12.85 minutes)

These results verified that the road network was functional, spatially aligned, and ready for advanced routing analysis.

**Tools and Functions Used:**

- **Closest Facility Tool:** Calculates shortest-time or shortest-distance paths.
- **Network Barriers:** Optional constraints (e.g., road closures).
- **Attribute Table:** Stores travel metrics like distance and time.

**Objective of This Step:**
To confirm the road network's integrity and establish baseline time and distance metrics from collection zones to the landfill serving as a foundation for more detailed route optimization.

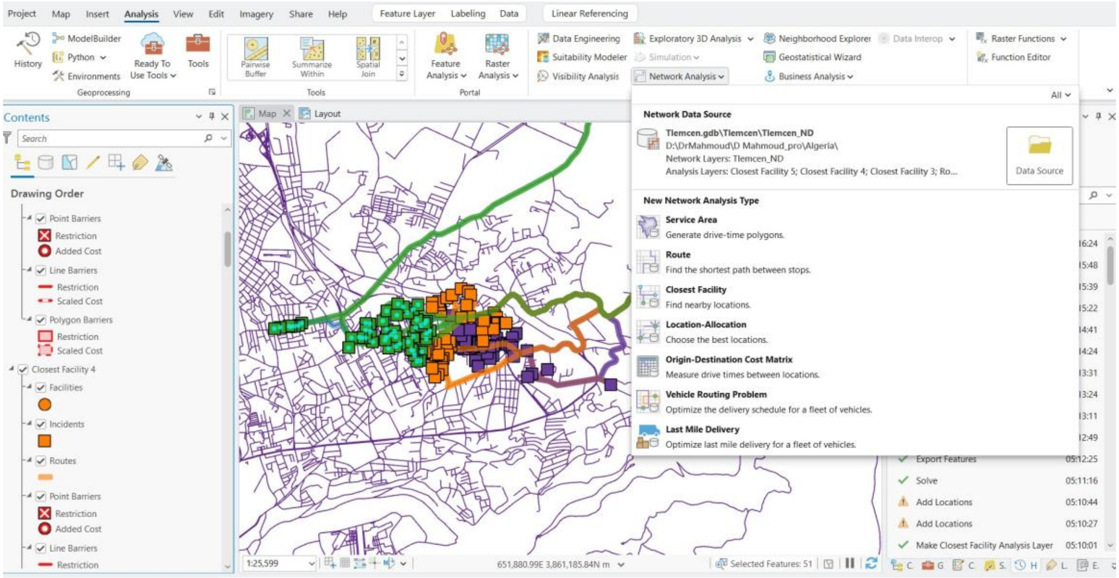


**Figure 36: Network Analyst Configuration in ArcGIS Pro**

### 4.3.8 Step 8: Estimating Intra-Zone Collection Route Distances (Excluding Landfill Leg)

**Objective:**
To quantify the travel distances and estimated durations required for each waste collection vehicle to complete its assigned intra-city route, without incorporating the landfill trip. This initial analysis provides a foundation for evaluating workload distribution and baseline routing efficiency.

**Methodology:**
Following the verification of topological accuracy in the road network dataset, the road segment lengths were computed using the **"Calculate Geometry"** tool within the attribute table of the road network shapefile. Each vehicle (Truck 1, 2, and 3) was assigned a sub-area based on **spatial clustering of collection points** and **road network accessibility**. The results reflect the total network-based travel distance required to cover all stops within a designated zone.

**Assumptions:**

- Constant vehicle speed fixed at **40 km/h**
- Exclusion of **landfill travel segment**
- No inclusion of **real-world operating factors** such as loading time (typically 3–5 minutes per stop), road surface conditions, or traffic congestion

**Results:**

- **Network Distance (Meters):**
    - Truck 1 (Red Route): 4982.9 m
    - Truck 2 (Blue Route): 3876.39 m
    - Truck 3 (Green Route): 5184.28 m
- **Estimated Travel Time (Minutes):**
    - Truck 1: 7.47 min
    - Truck 2: 5.81 min
    - Truck 3: 7.77 min

**Tools and Functions Used:**

- ArcGIS Pro – **Network Analyst Extension**
- **Calculate Geometry Tool** – for route length measurement
- **Symbology and Classification** – to distinguish truck routes visually

**Discussion:**
The intra-zone routing distance offers a controlled baseline for route optimization. These results will later be adjusted with realistic operational constraints in future stages, including service times, traffic variation, and actual vehicle performance.

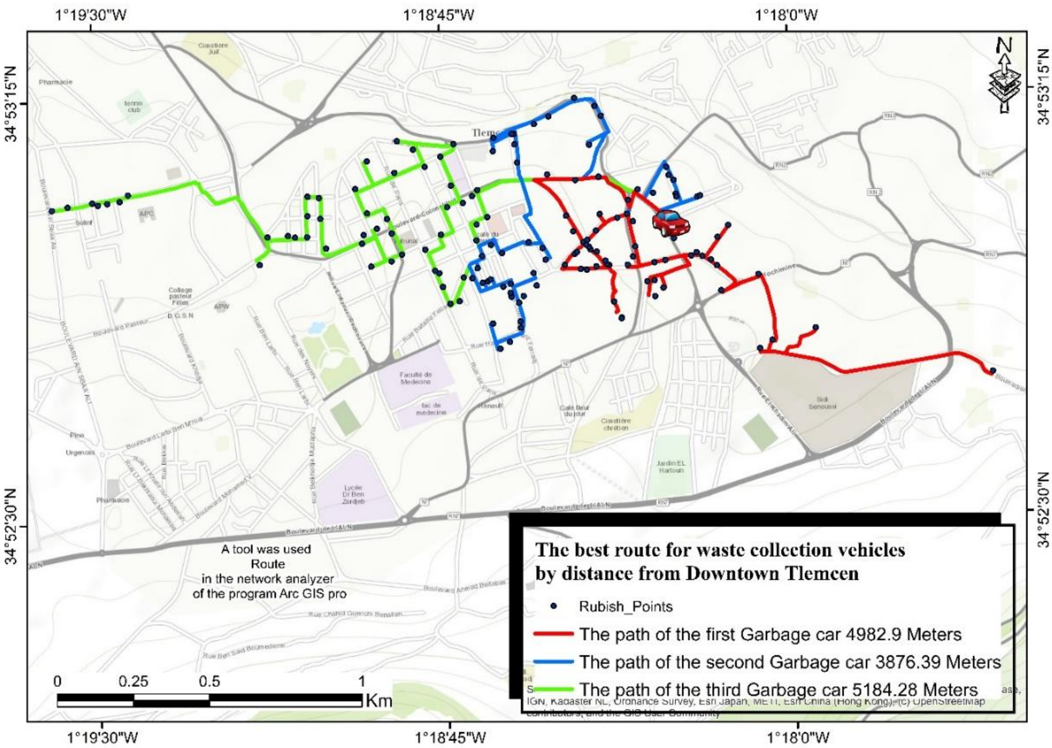


Figure 37: Optimized Waste Collection Routes Based on Travel Distance in Downtown Tlemcen

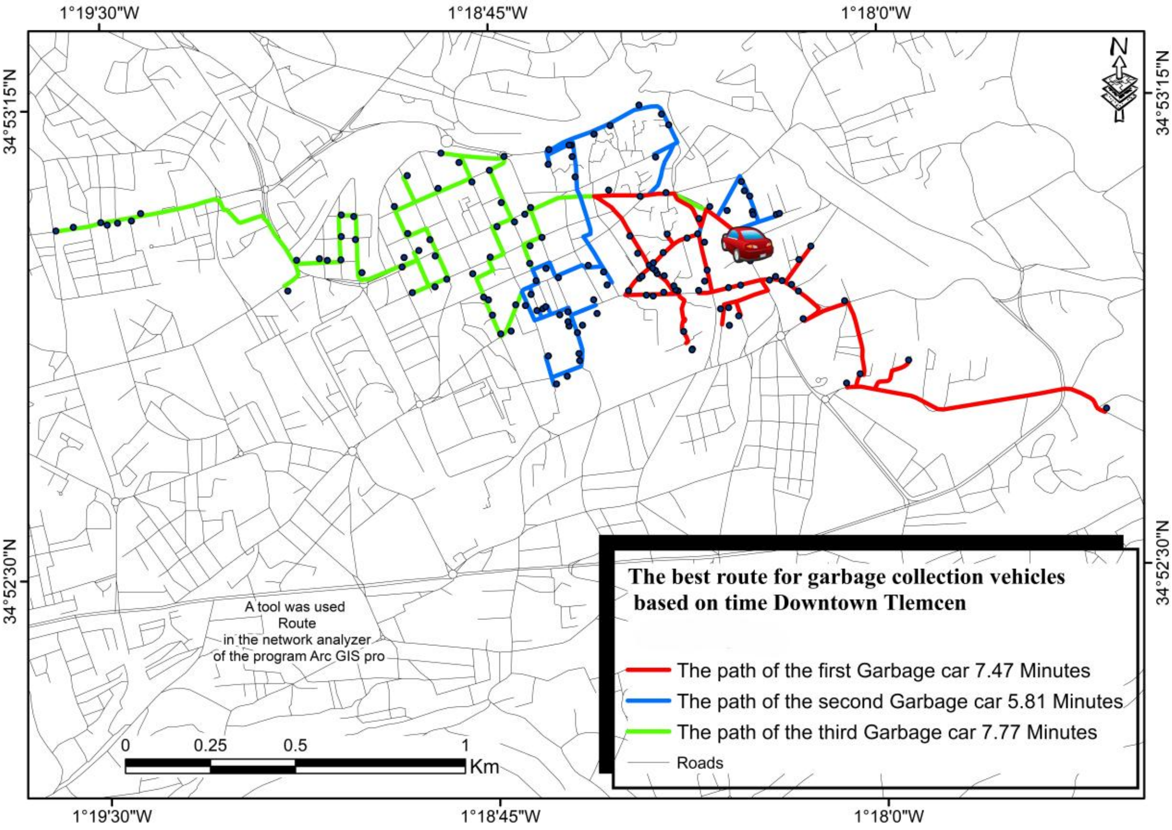


Figure 38: Estimated Travel Time (Minutes)

#### 4.3.8.1 Step 9: Estimating Travel Distance and Time from Final Collection Point to Landfill

**Objective:**
To calculate the outbound leg of each waste collection route—from the final collection point within the assigned sub-zone to the municipal landfill site. This segment is essential for evaluating the complete travel demand, fuel requirements, and disposal efficiency of each vehicle.

**Methodology:**
The **Closest Facility Tool** from ArcGIS Pro's Network Analyst extension was used to determine the shortest path between each truck's **last collection stop** and the landfill facility. Each final point in the collection route was designated as an "incident," while the landfill was defined as the "facility." The model computed the most efficient route along the road network based on travel time at a constant speed.

**Important Clarification:**
The following distances and times represent **only the outbound disposal leg**, calculated **from the final collection point to the landfill**. They are **not included** in the intra-zone collection routes calculated in Step 8.

**Results:**

- **Landfill Segment Distances (From Final Collection Stop):**
    - Truck 1 (Red): **8.568 km**
    - Truck 2 (Blue): **8.828 km**
    - Truck 3 (Green): **9.361 km**
- **Estimated Travel Time (Assuming 40 km/h Speed):**
    - Truck 1: **12.85 minutes**
    - Truck 2: **13.24 minutes**
    - Truck 3: **14.04 minutes**

**Tools and Functions Used:**

- ArcGIS Pro – **Closest Facility Tool**
- **Attribute Table** – for extracting travel metrics
- **Symbology and Labeling** – for mapping landfill routes

**Discussion:**
These distances reflect the critical outbound leg to the landfill, which directly affects operational costs and scheduling. For instance, although Truck 2 has the shortest intra-zone route, it experiences a longer landfill journey than Truck 1. Truck 3's longer landfill segment, despite moderate collection distance, highlights a trade-off between efficient pickup and disposal logistics.

**Limitations:**

- Results are based on **ideal conditions** (no traffic, delays, or terrain variation).
- Stop service times and external variables were **not considered**.
- For greater accuracy, **field-based GPS validation** is recommended in future stages.

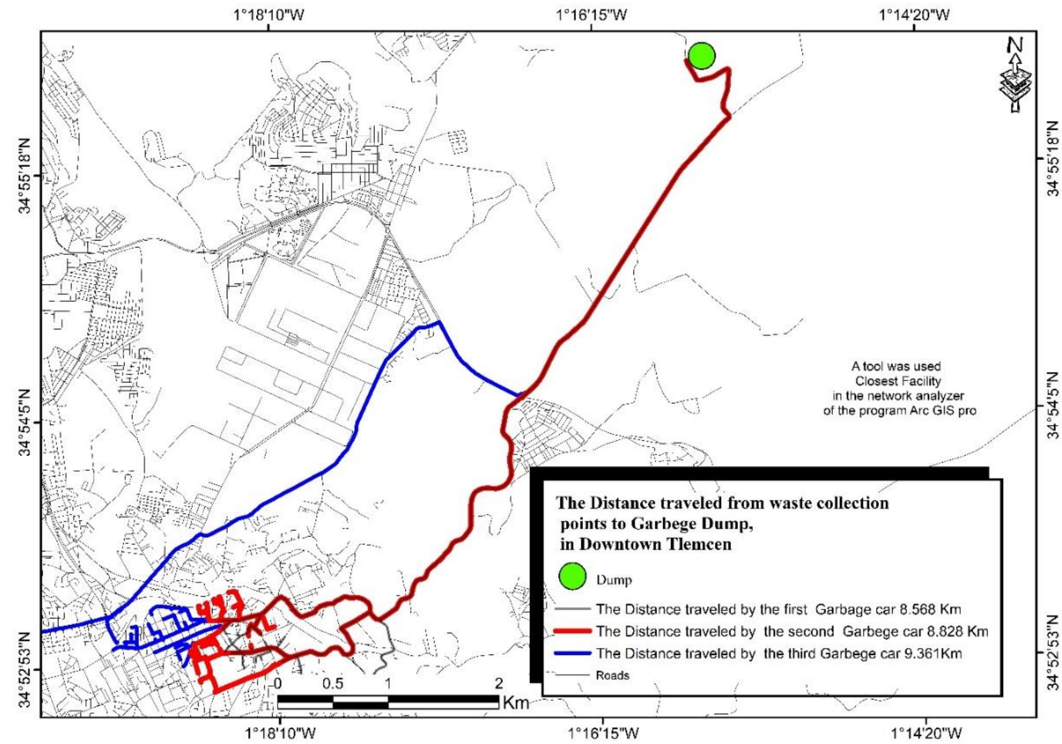


**Figure 39: the total distances**

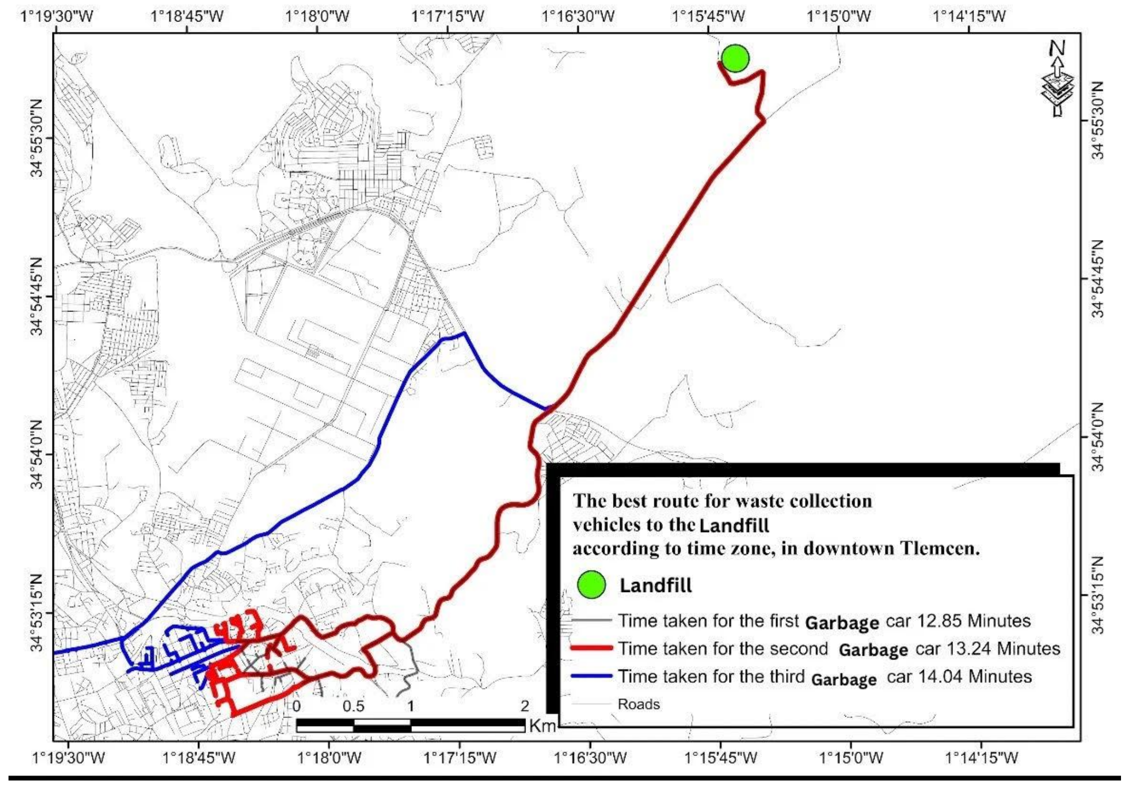


**Figure 40: The distance traveled from waste collection points to landfill**

## 4.4 Total Route Distance per Vehicle

**Objective:**
To consolidate the routing results by calculating the **total travel distance** each collection vehicle covers, combining its intra-zone collection segment (Step 8) and the outbound trip to the landfill (Step 9). This integration provides a clearer picture of each vehicle's operational load.

**Approach:**
The distances obtained from the two previous steps were summed to reflect the **entire network-based route** per truck. This total represents the full length each vehicle travels during a complete collection and disposal cycle.

**Table 16: Total Operational Distance per Vehicle**

| Truck | Intra-Zone Distance | Landfill Segment | Total Distance |
|---|---|---|---|
| Truck 1 (Red) | 4.98 km | 8.568 km | **13.55 km** |
| Truck 2 (Blue) | 3.88 km | 8.828 km | **12.71 km** |
| Truck 3 (Green) | 5.18 km | 9.361 km | **14.54 km** |

### 4.4.1 Summary

**Table 17: Estimated Total Operational Time per Garbage Collection Truck**

| Truck | Collection Time (min) | Landfill Time (min) | Stops | Loading Time (min) | Base Time (min) | Delay Buffer (10%) | Total Time (min) |
|---|---|---|---|---|---|---|---|
| **Truck 1 (Red)** | 7.47 | 12.85 | 50 | 150 | **170.32** | 17.03 | **187.35** |
| **Truck 2 (Blue)** | 5.81 | 13.24 | 50 | 150 | **169.05** | 16.91 | **185.96** |
| **Truck 3 (Green)** | 7.77 | 14.04 | 50 | 150 | **171.81** | 17.18 | **188.99** |

***Note:***
*The collection time values presented in the table above represent idealized travel durations generated using ArcGIS Pro's Network Analyst extension, based on fixed travel speed and uninterrupted movement assumptions. These times reflect model-based estimates and do not*

*account for real-world variables such as waste loading operations, traffic delays, or road condition impacts.*

To improve the realism of the operational time estimates, additional components were incorporated into the analysis. The **loading time** was computed assuming a standardized waste collection scenario of **50 stops per vehicle**, with an average service time of **3 minutes per stop**, yielding a total of **150 minutes** per truck. The **landfill travel time** was determined based on the distance from each vehicle's final collection point to the landfill (as established in Step 9), assuming a uniform travel speed of **40 km/h** to reflect conditions for fully loaded trucks navigating urban and peri-urban routes.

Furthermore, a **10% delay buffer** was applied to the total base task time consisting of collection time, landfill travel time, and loading time to account for typical operational inefficiencies. These may include traffic congestion, deceleration and acceleration patterns, intersection waiting times, road obstructions, and vehicle maneuvering delays.

The total operational time for each vehicle was therefore calculated according to the following procedure:

- **Collection time** was taken from Step 8.
- **Landfill travel time** was obtained from Step 9.
- **Stops** were standardized at 50 per truck.
- **Loading time** was calculated as 50 stops × 3 minutes, resulting in 150 minutes.
- The **base time** was calculated as the sum of collection time, landfill travel time, and loading time.
- The **delay buffer** was estimated as 10% of the base time.
- The **total operational time** was derived by adding the delay buffer to the base time.

This integrative approach provides a more realistic estimation of the total time required for each garbage collection vehicle to complete its daily route. It strengthens the operational relevance of the routing model and supports more informed decision-making related to vehicle scheduling, crew deployment, and resource planning in municipal waste management operations.

### 4.4.2 ArcGIS-Based Total Time Estimation (with 5-Minute Loading Time)

To complement the previously calculated estimates based on a 3-minute loading duration, this section presents the final ArcGIS Pro simulation results, assuming a more conservative loading time of **5 minutes per collection point**. This adjustment offers a more robust estimation of the total operational duration for each truck, including intra-zone collection and disposal routing.

The cartographic output in **Figure 41** illustrates the complete optimized routing of the three municipal waste collection trucks. Each route includes the **starting depot** (indicated by the car symbol), all assigned waste collection points, and the final leg to the landfill.

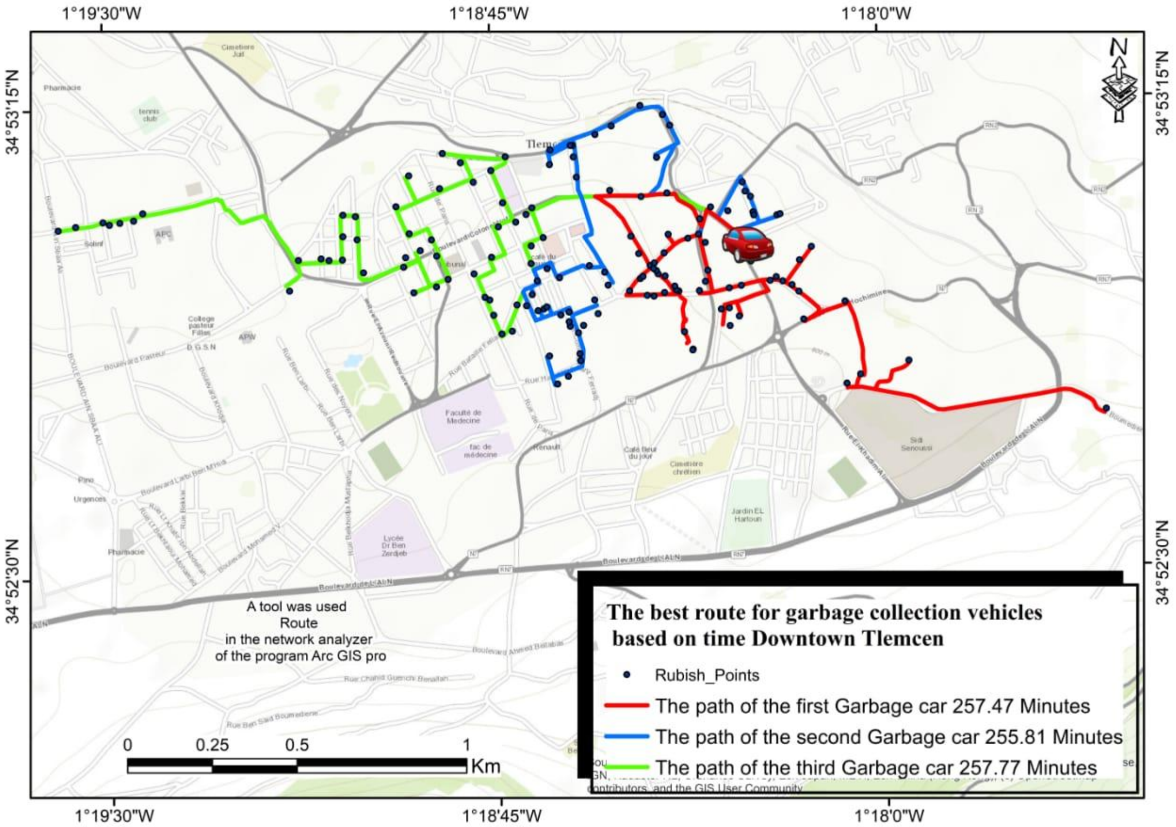


Figure 40: Final Route Map Showing Total Time per Truck (Based on ArcGIS Pro with 5 min/loading point)

***Notes:***

*The time estimates are derived from simulated conditions and do not reflect real-world variables such as traffic congestion, delays, or mechanical issues. Field validation is recommended for operational use.*

### 4.4.3 Vehicle-Specific Route Comparison: Simulated Annealing vs. ArcGIS Pro

This section provides a side-by-side comparison of vehicle-specific route distances generated by two metaheuristic VRP models Simulated Annealing (SA) and the Blob Algorithm with actual route measurements derived from ArcGIS Pro. While the SA and Blob models computed optimized paths using abstract distance approximations and capacity constraints, ArcGIS Pro calculated real-world travel distances using detailed road network geometry, including all turns, intersections, and the final segment to the landfill. The table below summarizes the total route length per truck from each method, along with the percentage difference between each model and the GIS-based reference values.

**Table 18: Vehicle-Specific Route Distance Comparison – VRP (SA & Blob) vs. ArcGIS Pro**

| Truck | VRP Distance – SA (km) | VRP Distance – Blob (km) | ArcGIS Pro Distance (km) | % Difference vs. SA | % Difference vs. Blob |
|---|---|---|---|---|---|
| **Truck 1** | 24.82 | 20.51 | 13.55 | −45.42% | −33.94% |
| **Truck 2** | 22.14 | 21.22 | 12.71 | −42.56% | −40.10% |
| **Truck 3** | 33.92 | 22.91 | 14.54 | −57.13% | −36.54% |

***Note:*** *The route distances reported from* ***ArcGIS Pro*** *represent complete operational paths, including travel from the depot, intra-zone waste collection, and the outbound segment to the landfill. These measurements are based on actual road geometry and are more representative of realistic conditions.*

The percentage difference was calculated using the following formula:

$$\text{Difference (\%)} = \frac{\textbf{ArcGIS Distance} - \textbf{VRP Distance}}{\textbf{VRP Distance}} \times 100$$

### 4.4.4 Total Route Distance Comparison: VRP vs. ArcGIS Pro

The cumulative comparison below highlights how both Simulated Annealing (SA) and Blob Algorithm-based VRP models compare to ArcGIS Pro in estimating total travel distances.

**Table 19: Total Distance Comparison (All Routes)**

| Routing System | Total Distance (km) |
|---|---|
| VRP – Simulated Annealing (SA) | 80.87 |
| VRP – Blob Algorithm | 64.63 |
| ArcGIS Pro | 40.80 |
| **Difference vs. SA (%)** | **−49.56%** |
| **Difference vs. Blob (%)** | **−36.85%** |

### 4.4.5 Analysis and Discussion

The comparative results reveal a significant overestimation of route distances in both the Simulated Annealing and Blob Algorithm-based models when benchmarked against the GIS-based ArcGIS Pro results. The SA model generated a total route length of **80.87 km**, overestimating by nearly **49.56%**, while the Blob model estimated **64.63 km**, exceeding the ArcGIS Pro measurement by **36.85%**.

These discrepancies can be largely attributed to the internal assumptions of each optimization model. Both SA and Blob algorithms operate on simplified network abstractions often using Euclidean or graph-based distances and do not incorporate real-world elements such as:

- Road curvature and hierarchy
- Turn restrictions and intersection delays
- Traffic regulations and flow direction
- Access limitations or physical barriers

In contrast, **ArcGIS Pro** employs a digitized urban road network with embedded topological accuracy and constraint-aware navigation. As such, it offers spatially grounded, realistic routing solutions that are more applicable for implementation in municipal operations.

Despite their simplifications, both VRP models hold value in preliminary planning contexts. The **Simulated Annealing** approach provides fast approximations for constrained routing problems, whereas the **Blob Algorithm**, inspired by decentralized biological systems, offers increased flexibility and robustness for complex, capacity-sensitive scenarios.

This analysis underscores the importance of validating algorithmic models with geospatially accurate tools such as ArcGIS Pro to ensure the operational feasibility of waste collection strategies.

## 4.5 Conclusion

This chapter has presented a comparative analysis between GIS-based and algorithmic approaches to optimizing municipal solid waste collection routes in the urban context of Tlemcen. The primary objective was to assess the effectiveness, practicality, and realism of route optimization models developed using **ArcGIS Pro**, **Simulated Annealing (SA)**, and the **Blob Algorithm**.

The ArcGIS Pro-based methodology employed a topologically accurate urban road network to generate detailed route maps and calculate distances and travel times under controlled assumptions. This approach allowed for the inclusion of realistic network geometry, turn restrictions, and access constraints, leading to a more reliable representation of actual waste collection operations. Intra-zone distances and outbound landfill travel were analyzed separately, then combined to estimate total operational coverage for each vehicle. Time estimates were further refined by incorporating service loading time and a delay buffer to simulate real-world inefficiencies.

Parallel to the GIS workflow, two metaheuristic VRP models Simulated Annealing and the bio-inspired Blob Algorithm were implemented to develop theoretically optimized collection routes under capacity constraints. While these models produced feasible solutions, the results significantly overestimated total route distances when compared to ArcGIS Pro outputs. Specifically, the SA model overestimated total distance by approximately **49.56%**, and the Blob model by **36.85%**, highlighting the limitations of abstract distance modeling when applied to real-world environments.

The findings underscore the trade-off between algorithmic flexibility and geospatial realism. While SA and Blob models are beneficial in the early planning phases particularly for generating scenarios under various constraints they lack spatial fidelity due to their simplified treatment of road network structures. Conversely, ArcGIS Pro provides a spatially grounded, constraint-aware routing solution that is more directly implementable in operational contexts.

In conclusion, the integration of **computational optimization techniques with GIS-based spatial analysis** offers a robust framework for waste collection route planning. Metaheuristic algorithms can inform initial routing configurations and capacity balancing, whereas GIS ensures alignment with real-world infrastructure and municipal logistics. This dual-strategy approach enables municipalities to develop collection strategies that are not only efficient in theory but also feasible in practice, ultimately supporting more sustainable and cost-effective public service delivery.

## General Conclusion

This study set out to optimize municipal waste collection in the city of Tlemcen, Algeria, by addressing the Vehicle Routing Problem (VRP) through both algorithmic modeling and spatial analysis. By combining metaheuristic approaches particularly Simulated Annealing (SA) with the geospatial capabilities of ArcGIS Pro, the research sought to bridge the gap between theoretical route optimization and practical implementation on real-world road networks.

The methodology was grounded in the integration of real-world data specifically, waste collection point coordinates into an algorithmic VRP framework. Simulated Annealing was employed to generate routes that respected vehicle capacities and minimized travel distances. While algorithmic results were computationally efficient and structurally sound, subsequent validation in ArcGIS Pro revealed significant spatial discrepancies. In some instances, the actual distances computed within ArcGIS exceeded algorithmic estimates by up to 100%, highlighting the limitations of pure mathematical modeling in representing real urban road constraints.

ArcGIS Pro brought a vital dimension to the analysis: its ability to account for topography, traffic regulations, and the true geometry of the road network proved essential in evaluating the feasibility of proposed routes. This comparison illuminated a key takeaway algorithmic models are powerful for generating structured, fast solutions, but without geospatial context, they risk underestimating real-world operational requirements.

Ultimately, the study demonstrated that neither algorithmic optimization nor GIS tools alone are sufficient for complex urban logistics. However, when combined, they offer a robust and scalable framework capable of producing routes that are both operationally efficient and geographically accurate. This dual approach is particularly relevant for municipal services like waste collection, where optimized routing has direct implications for cost, fuel consumption, labor efficiency, and environmental impact.

Looking forward, future research could build upon this foundation by incorporating dynamic data sources such as real-time traffic, waste volume predictions, or adaptive routing based on IoT sensors. Exploring hybrid algorithms and integrating mobile applications for live data feedback could further improve adaptability and responsiveness.

In conclusion, this thesis reinforces the importance of integrating computational intelligence with spatial analysis for urban planning. The synergy between metaheuristic optimization and GIS validation emerges as a powerful strategy for addressing complex, real-world routing challenges transforming theoretical models into actionable, effective solutions.

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