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Hadjer LOUZIM

Subject

Development of a Location Routing Problem model in a Physical Internet Context

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

Mr Mohammed BENNEKROUF	MCA	ESSA. Tlemcen	President
Mr Fouad MALIKI	MCA	ESSA. Tlemcen	Thesis Director
Mr Tarik CHARGUI	MC	UPHF Valenciennes	Thesis co-Director
Mr Abdelghani BEKRAR	Prof	UPHF Valenciennes	Examiner 1
Mr Khalid MEKAMCHA	MCB	Univ. Tlemcen	Examiner 2

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Contents

Abstract

This thesis explores logistics optimization within the framework of the Physical Internet conceptfocusing on the Location Routing Problem (LRP). Initially, the thesis addresses a single-objective LRP aiming to minimize transportation and opening costs using various solution methodologies, including classical solvers like CPLEX and metaheuristic approaches such as simulated annealing and hybrid strategies. Subsequently, it extends to a multi-objective optimization that considers environmental factors (CO2 emissions). The multi-objective problem is solved using Gurobi and the Archive-based Multi-Objective Simulated Annealing (AMOSA) algorithm. The results demonstrate the effectiveness of the proposed approaches in achieving economic efficiency and environmental sustainability in logistics operations.

Keywords: Physical Internet, LRP, Mono-objective optimization, Multi-objective optimization, Cplex, Gurobi, SA, Epsilon-greedy, AMOSA

Résumé

Cette thèse explore l'optimisation logistique dans le cadre de l'Internet Physique, en se concentrant sur le Problème de Routage et de Localisation (LRP). Elle aborde d'abord un LRP mono-objectif visant à minimiser les coûts de transport et d'ouverture des hubs en utilisant des méthodologies variées, dont les solveurs CPLEX et des approches métaheuristiques comme le recuit simulé et des stratégies hybrides. Ensuite, elle étend l'optimisation à une dimension multi-objectifs en prenant en compte les émissions de CO2. Le problème multi-objectifs est résolu avec Gurobi et l'algorithme AMOSA (Archive-based Multi-Objective Simulated Annealing). Les résultats montrent l'efficacité des approches proposées pour améliorer l'efficacité économique et la durabilité environnementale dans les opérations logistiques.

Mots clés: Internet physique , LRP, optimization mono-objective, optimization multi-objective, Cplex, Gurobi, SA, Epsilon-greedy, AMOSA

تلخيص

تستكشف هذه الأطروحة تحسين الخدمات اللوجستية في إطار مفهوم الإنترنت المادي. تركز على مشكلة التوجيه والموقع (LRP) . في البداية، تتناول الأطروحة نغع بهدف وحيد وهو تقليل تكاليف النقل باستخدام منهجيات مختلفة للحل، بما في ذلك الحلول التقليدية مثل CPLEX والمناهج الميتاستكشافية مثل التبريد المحاكي Simulated annealing والاستراتيجيات الهجينة. بعد ذلك، تتوسع لتشمل تحسينًا متعدد الأهداف يأخذ في الاعتبار أيضًا العوامل البيئية مثل انبعاثات ثاني أكسيد الكربون. يتم حل المشكلة متعددة الأهداف باستخدام Gurobi وخوارزمية ايوصا (التبريد المحاكي متعدد الأهداف المستند إلى الأرشيف). تظهر النتائج فعالية المناهج المقترحة في تحقيق الكفاءة الاقتصادية والاستدامة البيئية في العمليات اللوجستية.

الكلمات المفتاحية: الإنترنت الفيزيائي، LRP ، التحسين الأحادى الهدف، التحسين متعدد الأهداف، CPLEX ، Gurobi ، التلدين المحاكى SA ، Epsilon-greedy ، AMOSA

List of abbreviations

PI	: Physical Internet
LRP	: Location routing problem
FLP	: Facility location problem
VRP	: Vehicle routing problem
SA	: Simulated annealing
AMOSA	: Archived multi-objective simulated annealing
OSI	: Open system interconnection
OLI	: Open logistics interconnection
ALICE	: Alliance for logistics innovation through collaboration in Europe
TC	: Fixed unit transportation cost per kilometer
MILP	: Mixed integer linear programming

General Introduction

In today's rapidly evolving landscape of global commerce and logistics, achieving efficiency, sustainability, and resilience is more critical than ever. Traditional supply chain models, while once effective, now struggle to meet modern demands. The Physical Internet offers a transformative solution, inspired by the Digital Internet, to create a seamless and interconnected network for moving physical goods.

The Physical Internet aims to revolutionize the transport, storage, and distribution of goods by adopting modular and standardized containers along with dynamic routing algorithms. This innovative approach seeks to enhance efficiency, reduce costs, and minimize environmental impacts in logistics operations.

This thesis explores various aspects of logistics optimization within the Physical Internet framework. We start by examining the Location Routing Problem (LRP), which combines the Vehicle Routing Problem (VRP) and the Facility Location Problem (FLP). The LRP focuses on optimizing goods distribution from multiple facilities to various customers, considering both transportation and facility location decisions. Through a detailed review and classification of FLP and VRP, we establish a foundational understanding of the LRP and its practical implications.

Building on this foundation, we first address a single-objective version of the LRP, concentrating on minimizing transportation costs. We develop a mathematical model and explore solution methodologies, including classical simulated annealing and an innovative hybrid approach combining simulated annealing with the epsilon-greedy strategy from reinforcement learning. Our experiments reveal that both methods are effective, showing promising results with minimal deviation from the optimal solution.

In the final section of this thesis, we expand our focus to a multi-objective optimization problem by introducing an environmental objective: CO2 emissions. This dual-objective approach balances economic efficiency with environmental sustainability. We develop a multi-objective model and solve it using Gurobi, supplemented by an AMOSA (Archive-based Multi-Objective Simulated Annealing) algorithm. Our results indicate that AMOSA performs well for both objectives, maintaining a small gap for transportation costs and a reasonable gap for CO2 emissions.

In summary, this thesis focuses on investigating a location routing problem within the context of the Physical Internet, considering both economic and environmental aspects while employing various resolution approaches.

Chapter 1

Physical Internet concepts : State of the art

Introduction

In today's rapidly changing world of global commerce and logistics, the quest for efficiency, sustainability, and resilience stands as a top priority. Traditional supply chain models, while effective in their time, are increasingly facing challenges. These challenges manifest in various aspects of supply chain operations: in an economic, environmental and societal aspect.

Recognizing the need for transformation and changing, the concept of the Physical Internet emerges as a promising solution to overcome the limitations of classical supply chains. At its core, the Physical Internet is a new paradigm drawing inspiration from the principles of the Digital Internet to create a seamless and interconnected network to the movement of physical good easier.

Key concepts of the Physical Internet, such as modular and standardized containers and dynamic routing algorithms, are introduced as fundamental building blocks of this transformative vision. By adopting these principles, the Physical Internet aims to change and revolutionize the way goods are transported, stored, and distributed.

In this chapter, we explored in the first place the transition from traditional logistics to the innovative concept of the Physical Internet. Then, we delved into the concept of the Physical Internet, exploring its core principles and comparing it with the Digital Internet to enhance comprehension of its potential. Additionally, we touched upon ALICE, a collaborative platform driving logistics innovation. Finally, we wrapped up with a state-of-the-art overview, discussing recent articles and research pertaining to the Physical Internet.

1.1 Logistics and supply chain

1.1.1 Logistics definition

"Logistics" was initially a military-based term used in reference to how military personnel obtained, stored, and moved equipment and supplies. The term is now used widely in the business sector, particularly by companies in the manufacturing sectors, to refer to how resources are handled and moved along the supply chain. It refers to the overall

process of managing how resources are acquired, stored, and transported to their final destination.[Kenton, 2024].
In the pure context of industry,[Ballou et al., 1973] defined logistics as "the process responsible for planning, implementing, and controlling the flow and storage of materials, goods, services, and information from origin to the consuming point."
[Frazelle, 2020] proposed another definition for logistics: " the flow of material,information, and money between consumers and suppliers"

1.1.2 Supply chain definition

A supply chain is the network of all the individuals, organizations, resources, activities and technology involved in the creation, distribution ans sale of a product. A supply chain encompasses everything from the delivery of raw materials from the supplier to the manufacturer through to its eventual delivery to the costumer and the end user.[Lutkevich,]
[Christopher, 2022] also defined supply chain as "the network of organizations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services delivered to the ultimate consumer".

1.1.3 Supply chain network

Supply chain network design means figuring out the best way to set up the supply chain so we can see how much it costs and how long it takes to get the products to market with the resources and places we have. In this process, there are many factors and models involved. This includes the strategic placement of distribution centers that are served from manufacturers, retailers and possible routes to serve those stores.[Forrest, 2024]
Classical supply chain network has actually a hierarchical distribution form, from suppliers to manufacturers, to warehouses to distribution centers and finally to retailers.

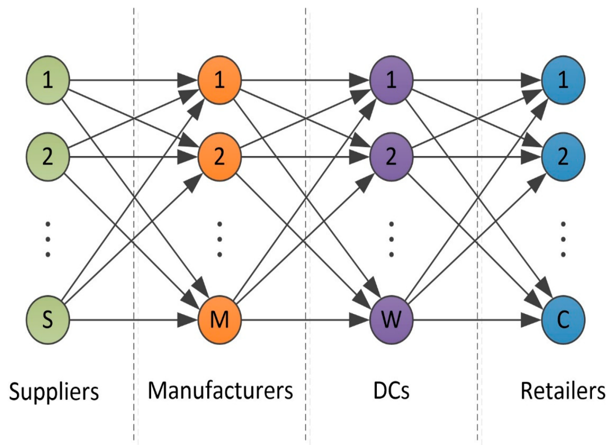

Figure 1.1: Supply chain network

1.1.4 logistics management and supply chain management

According[Tien et al., 2019] to Supply chain management is the seamless coordination of activities from customer orders to cash flows, linking distributors, inventory, manufacturers, and suppliers.SCM operates on the principle that almost every product reaching the market is the outcome of collaboration among multiple organizations forming a supply chain.

Logistics management refers to the process of strategically planning, executing, and managing smoothly the flow and the storage of goods, services, and associated information from their origin to the end-user, ensuring they meet customer requirements and expectations efficiently and effectively.
The author supposed that Logistics management is a part of supply chain management, which covers all the logistics activities of firms, their partners, and the combined benefits of these activities, among other components. The main idea is that supply chain is composed of the different activities of logistics and he explained that in the figure below 1.2

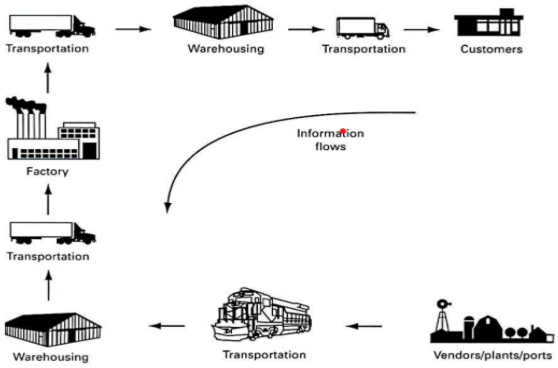

Figure 1.2: logistics and supply chain

1.1.5 Efficiency and sustainability of the current logistics system

According to [Montreuil, 2011] logistics is efficient when it satisfies the demand and the needs for moving, storing, supplying and using physical goods while minimizing the utilization of economical, environmental and societal resources. It is sustainable when it upholds high economical, environmental and societal performance over the time while facing and confronting risks in a dynamic context.

Today, the world is facing an inefficiency and unsustainability of the current logistic system due to its limitations. These limitations are seen from different aspects [Montreuil, 2011]:

- **The economic aspect :**Represented by different logistics costs that can be divided into five main components depending on the point at which the product is situated within the supply chain :Warehousing costs(Incoming goods),Warehousing costs(Storage),Fulfillment costs(Pick pack),Shipping costs(Delivery) and finally other logistics Costs(Returns). Logistics costs have increased by approximately 5% since 2010, mainly due to the growing intricacy of e-commerce logistics, these costs currently represent 12 to 20 percent of e-commerce revenues.[cos,]

  In 2021, the total transportation logistics costs in the United States reached approximately $1.2 trillion. Specifically, transportation costs for motor carriers (including full truckload, less-than-truckload, and private or dedicated) accounted for $830.5 billion[Placek, 2024].

- **The environmental aspect :** Represented by energy consumption, pollution, material waste and greenhouse gas emissions. Actually freight transportation accounts

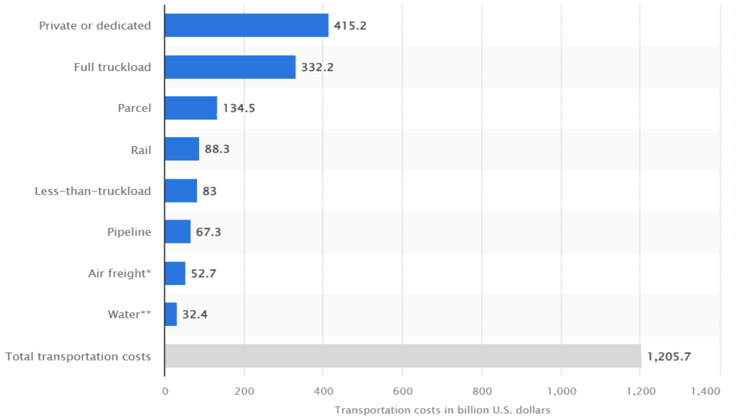

Figure 1.3: Transportation costs by type in the united stats in 2021

for 14% of France's gas emissions, showing a yearly growth rate of around 23% between 1990 and 2006.
In 2022, global transportation-related emissions totaled 7.97 billion metric tons of carbon dioxide (GtCO2), marking a 4.7 percent increase compared to 2021 levels. These emissions have surged over the past 50 years, rising from just 2.8 GtCO2 in 1970. Actually, between 1990 and 2022, global transportation emissions increased by more than 70 percent. These results and statistics were provided by Statista website [Tiseo, 2024], and the statistics are presented in the figure below 1.4

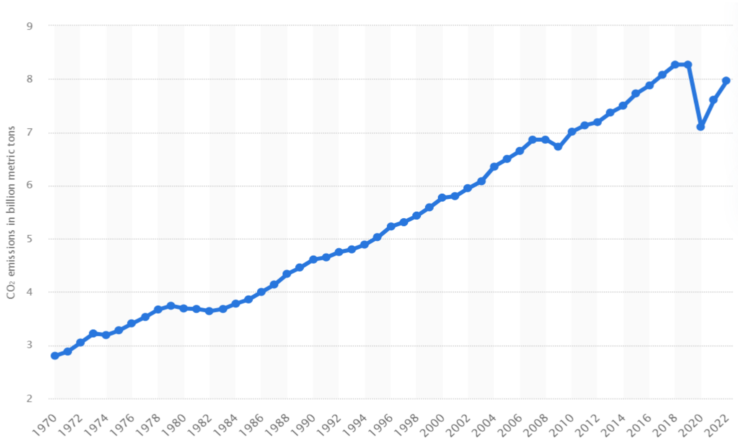

Figure 1.4: Global transportation sector CO emissions 1970-2022

- **The societal aspect :** Represented by drivers work conditions,the security of our logistics system, job opportunity creation, regional development promotion and safety concern[Peng et al., 2021].

  Some studies showed that prevalence of minor psychiatric disorders, depression, and anxiety among truck drivers is in the range of 6.1%, 13.6%, and 7.9%, respectively and approximately, 8,000 truck accidents each year are attributed to truck driver fatigue [Lindner, 2024].
  In 2020 in the USA, Texas stands out as being the most dangerous state for truck accidents with 568 accident per year.1.5 showed how Texas and the other high-risk states fare when it comes to fatal truck accidents in 2020. [Adam Ramirez, 2024]

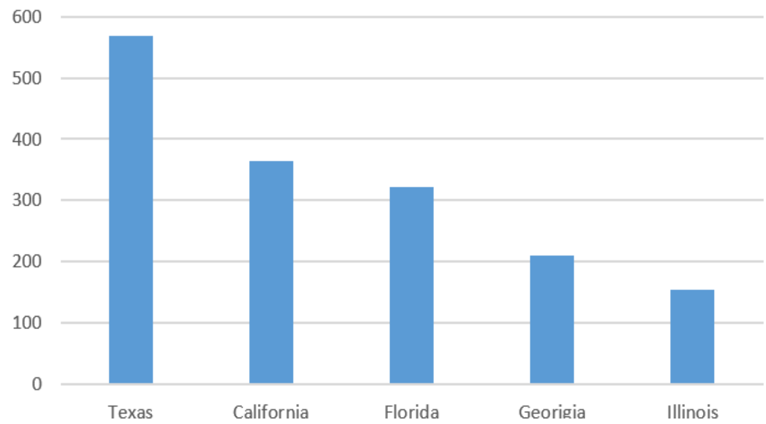

Figure 1.5: truck accidents in USA on 2020

1.1.6 Unsustainability symptoms

[Montreuil, 2011] summarized the symptoms of economic, environmental and societal unsustainability in 13 main principles:

- **Low rate of vehicle loading** : because of the half-emptiness of trucks, wagons and containers at the departure and they aren't fully loaded to their capacity. in 2004 in Germany, a study done with 50 German transport providers, obtained an average load capacity of 60% by volume and 44% by weight for all categories of vehicles studied.[Léonardi and Baumgartner, 2004]

Figure 1.6: Truck's emptiness rate

- **Empty travel** :Most of the time vehicles and containers returns empty. This occurs when trucks or vehicles travel back to their origin empty after delivering goods. Factors contributing to empty travel include uneven demand, logistical constraints, and the need for fleet flexibility.

- **Truckers work conditions** : Because of the high demand of truck drivers coupled with the essential role they play in transporting goods, means they often face rigorous schedules, tight deadlines and long working hours, so that's why they are most of the time away of their homes,families and social life.

- **Unneeded storing and unavailability of products when and where needed** : Products are often stored in warehouses or distribution centers where they may sit idle for extended periods, especially if there isn't immediate demand in that location. As a result, even though products may be in stock somewhere, they might not be easily accessible to meet urgent requirements.

- **Production and storage facilities are poorly used** : For example in the case of seasonal products, production and storage facilities may face unique challenges in utilization. However, during off-peak seasons, facilities may operate at reduced capacity or even sit idle. Similarly, storage facilities may experience fluctuations in occupancy, with increased demand for storage space during peak seasons and decreased demand during off-peak periods.

- **So many products are never sold, never used**: Many products end up never being sold or used, contributing to waste and inefficiency in production and consumption. This is well-known in clothing,food and cars industry.

- **Products do not reach those who need them the most** : A significant challenge in global trade is ensuring that essential products reach those who need them most, particularly in non-developed countries and disaster zones in where logistics infrastructures and services decrease significantly.

- **Fast and reliable intermodal transport is still a dream or a joke** : The realization of fast and reliable intermodal transport remains a distant goal rather than a reality for many regions because of badly designed interfaces,poor synchronization and risky intermodal routes.

- **Flexible City logistics is hard to reach** : Transporting goods in cities is a logistical nightmare due to congestion, limited space, and complex infrastructure. Delivery vehicles struggle with traffic, narrow streets, and parking issues, while last-mile delivery presents additional challenge.

- **Products unnecessarily move, crisscrossing the world**: Products frequently take unnecessary trips around the world, moving inefficiently due to disjointed supply chains and poor coordination.

- **Networks are neither secure nor robust** : Because many businesses concentrate their operations in only a few centralized facilities, their logistics networks and supply chains become vulnerable to terrorism and natural disasters.

- Smart automation and technology are hard to justify

- **Innovation is strangled** : Innovation faces obstacles, particularly due to the absence of universal standards and protocols, as well as a lack of transparency and open infrastructure..

To address these challenges, a novel concept known as **the Physical Internet** has emerged. The Physical Internet paradigm is a new concept that aims to change how goods are transported, with a main objective to optimize the efficiency and sustainability of global logistics networks. At its core, the Physical Internet draws inspiration from the digital internet, envisioning a seamlessly interconnected and standardized physical network for the movement of goods.

1.2 Physical internet

1.2.1 Physical Internet definition and main concepts

The Physical Internet (PI,π) concept has been recently introduced as a response to the Global Logistics Sustainability Grand Challenge [Montreuil, 2011]. It is defined as an open global logistics system founded on physical, digital and operational interconnectivity through encapsulation, interfaces and protocols aiming to change the way physical objects are moved, handled, stored and transported based on the structure and the principles of Digital internet. [Montreuil et al., 2013]. The main objective of PI is to move from a closed,independent logistics network into an open,dependant logistics network.

The Physical Internet changes how goods are moved and stored by creating a super-connected logistics system. Everything is packed in smart, standardized PI-containers, from small cases to large cargo containers. These containers are tracked and managed in real-time as they move through logistics centers. Handling systems and vehicles are designed to work smoothly with these containers, making the whole process more efficient.

Physical Internet concept is based on three key elements : PI-containers, PI-movers and PI-nodes. [Montreuil et al., 2010]

- **PI-containers:** Modular containers with standardized dimensions based on the concept of encapsulation. They are easy to manage, store, transport,interlock, load and unload. They are also smart to allow their proper identification and routing, recyclable and eco-friendly. According to [Sallez et al., 2015] PI-containers can be classified into three main categories : transport, handling and packaging containers.
  - Transport containers or T-containers :They are large entities transported by the different types of vehicles (trucks, trains, ships. . .) on the PI networks. They're made to be easy to carry, tough enough for harsh conditions, and stackable like regular shipping containers used in maritime transport. They can contain directly physical objects or containers of smaller size. They have all the same width and high (2.4m*2.4m) but with different lenghts(1.2, 2.4, 3.6, 4.8, 6 or 12 m).
  - Handling containers or H-containers :They are designed to be handled by PI-handlers (conveying systems, lifts. . .) and to resist handling conditions in the PI-nodes.They can also contain physical objects or containers of smaller size.The standard maximum external size of an H-container enables it to fit inside a T-container with external sides measuring 1.2 meters. Smaller modular dimensions along the X, Y, and Z axes range from approximately 50%, 40%, 30%, 20%, down to 10% of this maximum size.
  - Packaging containers or P-containers :They are the smallest type of PI-containers and they are used to contain directly the physical goods. They're made to easily fit inside H-containers, being thin and lightweight for effortless handling. They protect the product and can be stacked when required.Essentially they are designed to replace custom packaging.

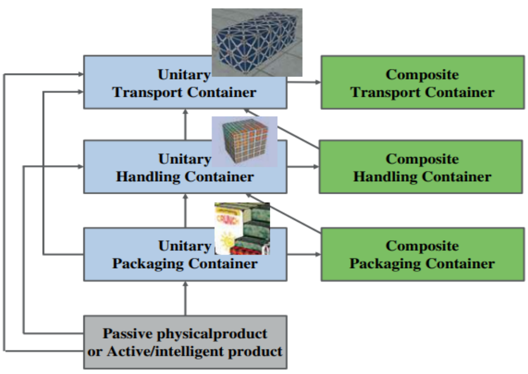

Figure 1.7: PI-containers [Sallez et al., 2015]

- **PI-movers:** used to move the PI-containers .PI-movers can temporarily store π-containers, even if that's not their main job.The main types of π-movers are π-transporters,π-conveyors and π-handlers.

  - **π-transporters** are designed to ensure a safe and efficient transportation of PI-containers. π-transporters includes π vehicles (π-trucks, π-locomotives, π-boats, πplanes, π-lifts and π-robots.) that are self-propelled and π carries that have to be pushed or pulled (π-trailers, π-carts, π-barges and π-wagons) that have to be pushed or pulled.

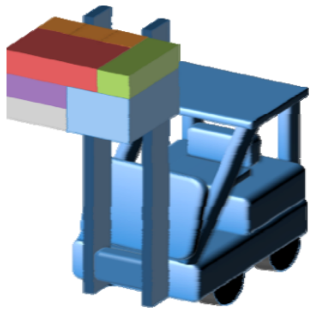

Figure 1.8: PI-lift-truck [Montreuil et al., 2016]

  - **π-conveyors** are designed specifically to continuously move π-containers along predefined routes, without the need for π-vehicles and π-carriers. π-conveyors defers from simple conveyors by the fact that π-conveyors doesn't use any belts or rollers to support goods during their continuous flow, theπ-containers are just attach to the π-conveyor gears and get pulled along.

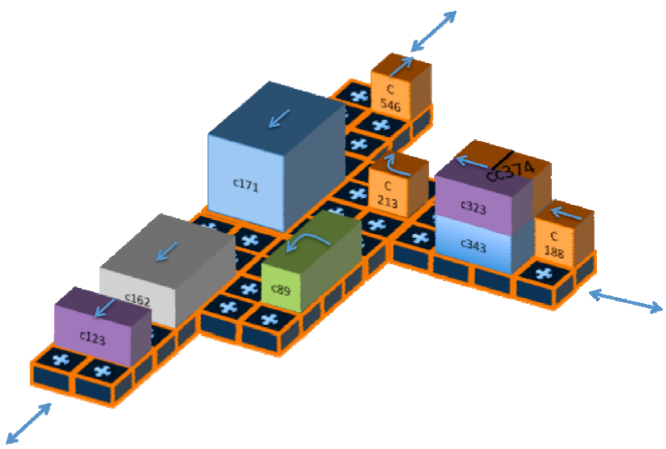

Figure 1.9: PI-conveyor [Montreuil et al., 2016]

- **PI-nodes:** Locations for receiving, sorting, storing and transferring PI-containers. They are equipped with automated and sophisticated handling systems. They are interconnected to the logistics activities.The PI-nodes include : PI-transits, PI-bridges, PI-switches, PI-hubs,PI-sorters, PI-composers, PI-stores and PI-geteways.

  - **PI-transits** ensure the transfer of π-carriers from their inbound π-vehicles to their outbound π-vehicles.
  - **PI-transits** and PI-bridges enable the unimodal transfer of π-containers from an incoming π-mover to an outgoing π-mover.

- **PI-hubs** having for mission to enable the transfer of π-containers from incoming π-movers to outgoing π-movers. There is many types of PI-Hub : Road-Road PI-Hubs, Rail-Road PI-Hubs, Road-Rail PI-Hubs... 1.10

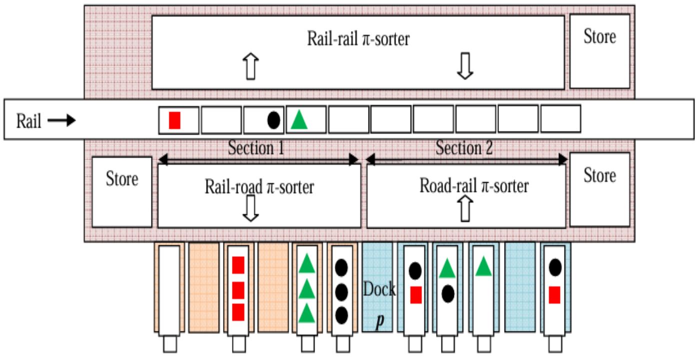

Figure 1.10: Rail-road PI-hub

- **PI-sorter** is designed to receive π-containers from one or multiple entry points and having to sort them so as to ship each of them from a specified exit point.
- **PI-composers** main mission is to construct composite π-containers from specified sets of π-containers according to a specific 3D layout.
- **PI-stores** ensure and facilitate the storage of π-containers for its clients within mutually agreed-upon time windows.Essential factors for their success include both the capacity and speed for receiving π-containers and dispatching them. PI-stores have two main functionalities : stacking and snapping of π-containers and they are mentioned in figure1.11

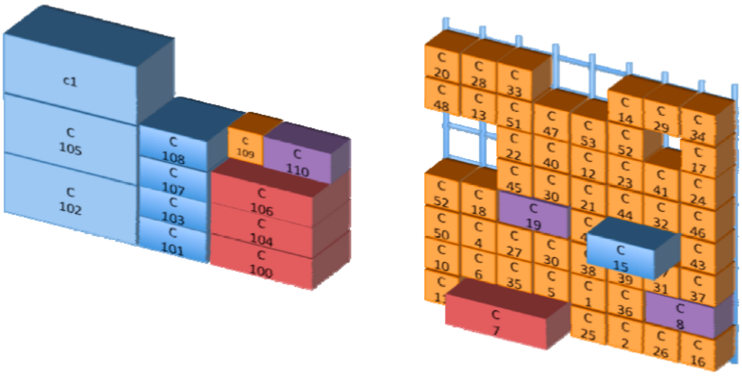

Figure 1.11: stacking and snapping functionalities in a PI-store [Montreuil et al., 2016]

- **PI-geteways** either receive PI-containers from PI-network and release them to a private network, or receive PI-containers from a private network and give them an access to PI-network.

In summary, PI-nodes are the connection and exchange points in our Physical internet network, PI-movers facilitate the transportation of PI-containers between the different PI-nodes. Together, these elements enable the efficient, flexible, and sustainable movement of goods within the global network.

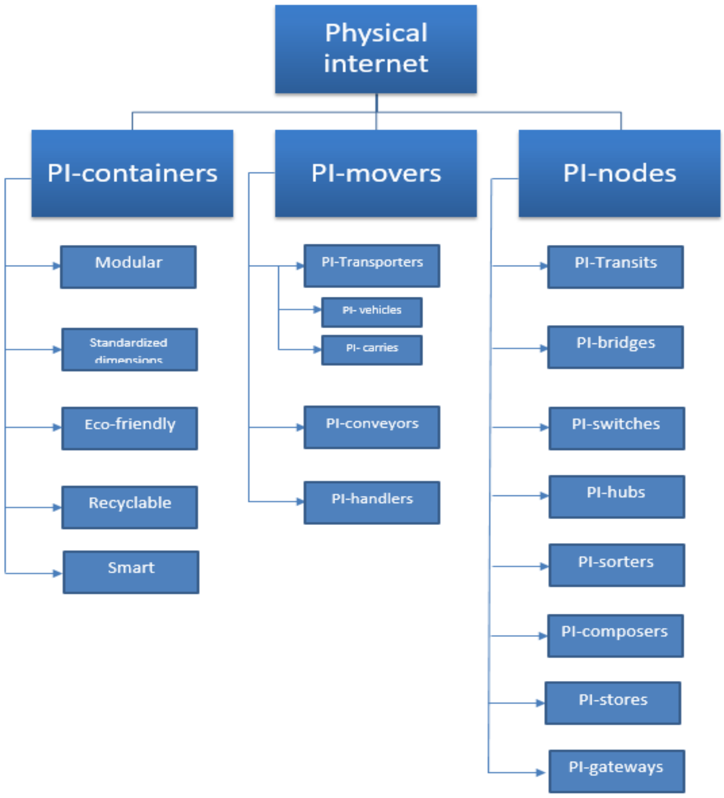

Figure 1.12: Key elements of Physical Internet

1.2.2 From the Digital Internet to the Physical Internet

According to [Montreuil et al., 2012] Physical Internet aims to establish a global inter-connectivity among logistics networks by adopting standardized containers, PI-interfaces and protocols to improve the supply chain sustainability and efficiency. PI aims to organize the transportation of physical goods in a manner similar to the way in which packets are moved in Digital Internet using a set of standardized protocols.

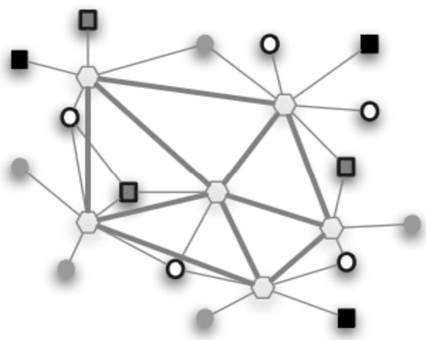

Figure 1.13: PI inter-connectivity

Digital Internet

[Dong and Franklin, 2021]The DI is a sophisticated engineering system that interlinks billions of devices globally, theoretically enabling each device to communicate with every other. Internet users, whether governmental, commercial, or private entities, utilize terminal devices like computers or smartphones. These users input data into the DI in the form of digital information, which is encapsulated into data packets and transmitted through a network of communication links. The term "router" is used as a general term to cover the functions of classic routers, switches and hubs.

Internet protocols

Internet protocols have been introduced to standardize and organize its operationalization. A protocol defines the format of the packets of digital information exchanged between peers in the DI, how hosts should be addressed, as well as the actions taken in the transmission of the packets across the DI. Among the most well-known protocols we found the TCP/IP and OSI(Open Systems Interconnection model) protocols.

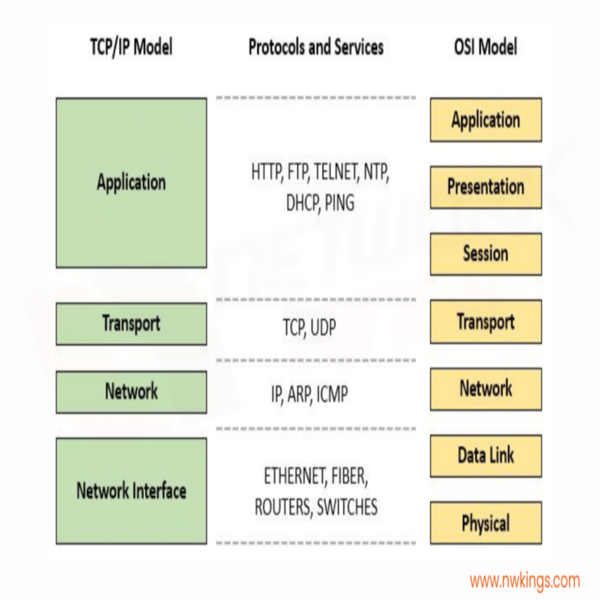

Figure 1.14: Internet protocols

OSI and OLI models

Just like how the digital internet relies on the OSI (Open Systems Interconnection) model to organize and regulate data exchange, the Physical Internet (PI) adopts its own framework, the OLI (Open Logistics Interconnection) model. This model acts as a blueprint for managing the flow of goods, information, and financial transactions within the PI network. It sets out different layers of interaction and protocols, guiding how different parts of the system communicate and work together smoothly. Through this structure, the PI ecosystem can achieve seamless integration and collaboration among its nodes, carriers, and stakeholders. The model also proposes seven layers to offer a richer representation.[Montreuil et al., 2012]

- Physical Layer: The physical layer deals with moving and operating PI-containers using PI-movers. The physical layer ensures that the physical connections within the Physical Internet are standardized.
- Link layer: The link layer focuses on detecting and possibly correcting unexpected events that arise from operations at the physical layer. It does so by ensuring consistency between physical operations and their digital counterparts.

- Network layer: The network layer is all about making sure that networks within the Physical Internet are connected smoothly, operate reliably, and can work together seamlessly.This layer also defines the composition and decomposition of π-containers, the assignment and control of flows of containers across π-networks.
- Routing layer: At this layer, π-routing protocols are established, implemented, and managed. It keeps track of the status, service capability, capacity, and performance of all π-means within each π-network.
- Shipping layer: The shipping layer establishes the functional and procedural methods necessary for an efficient shipping of sets of π-containers from shippers to final clients. It organizes, oversees, and finalizes the shipment process between the shipper and each client.
- Encapsulation layer: The encapsulation layer is responsible for providing the necessary procedures to efficiently package a user's products into uniquely identified π-containers before they enter the Physical Internet networks.
- Logistics Web layer: The Logistics Web layer acts as the intermediary between the Physical Internet and logistics service users, providing the necessary procedures for users to utilize the Physical Internet effectively. This layer facilitates dynamic decision-making regarding product supply, manufacturing, distribution, and mobility within a globally connected Logistics Web enabled by the Physical Internet.

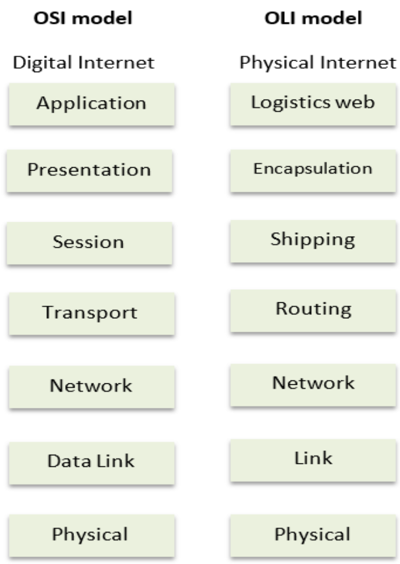

Figure 1.15: OSI and OLI models

Digital Internet and Physical Internet similarities

The main similarities between PI and DI can be summarized in five main points : users, unit of flow, routing of the flow, carrier of the flow and protocols.

- **Users**: Just as the digital internet serves as a platform for private and commercial users to exchange information and services, the Physical Internet allow private and commercial users to exchange physical goods. In both cases, users interact with the network to send or receive items.

- **Unit of Flow**: The digital internet operates by transmitting data packets, which are the fundamental units of information exchange. Similarly, the Physical Internet transmits standardized modular units which are the PI-containers, as the basic carriers of physical goods. These units ensure a seamless transfer between different nodes and modes of transportation within the PI network.

- **Routing of the Flow**: In the digital internet, data packets are routed through a network of interconnected nodes using the routers. Likewise, in the Physical Internet, PI-containers are routed through a network of interconnected PI-nodes.

- **Carrier of the Flow**: In the digital internet, data packets are carried across the network by various communication channels, including wired and wireless connections, fiber-optic cables... Similarly, in the Physical Internet, goods are transported between PI-nodes using PI-movers and by various modes of transportation.

- **Protocols**: Both the digital internet and the Physical Internet rely on standardized protocols to ensure compatibility, interoperability, and security within their respective networks. In the digital realm, protocols like TCP/IP.. Similarly, in the Physical Internet, protocols define how PI-containers are handled, transported, and exchanged between different nodes and carriers, ensuring seamless integration and operation within the PI network.

	Physical Internet	Digital Internet
User	Private and commercial shippers	Private and commercial users
Unit of flow	Modular and standardized PI-containers	Data packets
Routing of the flow	PI-nodes	Routers
Carrier of the flow	PI-movers with different transportation modes	Physical media (optical fiber...)
Protocols	Standardized sending/receiving processes	TCP/IP protocol

Table 1.1: DI and PI similarities

Differences between the DI and the PI

Same for differences between Physical and Digital Internet, the differences can be sorted into five major categories: cost, time, schedule, emissions and capacity.

- **Cost**:The cost of transmitting and processing data over the digital internet is generally much lower compared to the physical movement of goods and it depends only on the electricity consumption. But in the physical internet the transportation and handling of physical goods incur tangible costs, including transportation, holding, handling and fuel costs.

- **Time**: Data transmission over the digital internet is nearly instantaneously and negligible, with data packets traversing the network at the speed of light through fiber-optic cables or via wireless communication. In the other hand the transit times for physical goods within the PI network depends on various factors, like the distance, transportation mode and the congestion and it can take very long time.

- **Schedule**: Digital communications and transactions can occur asynchronously and instantaneously, allowing users to send and receive data at any time without strict adherence to predefined schedules. For the physical internet the scheduling of physical shipments within the PI network depends on numerous factors such as transportation capacity, route availability, demand fluctuations and logistical constraints. As a result, scheduling physical shipments often requires actually an advance planning.

- **Emissions**: Data transmission over the digital internet generally has a lower and negligible environmental footprint compared to physical transportation, as it consumes less energy and generates fewer emissions per unit of information exchanged. But the transportation of goods within the PI network can contribute to greenhouse gas emissions and environmental pollution which actually proportional to the goods delivery.
- **Capacity**: The digital internet has virtually unlimited capacity for transmitting and storing data, thanks to the infrastructure and to different technologies such as cloud computing and distributed networks. For the physical internet the capacity of the PI network to handle physical goods is constrained by infrastructure capacity, vehicle fleet availability, storage space, and handling capabilities at PI-nodes.

	Digital Internet	Physical Internet
Cost	Electricity consumption cost	transportation, loading an unloading cost
Time	negligible	Significant
Schedule	transmission almost instantaneous	dynamic process
Emissions	Fixed cost, negligible	proportional to the goods delivered
Capacity	flexible, more critical	Sophisticated capacity management

Table 1.2: DI and PI differences

1.2.3 Physical Internet road-map

ALICE : Alliance for logistics innovation through collaboration in Europe

The European technology platform ALICE is set-up to develop and implement a comprehensive industry lead strategy for research, innovation and market deployment in the field of logistics and supply chain management in Europe. It is currently researching and working about PI in collaboration with other companies in several fields for the deployment of this concept all over the world.

ALICE has worked on several projects, among these projects we find the SENSE in which a Physical Internet road-map was developed to explain the development of PI over the next years over five areas of research:

- Logistics nodes : The concept of the Physical Internet anticipates transforming Logistics Nodes into Physical Internet nodes, characterized by standardized operations and protocols, the utilization of a range of standard and interoperable modular load units, autonomous hubs and automated material handling.
- Logistics Networks : PI Networks are expected to develop door-to-door services that are seamless, flexible, and resilient. These services aim to consolidate and deconsolidate all shipments within a logistics network, ensuring that all capabilities and resources are seamlessly visible, accessible, and usable. It also consists on defining routing algorithms, rules and protocols.The ultimate goal is to maximize the efficient utilization of these resources within the network and a real time connectivity among the networks.
- System of Logistics Networks: The Logistics Networks System is the foundational framework of the Physical Internet, demanding secure, efficient, and extensible services to facilitate the seamless flow of goods, information, and finances across logistics networks. The objective is to share gains and to ensure a global interconnectivity.

- Access and Adoption : Definition of the main requirements to access the Physical Internet through a logistics network.
- Governance : Defined by stakeholders rules, sustainability and to build trust among users.

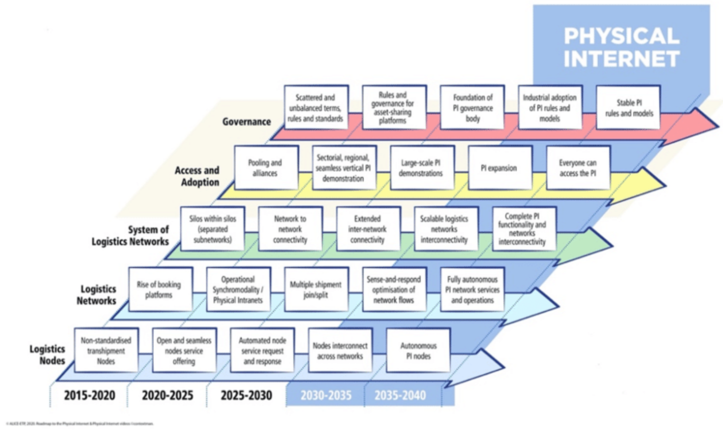

Figure 1.16: Physical Internet roadmap

A simulation experiment with Top retailers Carrefour and Casino in France and their 100 top suppliers was made to test the effectiveness of Physical Internet model. the results showed a potential for **32%** increase in profits, **60%** reduction of greenhouse gas emissions and **50%** of volume shifted from road to rail.

ALICE aims to make the Physical Internet a reality by 2030s with autonomous PI-nodes,stable PI-rules and models,interconnected nodes across the network where everyone can just access the PI.

1.3 Problems classification

Physical internet problems can be classified into two major groups [Chargui et al., 2022] :

- **Facility problems** where the problems related to the PI-Hubs design,scheduling, optimization and the internal routing are studied.
- **Network problems** where the problems related to the network design, the inter-connectivity,the location of PI-Hubs and the routing in a Physical internet network are studied.

1.3.1 Facility problems

Rail-Road and Road-Rail PI hubs

Many works and papers studied this type of PI hubs. Starting with [Ballot et al., 2012] that developed a functional design of Rail-Road PI hubs, the purpose of a PI road-rail node is to enable the transfer of PI containers from their inbound to outbound destinations. The authors provide an explanation of how PI-containers, vehicles, and trains move within the PI-hub. They were interested on two sets of key performance indicators (KPIs), from the customer's and from the operator's Perspective.

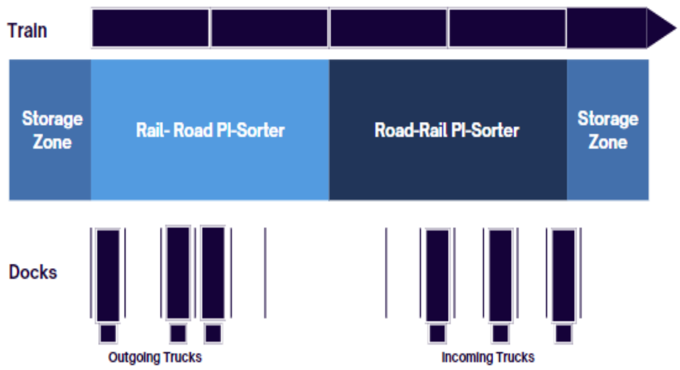

Figure 1.17: Rail- road and Road-Rail Pihub layout

Other works studied Rail-Road PI-hub optimization. Starting with this paper where [Walha et al., 2014] studied rail-road allocation and scheduling problem . This involves allocating each container to its truck and then assigning the docks to the correct destination. The -containers must be transferred from wagons to outgoing -trucks using the rail-road -sorters. The problem is identified as a special bin packing problem and the main performance objective is defined as the combination of two criteria to minimize :the number of used trucks and the distance covered by each container to reach the dock destination. Considering that the position of both containers and trucks affected to docks are changing over the time and that the containers are considered with same priority. This study proposed an heuristic based approach and a linear model and they are implemented in java and CPLEX respectively . In [Pach et al., 2014], a potential fields approach was developed to manage the unloading of a train, the routing of active -containers and the loading into trucks in rail-road PI hub context. The system was designed and simulated using Netlogo. This paper aims to examine the effectiveness and robustness of the routing mechanism considering many assumptions to make the system in critical conditions(considering a maximum number of -containers to manage and that the trucks are not properly aligned).The main performance indicator measured in the simulations is the evacuation time. It represents the time between the unloading of the first -container from the train and the loading of the last -container on its truck.The results indicated that the system bottleneck lies in the loading process, and the suggested approach demonstrated a decrease in both evacuation and loading times. [Walha et al., 2015]also identified the problem as a special bin packing problem with an objective is to minimize the distance covered by each container considering that the assignment of trucks to the docks must be done before the arrival of the train and the contents of wagons are known about 1 h before the arrival of the train. This study introduces a simulated annealing meta-heuristic which is then compared to the best Fit Grouping heuristic and they are both implemented in java. Various scenarios were tested to compare the effectiveness of all the methods. [Walha et al., 2016]worked about the same problem using the best Fit Grouping heuristic and simulated annealing meta-heuristic but also introducing a multi-agent based approach to generate reactive solutions and to deal with perturbations in a realistic context (considering the availability of the docks perturbation) and it was implemented in JADE. [Chargui, 2020]integrated energy consumption into the objective function. Several multi-objective approaches were introduced aiming to ensure the sustainability by minimizing both the cost of vehicle use as well as the energy consumption of PI-conveyors. Starting with the multi-objective model (MO-MIP) that formulated the problematic aiming to find the grouping of PI-containers as well as the allocation and planning of vehicles on the docks. The model is always implemented on CPLEX. A construction heuristic H0 and two meta-heuristics were subsequently introduced to adress the problem (MO-VNSSA et MO-VNSTS). These methods were implemented on C++. [Essghaier et al., 2023]studied the problem of uncertain multi-objective truck scheduling in Rail -Road PI-hubs. The problem was formulated as a fuzzy multi-objective mixed integer program (FMO-MIP) model considering two criteria to minimize which are the delay of trucks and the traveled distance of containers considering an uncertain arrival time of trucks that was defined as triangular fuzzy number. The resolution approach combines PI-constraint method for the minimization of the objective function and chance-constrained programming for uncertainty handling. The results of this work demonstrated that considering uncertainty during optimization process leads to an improvement in the quality of results and to obtain more robust solutions for case study.

[Chargui et al., 2018]considered a Road-Rail Pi-hub assignment problem where the PI-containers are unloaded from the trucks and transferred through the PI-Sorter and then loaded into the wagons. A mixed integer linear programming MILP model was developed with the main objective to minimize the number of used wagons and the total internal traveled distance of PI-containers considering that the inbound trucks can unload containers with different lengths, and each one of those containers has a specific destination, PI-containers with the same destination must be loaded in consecutive wagons, each one of the train's wagons must load only PI-containers that have the same destination and finally for simplification, one block of 5 wagons is considered for loading the PI-containers. A tabu search meta-heuristic was proposed to solve this model, starting by the assignment of the containers to the wagons where the first fit bin packing algorithm of Johnson was used to generate the first solution that was improved by Tabu search meta-heuristic to find all the possible combinations and they were both implemented in C++. [Chargui, 2020]also studied this problem. At first a MILP was proposed with the objective of minimizing the number of wagons used, the distance traveled by the PI-containers from the vehicles to the train wagons as well as the delay of the vehicles on the platforms considering wagon's capacity and PI container's destinations constraints and the model was implemented on CPLEX. Then a multi agent system combined with 3 hybrid meta-heuristics (VNS-SA, GRASP-SA et TS-SA) was proposed ,based on the same objective and constraints. The three hybrid meta-heuristics are developed in Java and the agents are created and implemented in the JADE platform (Java Agent Development framework).

[Chargui et al., 2019]developed a simulation-optimization approach to optimize Rail-Road and Road-Rail PI hub. This work aims to develop a robust solution that can handle unexpected perturbations(PI-conveyors failure). They suggested a mixed integer linear programming model with an objective to minimize the number of used wagons and outbound trucks, the distance traveled by PI-containers form inbound trucks to the wagons and from the wagons to the outgoing trucks and finally the tardiness of inbound trucks and the end time of processing outbound trucks. for the resolution approach they combined the Modified Threshold Accepting meta-heuristic and a perturbation simulator which generates perturbations at each local iteration of the MTA meta-heuristic to ensure that each new generated solution S is robust before considering it as the current best robust solution.

	Meta-heuristics	heuristics	Simulation
[Walha et al., 2014]		x	
[Pach et al., 2014]			x
[Walha et al., 2015]	x	x	
[Walha et al., 2016]	x	x	x
[Chargui, 2020]	x	x	x
[Chargui et al., 2018]	x	x	
[Chargui, 2020]	x		x
[Chargui et al., 2019]	x		x

Table 1.3: Resolution approaches

1.3.2 Network problems

Starting with [Montreuil et al., 2013], they studied the interconnectivity in the context of Physical Internet similarly to the case of Digital Internet. From a logistic perspective, the interconnectivity refers to making the transportation and transfer of physical goods smoother and easier, to handle their storage and treatment efficiently and finally to share the responsibilities between the different actors and stakeholders within the logistics chain. Universal interconnectivity is the key to make Physical Internet an open, global, efficient and sustainable system.

They supposed that universal interconnectivity could be attend through physical, digital and operational interconnectivity :

- **physical interconnectivity:** The idea is to guarantee a seamless movement of Physical objects within the Physical Internet network by encapsulating the goods in standardized and modular containers.
- **Digital interconnectivity:** It is about ensuring a meaningful information exchange between the different nodes and actors of our PI network. This includes the tracking of objects using the Internet Of Things.
- **Operational interconnectivity:** It consists on using business constraints and respecting operational protocols to make the exploitation of Physical Internet easier.

[Sarraj, 2013]proposed in his work the main concepts,protocols and the operating principles for the routing of PI-containers in the physical internet network. He supposed that the Physical Internet would have a hierarchical architecture in the form of several autonomous systems(AS) where a node will no longer have knowledge of the complete state of the network but only that of the SA to which it belongs. A routing algorithm based on the juxtaposition of arcs was introduced for the routing in PI supply chain network. His studies were based on a real supply chain network in France 1.4 and he considered three databases: real flows of mass retail products: liquids, groceries and DPH (Drugstore, Perfumery and Hygiene)like mention in ??.Infrastructure (roads, rails) from original IGN© and finally a PI network, this database was the subject of research work carried out by EPFL-Lausanne in Switzerland during the research project carried out with PREDIT. A multi-agent model based on the discrete event approach, implemented in XJ's AnyLogic simulation software was introduced as a resolution approach. Various scenarios are tested to evaluate the performance of the network considering many key performance indicators (KPI): Economic, Environmental and societal KPIs. The results of this simulation demonstrated that PI gives very encouraging results. The load is increased by almost 20percent the use of rail transport leads to a 60percent reduction in CO2 emissions in France, this also includes a reduction on delivery times. Finally, all the scenarios showed a reduction in transport costs comparing to the classical SC (between 4percent and 33percent depending on the scenarios).

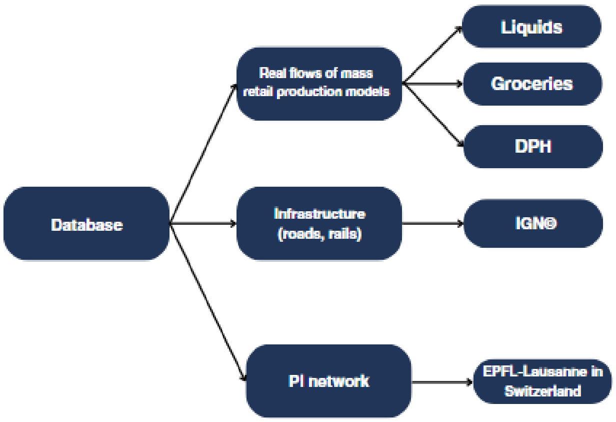

Figure 1.18: Database

Nodes	Facilities	Warehouses	Distribution centers	Total
Number	303	57	58	418

Table 1.4: Network nodes.

The work of [Fazili et al., 2017] is based on [Sarraj, 2013] paper. In order to understand the Physical Internet (PI), the conventional (CO), and the hybrid (HY) logistics systems, a simplified road network in Eastern Canada was considered. Eleven cities in eastern Canada are the nodes in the network (The network has a tree structure) and only five of this nodes are PI transits (using maps.Google.com). VRP-like routing and BPP (Bin packing problem)techniques are used in this paper .A three-phased optimization framework was proposed to compare the performance of logistic systems based on Monte-Carlo simulation: Container packing optimisation,Truck routing optimisation and Truck scheduling optimisation. Physical internet demonstrated superior performance from an environmental point of view and it benefits from lower total driving time and social costs associated with truck driving. Finally, the results showed that the efficiency of PI depends on the efficiency of its transit centers.

[Yang et al., 2017] were interested in a single-product inventory problem with network supply disruptions with uncertain demands and stochastic supply disruptions. The main objective of this work was to minimize the total annual logistics costs and to determine suitable inventory control decisions. A simulation- optimization approach with heuristic based on a dynamic source selection strategy named Minimum Distance strategy from [Pan et al., 2015] and Pan et al. (2015) works was proposed. Many scenarios were tested to evaluate the performance of the physical internet supply chain network. The results of their experiments indicate the superiority in terms of resilience of the Physical Internet inventory model against classic inventory models. His studied were also based on a real network in France 1.19

[Kantasa-Ard et al., 2021b] worked about demand forecasting in the context of Physical Internet. This studies were based on a real network in the lower northern region of Thailand, this network is composed of one production lines, three hubs and two retailers. The experimental data were obtained from the Thai Office of Agriculture of the consumption of Corn, Pineapple and Lassava for the period from January 2010 to December 2017. As a resolution approach they proposed a machine learning resolution approach to

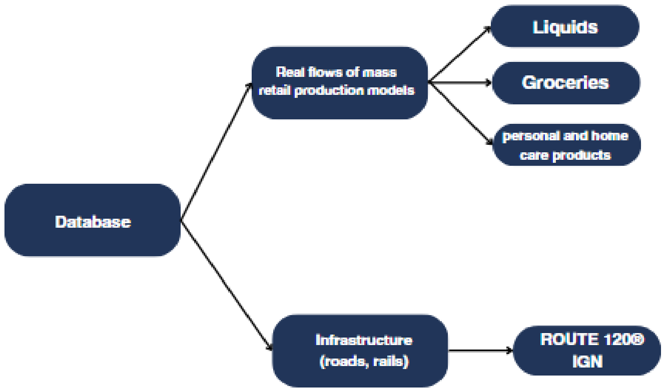

Figure 1.19: Network database

improve the predictions because classical methods have many limitations. At first, they proposed a forecasting model based on LSTM(Long short term memory) recurrent neural network, then they tuned the hyper-parameters of the model using a hybrid meta-heuristic combining Genetic algorithm and Scatter Search to improve the predictions.Finally, they simulated the Physical Internet network using forecasting data to evaluate its performance on reducing holding and transportation cost.The model was then introduced in NetLogo multi-agent plateform. The results showed a variation of around 0.09–1% in holding costs when comparing forecast and real demand, and a range of 0.3–1.07% in transportation costs.

In [Kantasa-Ard et al., 2021a], a multi depot vehicule routing problem (MDVRP) was studied and compared between classical supply chain and Physical internet. The problem of routing was formulated with a Mixed Integer Linear Programming (MILP) model and this research focuses only on the delivery part from PI-hubs to retailers. Two main assumptions were considered: first the truck can return to the closet hub and it is not forced to return to the starting hub, and secondly inventory level at each hub were considered and not only trucks capacity. The experiment was based on real data of the daily forecasting demand of a commodity crop in the Thailand's northern region from [Kantasa-Ard et al., 2021b]. For the problem resolution, a random iterated heuristic was proposed to generate the first solution that was improved using Nearest Neighbor Search (NNS). The results of the two solutions (MILP and IRH) were performed by comparing the transportation cost and computational time. The results showed that IRH-NNS demonstrated better performance for a large number of PI-hubs and retailers and it takes less computational time than the MILP method. For a realistic context, a vehicle routing problem with simultaneous pickup and delivery problem VRPSPD [Kantasa-ard et al., 2023] was after that proposed to solve routing problems always in the context of Physical Internet. As a resolution approach a MILP, Itarated random heuristic and two meta-heuristics (Simulated annealing and random local search) were introduced always comparing transportation and holding costs.

[Nouiri et al., 2021] proposed a multi-agent model to compare the performance of a Physical internet network with the one of a classic supply chain based on transportation and holding costs as main performance indicators to measure and compare the resilience of the network. The model was proposed to generate reactive solutions and to deal with external perturbations in a realistic context. Each agent in the model represents a node in the Physical Internet (hub, plant, and retailer) or a transportation link (truck) between nodes. External perturbations were simulated as periods of unavailability at a random hub or distribution center, based on three levels of unavailability: low (node unavailable 1 day), medium (unavailable between 3-5 days) and high (5-8 days of unavailability). In the case of PISCN three replenishment policies were defined: Random, closet and hybrid method. The model was tested on a real network composed of one plant, three hubs and two retailers based on real data of monthly white sugar consumption rate from January 2015 to September 2019 in Thailand. The results of the simulation demonstrated the efficiency of PISCN compared to the classical SCN especially for the transportation cost. The simulation results also showed the importance of the replenishment policy on transportation and holding costs.

[Peng et al., 2021] studied a many to many network structure (many plants supply many retailers). In this paper the physical internet key components were captured, Physical Internet resilience was studied and pre-event(additional production, storage, and handling capacities,) and post-event (Reconfiguration of flows and the recovery from any production, storage, and handling capacities) mitigation strategies were considered. A two-level heuristic algorithm was proposed for the problem resolution. The results of this work showed that using the interconnectivity between the PI-nodes will increase the flexibility achieved by our Physical Internet system.

[Cassan et al., 2023]proposed a new capabilities-based theory for routing and data sharing in the PI network. PI capabilities refer to the specific services or functionalities offered at PI nodes.They supposed that the network is created by combining the PI-nodes with their PI-capabilities with a set of PI-transporters and they proposed that the network is decentral .A shortest-path algorithm was then build to find routes for containers depending on their performance. The performance is represented by an objective function that aims to minimize distance, monetary cost, duration and greenhouse gas (GHG) emissions. The algorithm was then validated using an Agent-Based Model (ABM). The results showed that this approach is feasible and can be applied in a decentralized system.

[Luo et al., 2021]A Physical Internet-enabled customized furniture delivery system(PI-CFDS) was introduced in this article. At the beginning they considered a PI-enabled smart logistics facility where they focused on PI-containers and material handling processes and their effects on transportation time, costs and profits. On second place, they introduced a mathematic modelization of a VRPSPD with profits maximization and a Genitic algorithm meta-heuristic for problem resolution. Finally they based this research on a real-life data of a leading customised furniture service in China. The results showed that Physical Internet demonstrated superior performance than the traditional solution in most of cases.

In [Peng et al., 2020] work, an integrated production inventory-distribution system was addressed always to study the sustainability of the Physical internet network. The problem was represented as a a multi-objective mixed integer linear programming model (MOMILP) with three different objective functions, each one represents and aspect out of the three aspects of sustainability. The economic aspect is represented by the total cost that combines production, loading and unloading, inventory and transportation cost. The environmental objective is measured by the overall green house gas emissions of all the network using a fuel conversion factor to assess GHG emissions based on fuel consumption. Finally the social aspect is calculated based on the social impacts of accident risks in all periods. The model was solved using using the augmented ϵ–constraint method, than the sustainability performance of the PI-enabled model was compared with that of models enabled by the traditional (TR) and horizontal collaboration (HC) networks. The results show that the PI actually showed better performances in term of different objectives and it guarantee significant sustainability performance advantages.

After categorizing existing research based on our state of the art, we noticed a significant gap and lack of works concerning the Location Routing Problem within the Physical Internet context. As a result, we chose to focus on this particular issue in our report.
Additionally, we observed that several studies have utilized the Simulated Annealing (SA) metaheuristic. Consequently, we have attempted to enhance this metaheuristic by combining it with other existing approaches.
We also noticed the widespread use of NSGA-II in the literature, which led us to work with the AMOSA (Archived Multi-Objective Simulated Annealing) algorithm. Consequently, we conducted a brief state-of-the-art review on AMOSA.

Combining artificial intelligence and meta-heuristics

Numerous studies have explored the combination of meta-heuristics with strategies and concepts from artificial intelligence to achieve superior results.

For example, [Spieksma et al., 2020] Combined deep learning and simulated annealing to solve Vehicle routing problem with time windows(VRPTW). The paper studied the case of taxi tours in a city to minimize service time while serving all the clients. A Convolutional neural network and a multilayer perceptron were introduced for full check of the feasibility of the generated solutions and to ensure the respect of the model's different constraints.

[Nezamoddini et al., 2020] studied a risk-based optimization model for integrated supply chains. The model aims to study the routing of vehicles in a supply chain network composed of :Suppliers, plants, distribution centers and Markets. The main objective is to maximize the profits in an environment with different disturbances and perturbations like natural disasters and delays. A genitic algotithm was proposed for the problem's resolution and it was combined with Back-propagation learning :a neural network based algorithm to guide the genetic algorithm with its findings and the solution improvement based on the feedbacks.

[Cooray and Rupasinghe, 2017] proposed a new combination of machine learning and genetic algorithm for the energy minimization vehicle routing problem (EMVRP). The main objective of the proposed model was the minimization of energy consumption while respecting capacity and other constraints. The authors introduced the a K-means clustering algorithm (3 clusters) for the genetic algorithm's parameters tuning :mutation rate, size of the population, and number of generations.

[El Midaoui et al., 2022] studied the case of blood delivery between hospitals and blood centers, starting with a single depot vehicle routing problem case, then the multi-depot case. The main objective of the proposed model was the minimization of both distance and total costs in the distribution network. The paper introduced fuzzy logic for data fuzzification and a reinforcement learning algorithm: Transfer learning for demand prediction.

[Vermeulen, 2019] combined simulated annealing with machine learning for the capacitated, periodic and stochastic vehicle routing problem. The proposed model studied the case of waste collection with real-life data of Van Gansewinkel group. . In his approach, the author introduced the Glove algorithm, an unsupervised learning technique, to modify the acceptance function within the simulated annealing meta-heuristic. The aim of this research is to develop an algorithm that combines these two methods by taking the information collected and obtained with GloVe and reincorporating it into Simulated Annealing, so that significantly better solutions can be obtained.

[Ma et al., 2018] addresses the road screening and the distribution of hazardous materials in a city. The authors proposed a multi-objective model with minimizing at the same time the road risks and the total vehicle travel time. The authors proposed the combination of Lavenberg- Marquart neural network using Gradient descent algorithm and Gauss- Newton methods with genetic algorithm. The proposed approach aims to use the GA to optimize the initial weight and threshold value of the neural network.

[Vincent et al., 2024]worked on a new proposed problem which is the set team orienting problem with time windows with a main objective to maximize the total profits. Clustering concept was considered in this paper while assuming that only one costumer is visited in each cluster. The authors combined simulated annealing meta-heuristic with the epsilon-greedy strategy which is a reinforcement learning strategy to balance the trade-off between exploration and exploitation for the neighborhood search strategy. The proposed combination aims to find the better movement between a list of different movements to generate new solutions that will lead to the best solution with the best objective function.

For our study, we were interested in the way [Vincent et al., 2024] proposed their combination of simulated annealing and the epsilon-greedy strategy to choose neighboring solutions. The proposed approach is explained in chapter 3.

Literature review about AMOSA

AMOSA Meta-heuristic has been employed in numerous fields as a resolution approach in various works.

Starting with [Haddou Benderbal and Benyoucef, 2019] that combined AMOSA with a exhaustive search based heuristic as a resolution approach for a Re-configurable manufacturing systems problem. The authors in this work studied the relationship of this system with two different environment: logical and physical environments. The main studied problem was the disposition and the layout of machines while considering the evolution of product's family. The main objective of this paper was the determination of the best machine layout for all the selected machines of the product family.

[Maliki et al., 2021] studied a dynamic ,mobile and multi-period facility location problem in the context of bloodmobiles network. A multi-objective model was addressed that aims at the same time to minimize the economic cost of inventory holding and transportation costs as a first objective and to maximize the blood quantity collected in the located bloodmobiles as a second objective. Since it is a bi-objective model the authors proposed AMOSA metaheuristic as a resolution approach that provides a set of non-dominated solutions. To deal with this issue, the TOPSIS technique (Technique for Order Preference by Similarity to Ideal Solution) was used for the classification and ranking of the solutions. The proposed approach was tested under real-life data of Tlemcen city in Algeria.

[Demir et al., 2022] worked on Multi-objective capacitated multiple allocation hub location problem that aims to study the connection between the different nodes and the routing of flow between them for the network construction. A bi-objective model was addressed that aims to minimize both the total cost (transportation cost and hubs opening costs) and the minimization of the maximum travel time. The authors proposed two metaheuristics: AMOSA with five different neighborhood operators and NSGA2 with two new problem-specific mutation operators. The effectiveness of both algorithms was tested under two known dataset: Turkish and Australian Post (AP). The results showed that AMOSA demonstrated better performance for small size instances, while NSGA2 for large size instances.

[Niyomubyeyi et al., 2020] used AMOSA to solve evacuation problems in disaster management to minimize the impact of disasters on urban communities. The author formulated the problem as a multi-objective optimization model. The first objective function aims to minimize the accumulated distance and focuses on assigning each building block to the nearest shelter, aiming to reduce overall travel distance while the second objective function aims to minimize overloaded capacity to distribute the overload of the evacuee population evenly among all shelters. The author compares four meta-heuristics including AMOSA : NSGA2, multi objective artificial bee colony MOABC and multi-objective standard particle swarm optimization MOPSO. The proposed meta-heuristics were compared according to different criteria : the effectiveness, efficiency, repeatability, and computational time of each algorithm where each algorithm showed better performance in one of them.

[Bandyopadhyay et al., 2013] combined AMOSA with the concept of epsilon-dominance to obtain a new variant of the algorithm that was tested using the classical knap-sac problem. The proposed algorithm was compared with several other algorithms : Classical AMOSA, NSGA2 and Multi-Objective Evolutionary Algorithm (MOEA) with a number of objective ranging from two to fifteen, and a number of variables, which can range from one to thirty.

Conclusion

In summary, this chapter addresses the need for innovative solutions in global logistics to address economic, environmental, and societal challenges. Traditional supply chains are insufficient, and the Physical Internet offers a transformative approach. By using standardized containers and dynamic routing, it aims to improve efficiency, reduce costs, and lower environmental impact. We also highlighted ALICE's role in promoting logistics innovation. Embracing the Physical Internet's principles will help create more resilient, efficient, and sustainable supply chains for the future.

After classifying different articles about the physical internet, We have chosen to focus on addressing the Location Routing Problem, recognizing its significance in optimizing logistics operations. In the forthcoming chapters, we will discuss the Location Routing Problem in detail, exploring its classification and implications within the context of the Physical Internet.

Chapter 2

Location routing problem

Introduction

This chapter delves into the Location Routing Problem (LRP), a significant logistical challenge that combines elements of the Vehicle Routing Problem (VRP) and the Facility Location Problem (FLP). The LRP aims to optimize the distribution of goods from multiple facilities to various customers, after choosing which facilities should be located to optimize the network to enhance efficiency in logistics operations.

We begin by exploring the classification of the FLP and VRP across different criteria, including problem structure, objectives, solution methodology and approaches, and application domain. This classification provides a structured framework for understanding the complexities of this problems and their various manifestations in real-world scenarios.

Throughout our analysis, we leverage insights from a diverse array of scholarly articles and research papers. These sources offer valuable perspectives on different approaches, algorithms, and applications related to the LRP. By synthesizing this wealth of knowledge, we aim to provide a comprehensive overview of the LRP and its implications for logistics optimization.

Ultimately, this chapter serves as a foundation for subsequent discussions on the Location Routing Problem (LRP). By establishing a comprehensive understanding of the problem and its classifications, we can delve deeper into specific methodologies, algorithms, and case studies in the following chapters. Through this exploration, we aim to uncover actionable insights that can inform decision-making and drive innovation in logistics management within the context of the Physical Internet.

2.1 Definition

The location routing problem (LRP) was defined by Bruns [Bruns, 1998] as "location planning with tour planning aspects taken into account." According to [Nagy and Salhi, 2007] location routing problem is not a well defined problem like the vehicle routing problem or like the travelling salesman problem. The main objective of LRP consists on solving a facility location problem FLP that we consider as the "master problem", but in order to achieve this we need at the same time to solve a vehicle routing problem (VRP) or the "subproblem". The FLP is part of the strategic decision level, where decisions typically have long-term validity. On the other hand, the VRP belongs to the tactical or operational decision level, where decisions are valid for a shorter period.

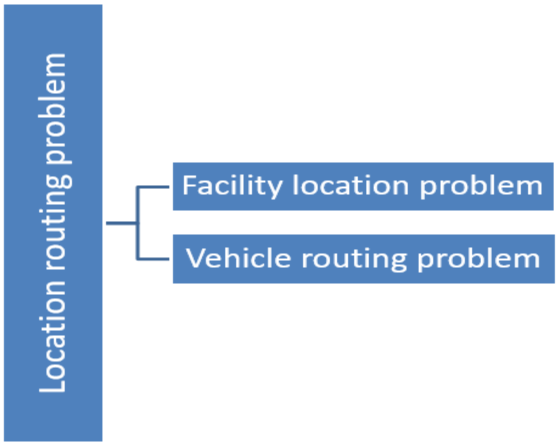

Figure 2.1: Location routing problem

2.2 Facility location problem

2.2.1 Definition

The study of location theory formally began in 1909 when Alfred Weber [Weber, 2002] considered how to position a single warehouse so as to minimize the total distance between it and several customers. In the facility location problem, we have a set of potential locations for facilities and a set of client demands that need to be satisfied.The goal is to open a fixed number of facilities at some of these locations and link each demand point (client) to an open facility to fulfill its demand. The primary objective is to minimize the total cost associated with opening facilities, as well as the distribution and assignment costs[Mahdian and Pál, 2003].
According to [ReVelle and Eiselt, 2005], the location model has four basic features:

- The customers those are located at points or routes.
- The facilities that must be located.
- The geographic space or surface where the customers and facilities are located.
- The metric that indicates the distance, cost, or time between the locations of clients and facilities.

Facility Location problem is presented as follows. We have a set of potential facilities F, that need to satisfy a set of clients D, we have also a weighted graph G defined over the vertex set $F \cup D$. Each edge in this graph is associated with a connection cost, denoted as c.[Mahdian and Pál, 2003]

2.2.2 Classification of Facility Location Problems

There are numerous classifications for the facility location problem in the literature, actually location problems may be divided into four main classes: analytic, network, continuous, and discrete models. I structured my classification according to the categories mentioned in this work [Adeleke and Olukanni, 2020].

Single Facility Location Problem (SFLP)

According to [Moradi and Bidkhori, 2009],Single facility location problem is the simplest type of location problems. These problems occur on a regular basis like layout problems (e.g., location of a machine in a shop, or items inside a warehouse), or on a larger scale like choosing the location of a warehouse to serve demands of customers.
Some typical examples of one-facility location problems are the location of:

- New warehouse relative production facilities and customers.
- Hospital, fire station or library in a metropolitan area.
- New classroom building on a college campus.
- New airfield to be used to provide supplies for a number of military bases.
- Component in an electrical network.

In real-life scenarios, different factors influence location decisions based on the scale of the problem, it can be an international, national, statewide, or communitywide problem. For example, when deciding on a manufacturing facility location in a foreign country, factors like political stability, exchange rates, business environment, and taxes are crucial. On a smaller scale, focusing on a few communities, factors such as local services, property tax incentives, business environment, and government regulations are important.
SFLP focuses on determining the optimal location of a single new facility , with the objective of minimizing the total distance (measured either in Euclidean or rectilinear metrics) between the new facility and existing locations on the plane. A simple general formulation of the problem is [Adeleke and Olukanni, 2020] :

$$Z1 = \min \left\{ f(x) : f(x) = \sum_{i=1}^{n} w_i d(x, p_i) \right\}$$

where x = (x, y) is the distance coordinate of the location of the new facility; d(xi,yi) is the distance between the new facility and the planar locations; pi = (ui,vi) are the coordinates of the planar locations; wi represents the weight of existing facilities; i and n are the index and number of existing facilities, respectively

Multi Facility Location Problem (MFLP)

Multi facility location problem consists on locating more than one new facilities in certain potential positions with respect to locations of a number of existing demand points, the locations of which are known. MFLP is an extension of SFLC, but with two main conditions:

- At least two facilities are to be located.
- Each new facility is linked to at least one demand point.

Some typical examples of multi-facility location problems are the location of:

- A system of warehouses to serve a set of predetermined regions.
- Industrial and commercial establishments.
- large organizations (such as the Federal government).[Daneshzand and Shoeleh, 2009]

Fixed Costs Capacitated Facility Location Problem (FC-CFLP)

The capacitated facility location problem is a classical and real-word optimization problem, where each facility's ability to meet demand is limited. Modeling such a problem necessitates fulfilling clients demand and respecting capacity limitations. The main objective is to minimize the total cost considering both variable costs related to the flow and fixed costs associated with an open facility. Many researches has focused

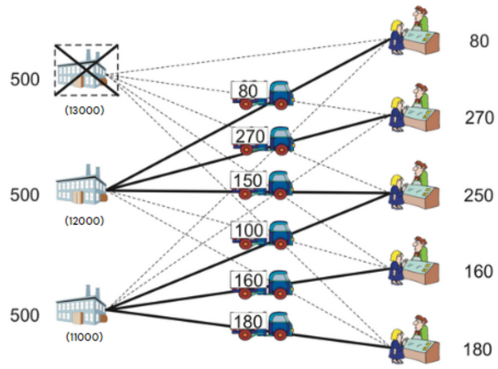

Figure 2.2: Example of FC-CFLP

Capacitated p-Median Facility Location Problem (CpMFLP)

This is a discrete problem where the main goal is to determine p facilities from n candidate facilities(n ¿ p) in order to satisfy a set of demands. The selected facilities are called the medians or concentrators.
To represent the problem, we can consider a connected graph where customers are represented as nodes and distances between them are defined by edges, the main objective is to open P new facilities to meet customer demands while minimizing the costs. This problem, known as the p-median problem, aims to strategically position these facilities to minimize the total weighted distance between each customer and their nearest facility in the network.

Some works that studied this problem, we have [Correa et al., 2004] where the authors addresses an application of the capacitated p-median problem for the selection of facilities for university's admission examination, precisely for The Federal University of Parana (UFPR), located in Curitiba, Brazil. The goal is to select 26 classes among 43 available ones. Each class has a fixed capacity(a maximum number of students who can take an exam at that class). At the same time each student must be assigned to exactly one facility. A Genetic algorithm was proposed as a resolution approach that was combined with a new heuristic called "hypermutation". Finally the proposed algorithm was compared with tabu search metaheuristic.
In a second work [Abareshi and Zaferanieh, 2019], a bi-level model was introduced to evaluate a CpMFLP. At the higher level of analysis, the classical capacitated p-median problem is addressed with the objective of minimizing the costs incurred in both locating facilities and fulfilling demands. then at the lower level, a log-based model is utilized, stemming from the minimum information approach, to determine the optimal allocation solution. Finally, a Lagrangian dual approach was proposed to reduce the bi-level model into a nonlinear problem, which is solved by comparing two linear mixed-integer problems.
In another context [Maliki et al., 2021] studied the p-Median Facility Location Problem in the context of blood collection for different periods. Two main objectives have to be opti-

mized : maximizing the collected quantity and minimizing the total cost of bleed delivery network. A multi-objective approach based on an Archived Multi-objective Simulated Annealing Approach (AMOSA) was proposed to address this problem. As an application case, this approach was applied on Tlemcen- city(Algeria) blood network.

Covering Location Problems (SCLP)

In SCL problem, clients can receive their requests from potential facilities depending on the distances between clients and facilities. A client's request can only be fulfilled at a facility if the distance between the customer and that facility is equal to or less than a predetermined value called the threshold distance or coverage radius. SCLP can be classified into two main cases based on customer demands. In **total SCLP**, every demand point is covered, while in **partial SCLP**, only a subset of locations is included.

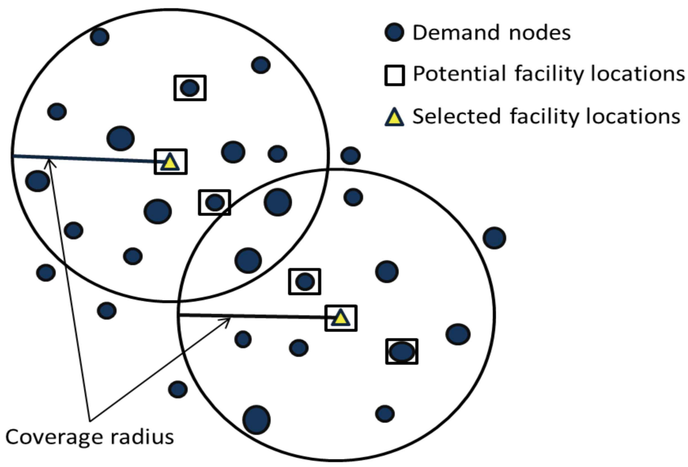

Figure 2.3: SCLP

[Bangun et al., 2022] worked on the determination of Temporary Waste Disposal Site (TWDS) in Sako District, Palembang City, Indonesia. The problem was formulated as a set covering location problem and p-median problem. The main objective was to minimize the number of candidate locations. The problem was solved using LINGO 18.0, then a greedy heuristic was introduced as a second resolution approach.

Another application of SCLP problem is locating first aid centers in humanitarian logistic services in Japan [Alizadeh and Nishi, 2020]. Actually the problem was represented as an SCLP combined with maximal covering location problem to obtain a hybrid covering model that considers strategic and tactical planning decisions in a multi-periods model. The main objective was balancing the revenue generated from covering demand points with the costs associated with opening facilities. The model was solved using IBM Cplex and the results were compared to another existing models using different scenarios.

[Šarac et al., 2016]introduced SCLP to organize the postal network in Serbia. The main objective was the minimization of the total number of located facilities. The authors compared their model to an existing model which is based on four different population criteria. Finally both models were compared while applying real date from the Serbian postal network.

Undesirable Facility Location Problem (UFLP)

The UFLP is a type of Facility Location Problem (FLP) categorized as a maxisum model. Unlike p-median problems, where facility drives the minimization of objective functions related to distance or cost, in maxisum models, the focus is about to strategically locate facilities farther away from intended users.[Melachrinoudis, 2011] Undesirable facilities are those facilities that have adverse effects on people or the environment. These facilities produce pollution, nuisance, potential health hazards, or pose dangers to nearby residents. Additionally, they may also cause harm to nearby ecosystems.

[Song et al., 2013] studied this type of facility location problem, where the authors cited many examples like electric transmission lines and recycling centers. They also used the expression “not in my backyard” (NIMBY) to describe correctly this type of problems. The objective function was expressed using three different representations : linear, convex and concave trend, these functions trends actually represents the cost while respecting a maximum distance restriction. The model was solved using CPLEX, then a Genetic algorithm meta-heuristic was introduced to compare the results of both approaches.

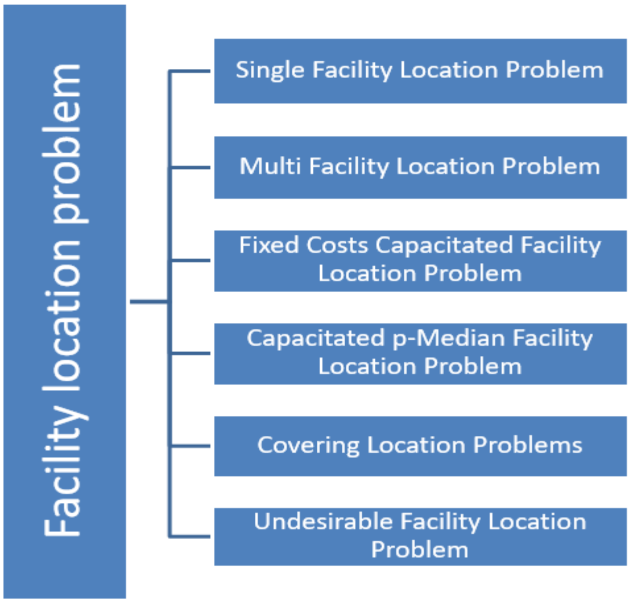

Figure 2.4: Facility location problem classification

2.3 Vehicle routing problem

2.3.1 Definition

According to [Christofides, 1976] The vehicle routing problem (VRP) is a generic name given to a whole class of problems involving the visiting of ”customers” by ”vehicles” starting from one or many center points (eg: depots). These problems take their name from the basic practical problem of supplying geographically customers with goods using a number of vehicles operating from a common goods depot. The problem aims to optimize different objectives like the total distance travelled, total time and total cost minimization. Vehicle routing problem can be represented as follows. We have a set of N costumer where:$X = \{x_i \mid i = 1, \dots, N\}$. D a set of depots where $Y = \{y_i \mid i = 1, \dots, D\}$ that may be equal to one where we have a depot with unlimited capacity, and finally a set of V vehicles where $Z = \{z_i \mid i = 1, \dots, V\}$ that will serve the clients starting from depots.

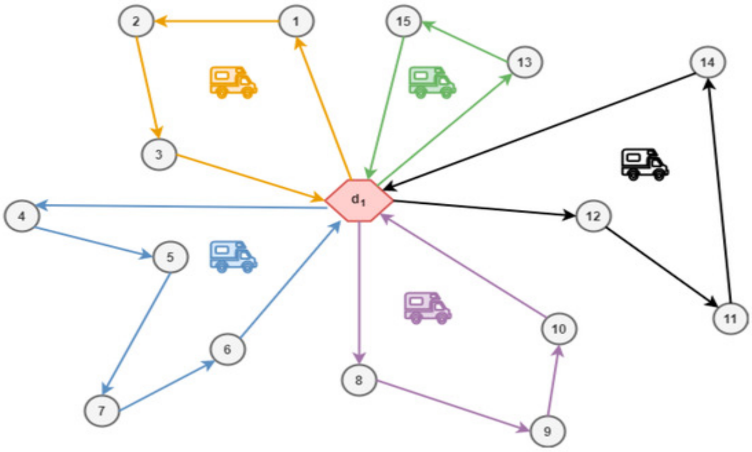

Figure 2.5: Vehicle routing problem

2.3.2 Classification of vehicle routing problem

The Vehicle Routing Problem (VRP) offers a range of classifications, each suited to different logistical scenarios. From simple cases like Capacitated VRP to more complicated ones like VRP with Time Windows and dynamic VRP that reflects real-life scenarios. These classifications play a crucial role in addressing a wide array of challenges in transportation planning and scheduling. By categorizing VRP variants based on specific constraints and objectives, many classifications have been proposed. My work and the following definitions are based on the paper by Zhang [Zhang et al., 2022].

Capacitated vehicle routing problem

CVRP is an extension of VRP, where load and vehicles capacity constraints are introduced. The optimization process must carefully balance the number of vehicles, cargo distribution, and route planning to minimize the total traveled distance. Actually these constraints limit the generation of new solutions for optimized objects and reduce the algorithm's global search capability.

Many works studied this type of problems, starting with [Ng et al., 2017] where a Multiple Colonies Artificial Bee Colony algorithm was introduced to improve the exploitation of solutions and to avoid the local optimum. The main objective of the proposed model was the minimization of the total travelling time. The proposed algorithm was tested under different scenarios and using existing benchmarks from the literature.
As a second example,Hannan [Hannan et al., 2018] studied waste collection while formulation this problem as CVRP, with different capacities for both trucks and bins.A modified particle swarm optimization (PSO) algorithm was proposed for the model's resolution, to determine the best waste collection and route optimization solutions. The proposed model was compared with existing works that used different algorithms, like Genetic algorithm [Wang et al., 2004], Simulated annealing and discrete particle swarm optimization [Chen et al., 2006].
Another case study of CVRP [Ibrahim et al., 2019] where the authors proposed another model that aims to minimize the total transport cost in a delivery network. The authors applied different techniques for large size models resolution to optimality like : Column generation, Google's OR Tool (OR-Tool) and a reinforcement learning algorithm. The model was also solved using gurobi to compare the results with the different proposed

approaches.

Vehicle routing problem with time windows

VRPTW involves adding time constraints to a vehicle routing problem. Each customer has a specified time window restriction at which service must begin and trucks must respect these constraints and might deliver the costumer's request at a specific time. These time windows can be either hard or soft. For hard time windows, vehicles must start service within the specified window, waiting if they arrive early and rejected by the customer if they're late. Soft time windows, on the other hand, allow service to begin outside the window but incur a penalty for doing so. The key distinction between the two is that hard time windows involve waiting or rejection, while soft time windows involve penalties instead.
This type of vehicle routing problem can be represented as follows. We have a set of N costumer where:$X = \{x_i \mid i = 1, \ldots, N\}$. D a set of depots where $Y = \{y_i \mid i = 1, \ldots, D\}$ that may be equal to one, here we are in the case of one depot with unlimited capacity, and finally a set of V vehicles where $Z = \{z_i \mid i = 1, \ldots, V\}$ that will serve the clients starting from depots. Each client x has a staring time S(x_i) and an ending time E(x_i) for the day which represents our time window.

For example, [Revanna and Al-Nakash, 2022] studied a VRPTW in the context of products pickup and delivery. The vehicles start their routes from a common depot, pickup from various warehouses and than deliver to the costumers within the time window defined by the this customer and return back to the depot. The main objective of the model was to minimize number of vehicles employed, the total logistics cost and to reduce carbon emissions and to maximize satisfaction.As a resolution approach the authors introduced an Ant Colony with K-Means Clustering hybrid algorithm.

Another work presented by Keskin [Keskin and Çatay, 2018] where an electric vehicle routing problem with time windows was introduced. Actually an electric vehicle has a limited driving capacity and range due to its battery capacity and it necessitate recharging to complete its route. The authors considered three recharging configurations: normal, fast and super-fast recharges depending on charging energy but also on the cost. The main objective is to minimize the total recharging cost and the number of used vehicles. For small size instances the model was solved using CPLEX, than for large size instances a two phase metaheuristich approach was introduced : in the first phase Adaptive Large Neighborhood Search (ALNS) metaheuristic was introduced than in the second phase the solutions were imrpved using an exact method.

Split Delivery vehicle routing problem SDVRP

In the traditional VRP each customer's demand, which is typically less than the vehicle's maximum loading capacity, must be fulfilled using a single vehicle and service operation. The concept of split delivery was introduced for the first time by Dror and Trudeau [Dror and Trudeau, 1989].Different studies worked on this type of problems while comparing it with the classical case, and the results showed that allowing the splitting and distribution of customer demands using different vehicles during product delivery from the distribution center leads to superior performance in terms of both driving distance and cost and the total number of vehicles required.

As I mentioned before, many works studied on this type of problems, for example Claudia [Archetti et al., 2014] proposed a branch and cut method to solve the SDVR problem. The main was the minimization of travelling cost using two relaxed formulations: Two-index vehicle flow formulation and Single commodity flow formulation. The model was tested under four different benchmarks to test the feasibility and the optimality of the proposed approach.

Marcos [Silva et al., 2015] also worked on a SDVRP model for two different cases : with unlimited fleet SDVRP-UF and with limited fleet SDVRP-LF .The author a introduced a multi-start Iterated Local Search (ILS) based heuristic that includes Multiple-k-Split perturbation mechanism.

Yong [Wang et al., 2014]studied a vehicle routing problem with split pickup and delivery (VRPSPDP). The authors introduced a two-stage hybrid heuristic that was then compared with the results of TSA, PSO, and PHA meta-heuristic for 18 existing benchmarks (solomon dataset).The computational results showed that the proposed algorithm demonstrated superior performance to these three algorithms for VRPSPDP in terms of total travel cost and average loading rate.

Dynamic vehicle routing problem DVRP

In classical VRP or Static vehicle routinf problem, customer demand, vehicle travel time and weather time are assumed to be known or "static" and will not change in the process of path planning and implementation.But in the actual logistics system and real life distribution networks there may be many dynamic factors such as customer demand, traffic conditions, weather conditions, personnel, vehicles, etc., which cause great troubles and perturbations to vehicle routing. It is necessary to dynamically arrange vehicle routing according to the constantly updated system information. This dynamic approach allows more flexible and responsive routing strategies to handle this changing and dynamic operational conditions more effectively.

DVR problem has many characterises :

- It can receive all of kinds of real time data.
- All this dynamic information are random and uncertain.
- Vehicle paths need to be updated dynamically.
- It has fast response to dynamic information.

According to [Zhang and Van Woensel, 2023] DVRP can be classified into three different classes :

- **The DVRP with random requests (DVRPRR)** : Customers, who are waiting for services, dynamically submit requests during the planning horizon but their exact numbers and locations are not fully known in advance.
- **The DVRP with random demands (DVRPRD)** : The costumers numbers and locations are know in advance, but not the amount of their demand.
- **The DVRP with random travel times (DVRPRTT)** : the travel times between locations or the travel speeds of vehicles are time-dependent and random and they depend on traffic conditions. (DVRPRTT)

But other DVRP variants exists with relatively uncommon dynamic aspects like unexpected vehicle breakdowns, changing customer locations and uncertain time windows...

As an example of DVRPRTT, Kim [Kim et al., 2016] introduced a dynamic vehicle routing problem (DVRP) model where non-stationary stochastic travel times influenced by traffic congestion were considered. The paper assumes that the traffic congestion status within the distribution network changes over time following a stochastic process. For the problem's resolution process, two different parts were studied : Dynamics of Traffic Congestion and Travel Time Estimation. A Markov decision process model was proposed to address this challenge then rollout-based approach was used for the solution. The model was tested under a real-life situation in Singapore and using authentic road traffic information.

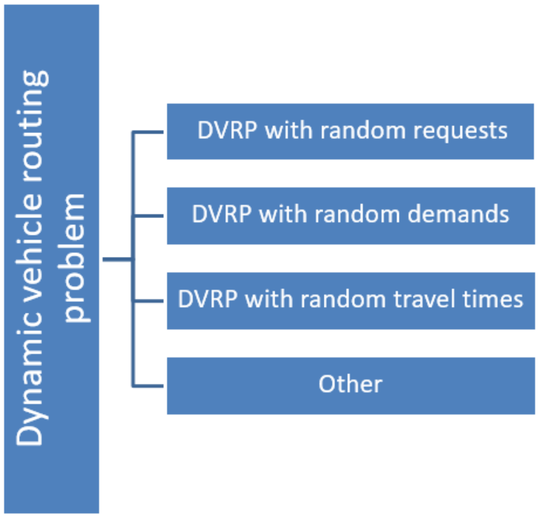

Figure 2.6: Dynamic vehicle routing problem

Vehicle routing optimization problem with simultaneous delivery and pickup (VRPSDP)

VPRSDP derives from classical VRP ,it combines delivery and pickup tasks within the same vehicle simultaneously. All transported goods start from the depot for delivery, and any pickups made are returned to the depot. The vehicle routing problem with simultaneous pickup delivery was proposed for the first time by [Min, 1989] to solve the problem of public library.
VRPSDP can be classified into the following three main classes:

- **Vehicle Routing Problem with Simultaneous Delivery -Pickup and Time Windows, VRPSDPTW :** The vehicle must serve each customer within a specific time window, neither earlier nor later than the allowed service times set for that customer.
- **Vehicle Routing Problem with Simultaneous Delivery -Pickup and Maximum Distance Length,VRPSDPMML** :Each vehicle begins at the central warehouse, serves customers, and then returns to this central warehouse, with a limited total travel distance.
- **Vehicle Routing Problem with Simultaneous Delivery—Pickup and Time Limit, VRPSDPTL** : The vehicle needs to return to the depot within a specified maximum travel time after serving customers.

Many works addressed this type of problems, for example in this paper [Ji et al., 2015], a vehicle routing optimization problem with simultaneous delivery and pickup (VRPSDP) in the context of cold-chain logistics was studied. Within a city, perishable products, known as cold-chain product are distributed, requiring delivery and pickup in each distribution cycle. The distribution center dispatches multiple refrigerated trucks, each with a fixed loading capacity to serve the appropriate clients. The main objective of the model is to minimize the total delivery cost that combines :total fixed cost of the used trucks, transportation cost, vehicle cooling cost and damage cost. A genetic algorithm metaheuristic was introduce as a resolution approach for the model. The proposed model was tested using real-life data of the cold-chain logistics of HX Co. Ltd. in each store in Zhengzhou, China.

In another context, [Avci and Topaloglu, 2016] studied a Heterogeneous Vehicle Routing Problem with Simultaneous Pickup and Delivery (HVRPSPD) where the fleet of vehicles is assumed to be heterogeneous. The main objective of the proposed model is to minimize the total fixed costs of vehicles and variable transportation costs. A hybrid local search integrated with tabu search algorithm was proposed for the problem's resolution. The model was tested under randomly generated instances that showed the efficient of the proposed algorithm.

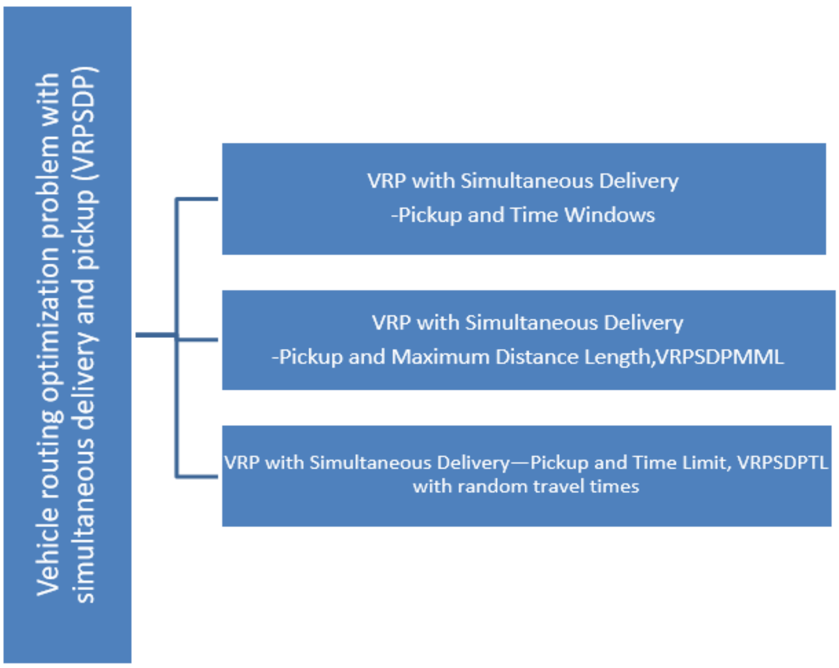

Figure 2.7: Vehicle routing optimization problem with simultaneous delivery and pickup

Open vehicle routing problem (OVRP)

When the vehicle returns to the original depot upon completing its distribution service, it's referred to as a closed vehicle routing problem. Typically, the distribution vehicle belongs to the distribution center in this scenario. Conversely, if the vehicle doesn't need to return after completing the distribution service, it's termed an open vehicle routing problem (OVRP), where the distribution vehicle is usually rented.

[Lalla-Ruiz and Mes, 2021]proposed a new two-index-based mathematic formulation for the Multi Depot Open Vehicle routing Problem MDOVRP and presented new constraints for sub-tours elimination. The authors supposed that each vehicle starts its route from one of the available depots and finishes at the last customer it serves. The main objective was the minimization of total travelling costs from depots to costumers. The proposed model was run on CPLEX and the results were compared to an existing works and benchmarks.

[Soto-Mendoza et al., 2020] also studied this type of vehicle routing problems with capacity and distance constraints. The proposed model aims to minimize the total number of vehicles and the total traveling cost. As a resolution approach, the authors proposed a Hybrid Grasshopper Optimization Algorithm with Local Search hybrid algorithm to solve OVRP's instances. The model was tested under different existing benchmarks and the experiment considered two cases of the problem :in the first, the primary objective is to minimize the total number of vehicles and then the total distance to be traveled then in the second case the total distance traveled by the vehicles is minimized.

Green vehicle routing problem

Efficiently planning the layout of freight nodes and distribution centers is crucial for green transportation. By optimizing vehicle routes and minimizing empty loads, we can significantly contribute to conserving energy and reducing emissions. Green Logistics became that much important because current logistics strategies aren't sustainable and efficient. That's why nowadays environmental, ecological, and social impacts are considered alongside economic costs when designing logistics policies.

Many papers worked on this type of VRP, for example [Xiao et al., 2012] proposed a Fuel Consumption Rate (FCR) to be added to the classical capacitated VRP, so that we can obtain a new variant of GVRP wich is the Fuel Consumption Vehicle Routing Problem FCVRP. The main objective of the proposed model was to minimize vehicle's fixed costs and the fuel costs of all the vehicles. A string-model-based simulated annealing algorithm was introduces for the model's resolution.

In another case, [Jabir et al., 2015] added measures of carbon dioxide (CO2) emission to the classical capacitated VRP. The authors proposed a multi objective that combines the environmental aspect: carbon dioxide (CO2) emission minimization and the economic aspect : total costs minimization. An Ant Colony Optimization (ACO)-Variable Neighborhood Search hybrid algorithm was proposed (ACO-VNS) as a resolution approach that was tested under randomly generated instances.

2.4 location routing problem related works

Location routing problems (LRPs) are grouped into various types depending on factors such as network characteristics, resource constraints, and optimization objectives.While numerous classifications exist in the literature, four main types have been the focus of research: Green LRPs with time windows, Dynamic LRPs, Inventory LRPs, and LRPs with simultaneous pickup and delivery. It's worth noting that there are additional types beyond these four that are not discussed here.

2.4.1 Green Location Routing Problem with Time Windows

[Schiffer and Walther, 2017]presented an electric location routing problem with time windows and partial recharging, in this case the routing is done using electric vehicles for the

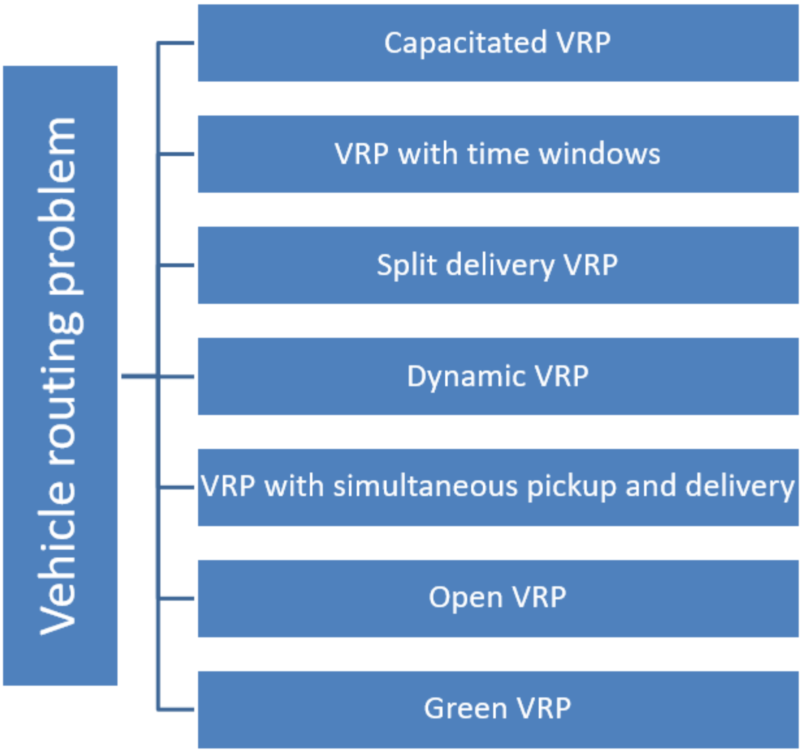

Figure 2.8: Vehicle routing problem

concept of green logistics. The authors assumed that vehicle speed is constant and the estimation of the consumed energy is modeled as a linear function. Many objectives were proposed to be studied : minimizing the total driven distance as the first objective, minimizing the number of charging stations as a second objective and finally minimizing the number of used vehicles as a last objective. These objectives might be be contradicting, that's why they were all combined in a single objective function that represents all these different aspects. The authors saw that time windows are most of the time not considered on location routing problems due to the strategic planning horizon that's why they added this type of constraints. Different recharging options were presented due to real world constraints. The presented model was compared with existing works for LRP and VRP to test the efficiency of simultaneous siting decisions and partial recharging concepts that were proposed in this paper. an

Another work [Dukkanci et al., 2019] addressed this type of problems (Green location routing problem) where classical location routing problem (LRP) and Pollution routing problem (PRP) were combined. So the main objective is to locate different depot from where limited capacity trucks will be dispatches to serve clients while considering energy consumption and gas emissions. In the proposed MILP model, the objective function aims to minimize the fixed cost of operating depots and the total cost of fuel consumption and emissions estimated by the comprehensive modal emission model (CMEM). The authors in this paper also have considered time-window constraints, but they were after that relaxed to obtain a Cumulative location-routing problem where both the distance and the load of the trucks matters in objective function contrary to the classical LRP where only distance matters for the routing. Once the location of depots and route of vehicles are known, the only remaining decision is the speed to be used over each arc so that time windows will be respected, that's why the authors have considered the speed of the vehicle as a decision variable, a speed optimization algorithm (SOA) was proposed to deal with this problem. Finnaly as a second resolution approach, the authors introduced an iterated local search algorithm. The performance of the proposed models and approaches were tested using adaptations of literature instances.

2.4.2 Dynamic location routing problem

[Gao et al., 2016] Worked on a DLRP 2.9c that combines both Location-allocation problem (LAP)2.9a and Vehicle routing problem (VRP)2.9b. In DLRP the environment keep changing over time which is more challenging than the classical LRP, for this paper, random traffic factor was addressed. A K-means clustering algorithm was proposed to deal with the location of depots and the allocation of different clients. Then an ant colony optimization with clustering (KANO) and three immigrants schemes algorithm : random immigrants, elitism-based immigrants and memory-based immigrants(KANO) is used to deal with the routing part. The proposed algorithm was compared to the classical ant colony meta-heuristic called WKANO where KANO showed better performance for solving this type of problems.

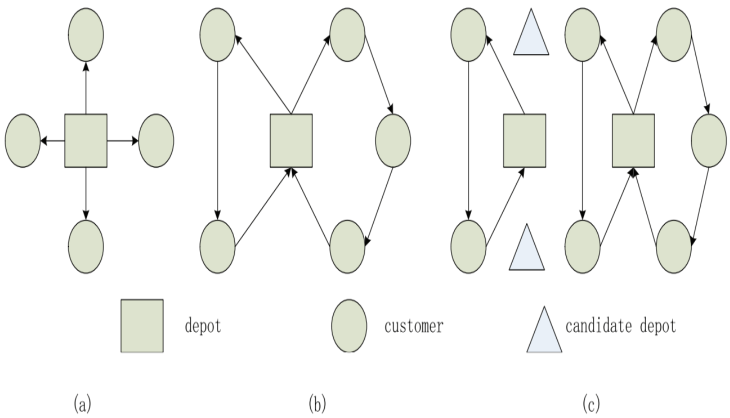

Figure 2.9: Difference between LAP, VRP and LRP

2.4.3 Inventory location routing problem

[Rafie-Majd et al., 2018] worked on an integrated inventory location routing problem ILRP that addresses three different decision levels : Strategic decisions(location-allocation decisions), Tactical decisions(inventory control and transportation decisions) and Operational decisions (scheduling and routing decisions). To represent the model, the authors proposed a three-echelon supply chain :suppliers, potential distribution centers and retailers, distribution centers are responsible to transfer several types of perishable products from supplier to customers in a limited time horizon, consisting of several time periods. They also supposed that the client's demand is stochastic and follows normal distribution with certain mean and standard deviation. The main objective is to minimize the total costs for all the different decision levels like the costs of opening distribution centers, inventory holding cost at customers, expected waste cost, driver cost..etc. Finally the authors used a Lagrangian relaxation algorithm to solve the proposed model.

[Saif-Eddine et al., 2019] also worked on this type of problems, Vendor Managed Inventory VMI was also considered in this paper that consists on keeping more inventory at the retailers and incurring a part of their holding cost to be able to make less frequent deliveries to the customers. A three-echelon supply chain was also proposed represented by : a manufacturer that produced a single type of products, depots that will be dispatching the products to the costumers. The main objective is to determinate which depots should be used while minimizing the total cost of all the supply chain. As a resolution approach for big instances, an improved genetic algorithm was introduced with two different improvement procedures : Assign-to-Cheapest-Depot Improvement (ACDI) and Depot closing improvement (DCI). The proposed algorithm was compared with classic genetic algorithm using existing benchmarks from the literature.

2.4.4 Location routing problem with simultaneous pickup and delivery

[Vincent and Lin, 2014] LRPSPD is a new variant of the location routing problem (LRP) with a main objective of total supply chain network costs minimization which achieved through depot placement and route planning to effectively meet both pickup and delivery requirements for each client using same vehicle. A Multi-start simulated annealing algorithm for LRPSPD was proposed that combined both simulated annealing algorithm advantages and the multi-start hill climbing strategy. The proposed algorithm is tested using 360 benchmark instances to verify its performance. Another work that focuses on this type of LRP problems [Karaoglan and Altiparmak, 2010] where a hybrid heuristic approach based on genetic algorithms (GA) and simulated annealing (SA) was proposed to solve the problem. The main objective was the minimization of the total system cost including transportation,depot and vehicle fixed costs. The proposed algorithm was compared with branch-and-cut to test its performance and ability of finding good quality solutions on a set of instances derived from the literature. The results indicate that the proposed hybrid algorithm is able to find optimal or very good quality solutions in a reasonable computation time.

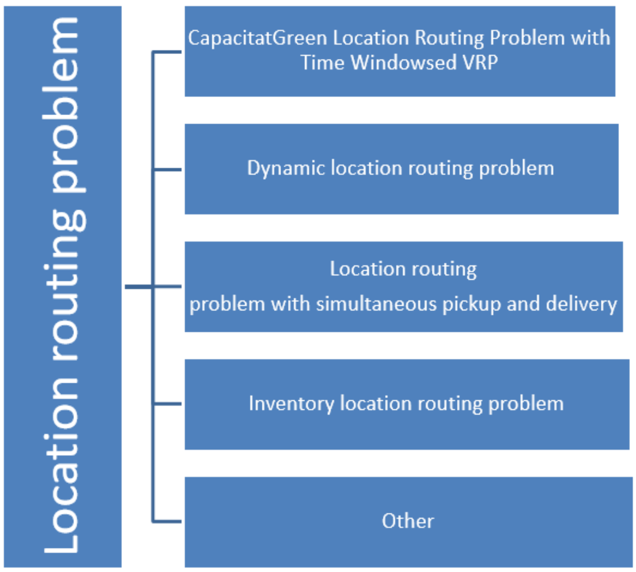

Figure 2.10: Classification of LRP

Conclusion

In conclusion, this chapter has provided an in-depth exploration of the Location Routing Problem (LRP), a significant logistical challenge at the intersection of the Vehicle Routing Problem (VRP) and the Facility Location Problem (FLP). By optimizing the distribution of goods from multiple facilities to various customers, the LRP plays a crucial role in enhancing the efficiency of logistics operations, that will applied in the next chapters within the context of the Physical Internet.

We began by examining the classification of the Facility Location Problem (FLP) and Vehicle Routing Problem (VRP) across different criteria. This classification framework offered valuable insights into the complexities of these problems and their diverse manifestations in real-world logistics scenarios.

Chapter 3

Location routing problem in the Physical Internet: Mono-objective

Introduction

In this chapter, we focus on addressing a mono-objective problem within the realm of logistics optimization in the context of physical internet. We begin by introducing the problem and its underlying assumptions, followed by the development of a mathematical model to formalize our approach. Subsequently, we explore various solution approaches, with a particular emphasis on our innovative methodology.

Initially, we present the problem statement and outline the key assumptions that guide our analysis. This provides a clear understanding of the scope and objectives of our optimization studies.

Next, we formulate a mathematical model to represent the problem that will be solved using CPLEX to obtain optimal and exact solutions.

We then proceed to discuss different solution approaches, highlighting the use of simulated annealing as a commonly employed optimization technique in the literature. However, recognizing the need for innovation and inspired by recent research, we delve into a brief state-of-the-art review on the combination of simulated annealing with artificial intelligence strategies. This exploration leads us to an article that aligns closely with our problem domain, motivating the development of an algorithm that combines simulated annealing with epsilon-greedy, a reinforcement learning strategy.

Finally, we put our proposed methodology to the test by conducting experiments across various scenarios. These experiments provide valuable insights into the effectiveness and robustness of our approach in solving the optimization problem under different conditions.

3.1 Problem description

3.1.1 General description

In our proposed model, we are working on a complex logistical challenge known as the location routing problem in the context of the physical internet. This problem involves the strategic placement of hubs and the operational routing of vehicles to efficiently meet the demands of our retailers. The main objective is to minimize the hubs opening cost and the transportation costs on our Physical Internet network.

Given a set of potential Hubs H where:{ h = 1, . . . , H } that must be located to serve a set of retailers R: { i = 1, . . . , R } with different demands Dem_i using a set of trucks T: { t = 1, . . . , T }

3.1.2 Assumptions

The proposed model addresses the location routing problem within the physical internet framework. Before we dive into our model, it's important to mention the assumptions guiding our approach:

- A fixed number of hubs will be opened based on the daily clients demands and based on their opening costs.
- A retailer's demand is satisfied using a single truck. Each retailer is visited once in a route.
- Trucks have a fixed capacity that must be respected.
- Hubs have an inventory level that must be respected.
- Hubs can share their different resources: trucks and drivers.
- The starting and ending hubs of a truck can be the same or different. The truck returns to the closet hub in the route.
- Trucks on a road must not exceed a certain maximum driving time.
- Breakdowns time are considered in a route(Maintenance of vehicle, gas stations, truck drivers rest time...).

3.1.3 Problem formulation

Notations:

H	: Set of PI-Hubs
I	: Set of retailers
T	: Set of trucks
$\mathbf{D}_{hi}$	: Distance matrix between hub h and retailer i
$\mathbf{Dist}_{ij}$	: Distance matrix between retailer i and retailer j
$\mathbf{Dem}_i$	: Demand of retailer i
$\mathbf{CAP}_t$	: Capacity of truck t
maxhrs	: Maximum working hours in a day
$\mathbf{S}_t$	: Speed of truck t
TC	: Fixed unit transportation cost per kilometer
$\mathbf{OCh}_h$	: Opening cost of hub h
BT	: Breakdowns time (maintenance of vehicle, gas stations..)
$\mathbf{I}_h$	: Inventory level at hub h

Decision variables:

$$Q_h : \begin{cases} 1 & \text{if hub } h \text{ is open} \\ 0 & \text{otherwise} \end{cases}$$

$$Y_{hi}^{t} : \begin{cases} 1 & \text{if truck } t \text{ goes from hub } h \text{ to retailer } i \\ 0 & \text{otherwise} \end{cases}$$

$$X_{ij}^{th} : \begin{cases} 1 & \text{if truck } t \text{ goes from retailer } i \text{ to retailer } j \text{ starting from hub } h \\ 0 & \text{otherwise} \end{cases}$$

$$Z_{ih}^{t} : \begin{cases} 1 & \text{if truck } t \text{ goes from retailer } i \text{ to hub } h \\ 0 & \text{otherwise} \end{cases}$$

U_i : to eliminate sub tours

Objective function:

$$\begin{aligned} Z1 = \min TC \Bigg(& \sum_h \sum_i \sum_k D_{hi} \cdot Y_{hik} + \\ & \sum_h \sum_i \sum_j \sum_k \text{Dist}_{ij} \cdot X_{ijhk} + \\ & \sum_i \sum_h \sum_k D_{hi} \cdot Z_{ihk} \Bigg) + \sum_h O_{Ch \cdot Qh} \end{aligned} \tag{3.1}$$

The first part of the equation represents the operational level of our model represented by the total transportation cost in our Physical internet network. It is composed of the distance traveled from hubs to retailers, from retailers to retailers and finally for retailers to hub. The second part represents the strategic lever represented by hub's opening costs.

Constraints:

$$I \cdot \sum_i Y_{hit} \geq \sum_i \sum_j X_{ijht} \quad \forall\, t\, \forall\, h \tag{3.2}$$

$$I \cdot \sum_i \sum_h Z_{iht} \geq \sum_i \sum_j \sum_h X_{ijht} \quad \forall\, t \tag{3.3}$$

$$\sum_h \sum_t Y_{hit} + \sum_h \sum_j \sum_t X_{ijht} = 1 \quad \forall i \tag{3.4}$$

$$\sum_h Y_{hit} + \sum_h \sum_j X_{jiht} = \sum_h Z_{iht} + \sum_h \sum_j X_{ijht} \quad \forall\, t\, \forall\, i \tag{3.5}$$

$$X_{iit} = 0 \quad \forall t \forall i \tag{3.6}$$

$$\sum_h \sum_i Dem_i \cdot Y_{hit} + \sum_h \left(\sum_i \sum_j Dem_j \cdot X_{ijht} \right) \leq \text{CAP}_t \quad \forall t \tag{3.7}$$

$$\sum_t \sum_i Dem_i \cdot Y_{hit} + \sum_t \left(\sum_i \sum_j Dem_j \cdot X_{ijht} \right) \leq I_h \cdot Q_h \quad \forall h \tag{3.8}$$

$$\left(\frac{\left(\sum_h \sum_i D_{hi} \cdot Y_{hit} + \sum_i \sum_h D_{hi} \cdot Z_{iht} + \sum_h \sum_i \sum_j \text{Dist}_{ij} \cdot X_{ijht}\right)}{St}\right) + BT \leq \text{maxhrs} \quad \forall t \tag{3.9}$$

$$U_i - U_j + I \cdot X_{ijht} \leq I - 1 \quad \forall\, i \,\forall\, j \,\forall\, t \,\forall\, h \tag{3.10}$$

$$\sum_i \sum_h Y_{hit} \leq 1 \quad \forall t \tag{3.11}$$

$$\sum_h \sum_i Z_{iHt} \leq 1 \quad \forall t \tag{3.12}$$

$$Y_{hit} \leq Q_h \quad \forall\, h \,\forall\, i \,\forall\, t \tag{3.13}$$

$$Z_{iht} \leq Q_h \quad \forall\, i \,\forall\, h \,\forall\, t \tag{3.14}$$

$$\sum_i Y_{hit} = \sum_i Z_{iht} \quad \forall\, h \,\forall\, t \tag{3.15}$$

$$Q_h, X_{ijt}, Y_{hit}, Z_{iht} \in \{0, 1\} \quad \forall\, i \,\forall\, j \,\forall\, t \,\forall\, h \tag{3.16}$$

$$U_i \in N \quad \forall\, i \tag{3.17}$$

Equation (3.2) and (3.3) indicate that each route must begin and terminate at a hub. The initial hub and the final hub may be identical or distinct. Equation(3.4) denotes that each retailer must be visited exactly once in a tour. Equation (3.5) ensures the preservation the the flow for each retailer and guarantees that every truck entering a retailer must exit it as well. Equation (3.6) indicates that the vehicle must move from one retailer to another retailer or the end hub and can't move from a retailer to this same retailer. Equation(3.7) states that the total loading quantity at the starting hub constructed of multiple retailers demands should respect the truck capacity. Equation(3.8) denotes that the total loading quantity at each hub for all trucks starting their tour from this hub should respect the hub's inventory level. Equation(3.9) expresses that the total duration of the tour should not exceed a fixed number of driving hours. This constraint represents the societal aspect of the Physical internet. Equation(3.10) eliminates sub tours in each route. Equation (3.11) ensures each truck starts from a hub only once on a route. (3.12) guarantees that each truck ends at a hub only once on a route. Equation (3.13) proposes that there is no route starting from a hub unless this hub is opened. Equation (3.14) indicates that there is no route ending at a hub unless this hub is opened. Equation (3.15) is used for the case of classical supply chain where the starting and the ending hub must be the same.

3.2 Resolution approach

3.2.1 CPLEX

The proposed model was solved using IBM ILOG CPLEX(version 13.8) solver on an i5 CPU with 16GB Ram laptop.

3.2.2 Metaheuristic

Simulated annealing

Simulated Annealing (SA) is a metaheuristic optimization technique introduced by Kirkpatrick, Gelatt, and Vecchi in 1983 to solve the Travelling Salesman Problem (TSP). SA stands out as one of the most commonly used and renowned metaheuristics, offering an effective and versatile optimization approach. It is useful in finding global optima in the presence of large numbers of local optima. "Annealing" refers to an analogy with thermodynamics, specifically with the way that metals cool and anneal. Simulated annealing uses the objective function of an optimization problem instead of the energy of a material.

Solution encoding

In our scenario, we've adopted a hybrid vector encoding approach, combining both binary and integer elements. The initial segment represents hub locations using binary encoding: a value of one signifies an open hub, while zero indicates closure. This binary representation reflects a strategic decision-making process.
The second segment addresses vehicle routing, utilizing the established open hubs to fulfill client demands. Trucks are distinguished and separated by zeros, delineating individual routes. Each truck initiates its tour from a hub, visits different retailers, and concludes by returning to a hub, which may be either the starting hub or a different one.
In a general case with N located hubs, M retailer, and K trucks, the indexing would be as follows:

- The hubs are indexed from 1 to N: $h = \{n = 1, \ldots, N\}$
- The retailers are indexed from N+1 to M :$r = \{m = N + 1, \ldots, M\}$
- and there would be K-1 zeros in the solution to separate the trucks.

For instance, consider a scenario with two located hubs (N=2), four retailers (M=4), and two trucks (K=2). Hubs are represented as nodes numbered from one to two$h = \{n = 1, \ldots, 2\}$, and the clients are numbered from three to six onwards $r = \{m = 3, \ldots, 6\}$. Furthermore, there's one zero to separate the trucks.

In the encoding described in figure(3.1), Truck 1 starts from Hub 1, delivers to retailers 4 and 6, then returns to Hub 2. Truck 2 starts from Hub 2, visits Clients 3 and 5, and returns to Hub 2.

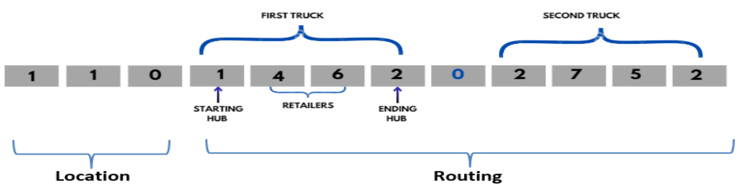

Figure 3.1: Solution encoding

Perturbation Function

A perturbation function is defined to generate new candidate solutions. This function should generate solutions that are close to the current solution but not too similar. In our case, four perturbations functions were introduced as follows:

- **Swap move(Hub Hub)**: This function randomly selects two fixed hubs and exchanges their positions. This move concerns only the routing phase. For example in figure (3.2), the starting hub and the ending hub of the first truck were swapped to obtain a new neighboring solution.

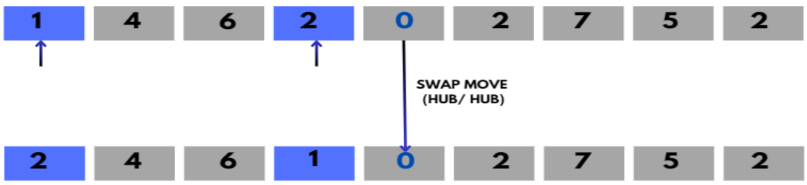

Figure 3.2: Swap move (Hub Hub)

- **Swap move(Retailer Retailer)**: Similarly, this function randomly chooses two retailers and swaps their locations. This move also concerns only the routing part of our solution.For example in figure (3.3), the retailer 3 and 4 swapped their positions to obtain a new neighboring solution. This swap introduces a change in the sequence of retailers visited by the trucks to explore different routing options.

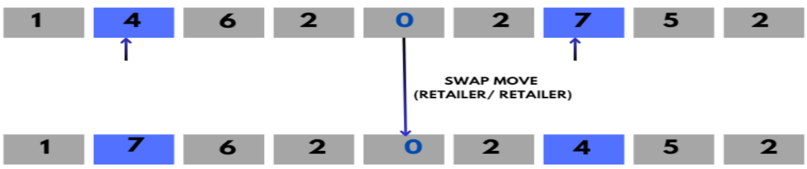

Figure 3.3: Swap move (Retailer Retailer)

- **Reversion move**: This function involves randomly selecting a truck's starting hub and its first visited client, and then reversing their locations with another truck.For example in figure (3.4), the starting hub and the first retailer visited by the first truck were reversed with the starting and the fist retailer visited by the second truck.

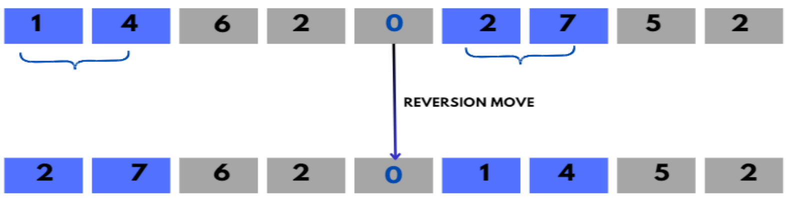

Figure 3.4: Reversion move

- **Location Swap move**: We choose randomly an opened and closed hubs, then we switch their statuses. Same for the routing we close the opened hub and we open the closed hub.

Acceptance Criterion

The acceptance criterion determines whether a new solution is accepted or rejected. The acceptance depends on the energy difference between the new generated solution and the

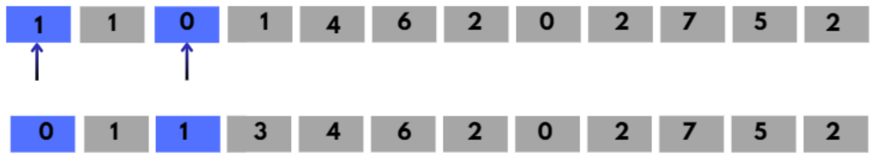

Figure 3.5: Location swap move

current solution, as well as the current temperature. The classic acceptance criterion of SA comes from statistical mechanics, and it is based on the Boltzmann probability distribution. A system in thermal equilibrium at temperature T can be found in a state with energy E with a probability proportional to :

$$P(E) \sim e^{-\frac{E}{kT}}$$

. For optimization models, the acceptance probability can be expanded as follows:

$$P(E) \sim e^{-\frac{\Delta E}{T}}$$

The proposed algorithm for the simulated annealing is presented in figure(3.6)

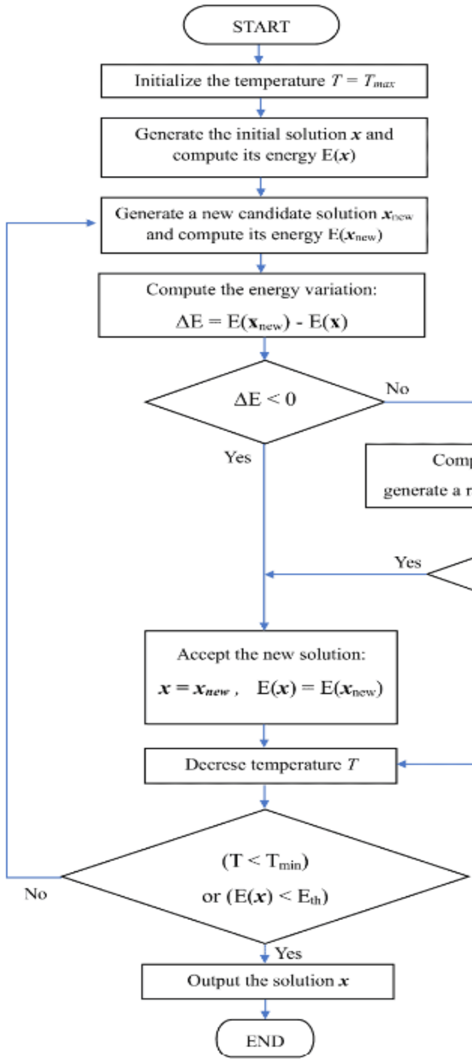

Figure 3.6: SA algorithm

Combining SA and the epsilon-greedy strategy

With the epsilon-greedy approach, we mainly choose the action that appears to have the best reward most of the time. The goal is to find a balance between exploring new possibilities and exploiting the ones we know are good. By exploring, we give ourselves a chance to try out new strategies, even if they seem different from what we've learned.

With a small probability of $\boldsymbol{\epsilon}$, exploring new possibilities is chosen, i.e., not to exploit what we have learned so far. In this case, the action is selected randomly, independent of the action-value estimates. and with a probability 1-$\boldsymbol{\epsilon}$ we can exploit our research space and our neighboring and make choices based on our existing understanding.
For our proposed algorithm, we attend to use the epsilon-greedy strategy to chose the best move that will lead to better solutions with better objective function based on the number of time each move was chosen.
The inputs of our algorithm are:

- **Table M** : a table that contains the list of all possible moves already mentioned before: Swap move(Hub/Hub), Swap move(retailer/retailer) reversion move and the location swap move: $\{q = 1, \ldots, 4\}$

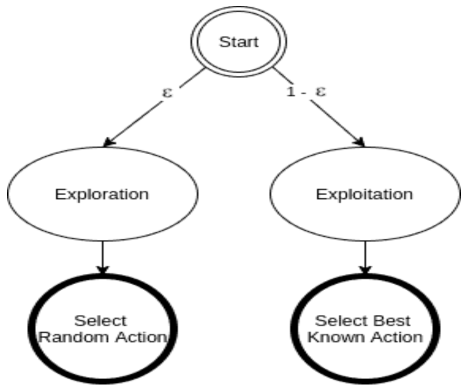

Figure 3.7: epsilon-greedy strategy

- **Table F** : a table that contains the fitness function of the different moves, in the first iteration fitness function is equal to the objective function of the solution using the move M, but for other iterations $\{i = 1, \ldots, Nbiter\}$ it is calculated using the formula mentioned below:

$$F_i^q = \frac{N^q - 1}{N^q} \cdot F_{i-1}^q + \frac{1}{N^q} \cdot \left(\frac{Obj(X)^p - Obj(X)}{Obj(X)} \right) \tag{3.18}$$

$\mathbf{N}^q$	: Number of times the move q was chosen
$\mathbf{F}_i^q$	: Fitness function of move q in iteration i
$\mathbf{Obj(X)}^p$	: Objective function of the best solution found
$\mathbf{Obj(X)}$	: Objective function of the current generated solution

- $\boldsymbol{\epsilon}$: a small number in the range of 10% and 30% in most of cases.

The output of our proposed algorithm will be the selected move determined by the epsilon-greedy approach.

In each iteration, we generate a random number between 0 and 1. If this number is less than $\boldsymbol{\epsilon}$, we choose a random move. Otherwise, we select the move with the lowest fitness function value because we're dealing with a minimization problem. The proposed algorithm is mentioned in figure (3.8)

Algorithm : Epsilon-greedy

Data : M= [M1, M2, M3,M4], F= [f1, f2, f3,f4], small number epsilon

Result : Selected move

Function Selected-action (M, F, epsilon)

```
    n ← uniform random number between 0 and 1;
    if n < epsilon then
        M*← random action from M
    else
        M* ← min (F)
    end
    return selected move M*
end
```

Figure 3.8: epsilon-greedy algorithm

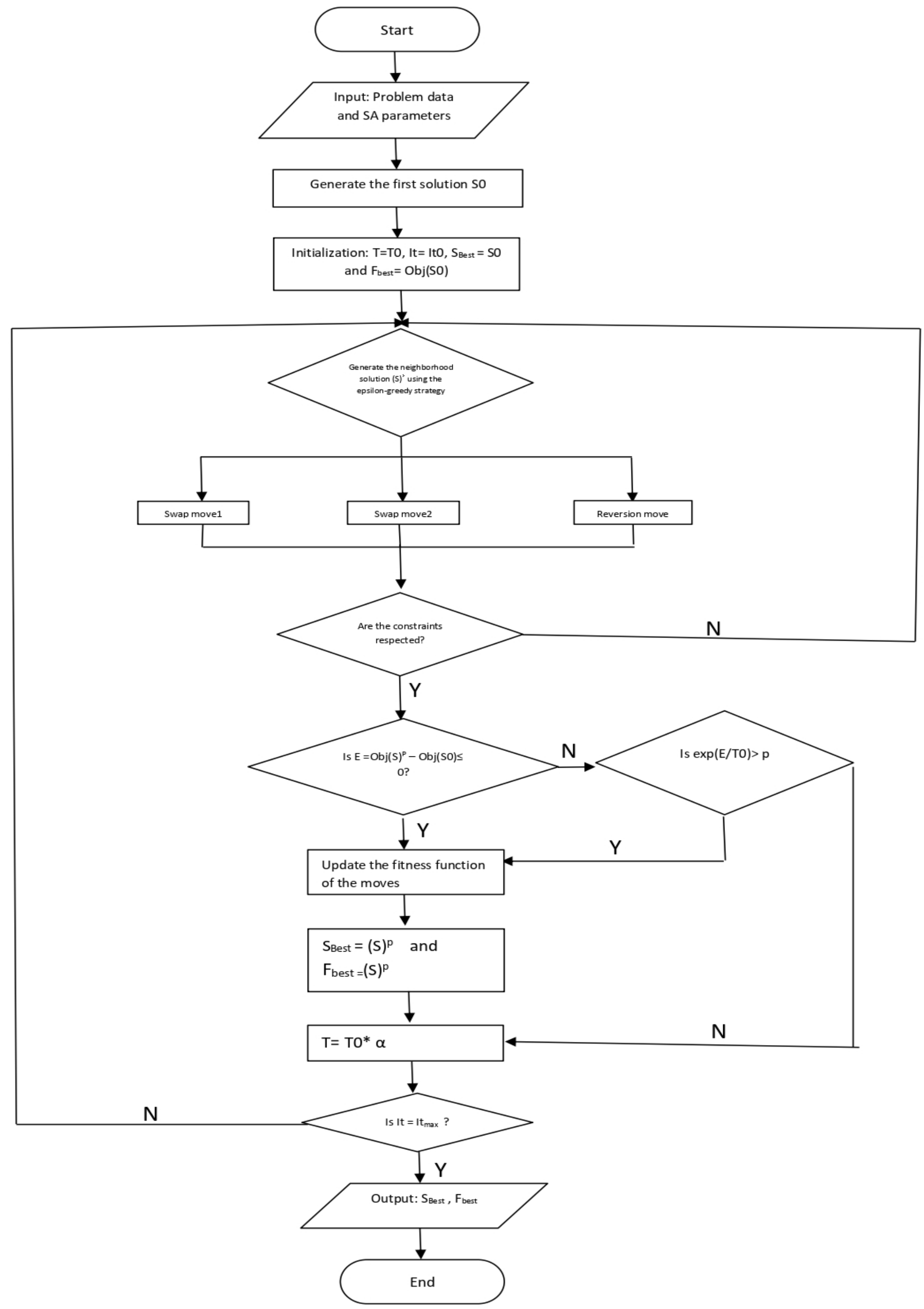

Figure 3.9: SA-epsilongreedy hybrid algorithm

3.3 Application

3.3.1 Data

The proposed model and data were inspired by the works of [Kantasa-Ard et al., 2021a] and [Kantasa-ard et al., 2023]. These studies examined banana transportation in Thailand. Distances between nodes were randomly generated within the range of 1 to 50 km, and client demands were based on the cited articles, falling between **15 and 30 tonnes**. Inventory levels at various hubs ranged from **80 to 100 tonnes**. All trucks used in the model have a capacity of **50.5 tonnes**, specifically semi-trailer trucks as described in [Thailand, 2017], with a consistent speed of **60 km/h**. Breakdown times were assumed to be around **1 hour**, with a maximum truck tour time of approximately **6 hours**. The transportation cost is set at **2 euros per kilometer**.

Data	values
Distance	random :[1 -50] km
Retailers demand	[15 -30] tonnes
Inventoryc levels	[80 -100] tonnes
Truck's capacity	50.5 tonnes
Truck's speed	60 km/h
Breakdown times	1 hour
Max truck tour duration	6 hours
Transportation cost	2 euros per kilometer

Table 3.1: Data

3.3.2 Scenarios

The model was evaluated and tested under four different scenarios, each characterized by different numbers of hubs, retailers, and trucks. The details of these scenarios are summarized in the table below:

Scenario	Nb of potential hubs	Nb retailers	Nb trucks
Scenario 01	3	4	2
Scenario 02	4	8	4
Scenario 03	7	12	6
Scenario 04	10	20	10

Table 3.2: Scenarios

For the different parameters used in the meta-heuristics : Temperature, Acceptance criteria, Cooling rate and the epsilon, they are resumed in the next table:

Parameter	value of the parameter
Temperature	10
Acceptance criteria	0.5
Cooling rate	0.6
Epsilon	0.3

Table 3.3: Data

3.3.3 Results

The results obtained are resumed in the next table. The metaheuristics were tested under 5000 iterations and for 10 replications for each scenario:

Scenario	CPLEX	SA-Epsilon greed	GAP%	SA	GAP%
Scenario 01	26225	26255,8	$< 1\%$	26282,4	$< 1\%$
Scenario 02	39352	39362,3	$< 1\%$	39370,5	$< 1\%$
Scenario 03	52447,2	52554,56	$< 1\%$	52545,9	$< 1\%$
Scenario 04	104948	105021,6	$< 1\%$	105026,7	$< 1\%$

Table 3.4: Scenarios

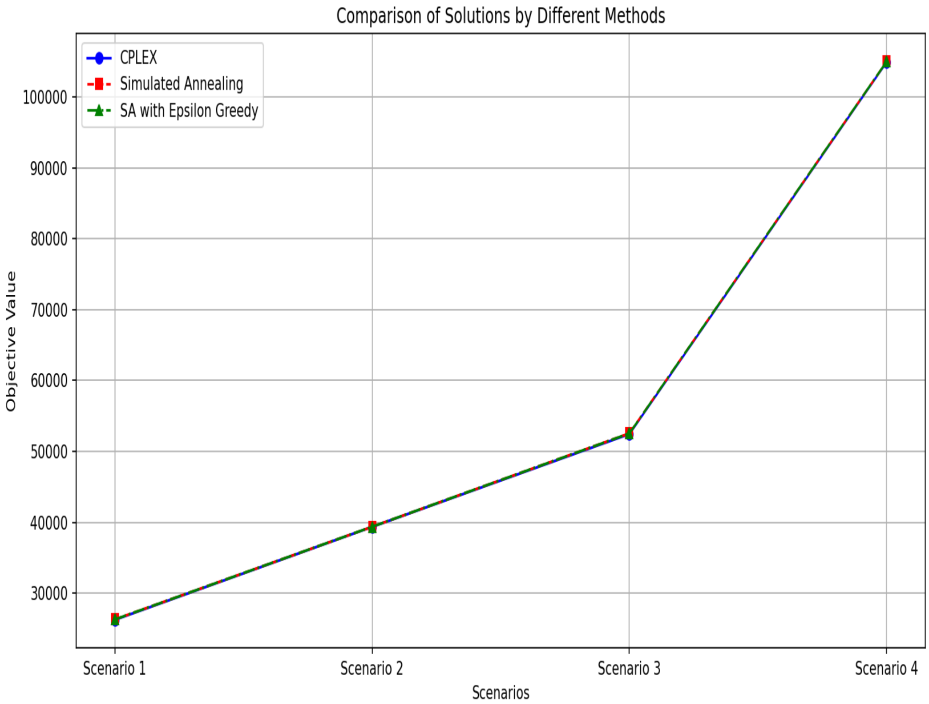

Figure 3.10: Comparison of solutions by different methods

The model was tested under four different scenarios with different numbers of potential hubs, retailers, and trucks. In all the scenarios, both algorithms showed good performance with a small gap of less than 1% compared to the optimal solution obtained using CPLEX. However, for the fourth scenario, the program was stopped at 6360s with a small gap of 0.17%.

Computational time

Scenario	CPLEX	SA-Epsilon greedy	SA
Scenario 01	0,11 s	1s	1s
Scenario 02	2,92s	5s	2.5s
Scenario 03	4200s	13,38s	7,22s
Scenario 04	6360s	14s	8,3s

Table 3.5: Scenarios

For small instances, CPLEX provided the results in a shorter time frame, but starting from the third scenario, CPLEX took longer times, while the meta-heuristics gave results in shorter time frames.

The comparison of computational time between SA and SA-Epsilongreedy 3.11 revealed that SA-Epsilongreedy required more time to obtain the results. This extended duration

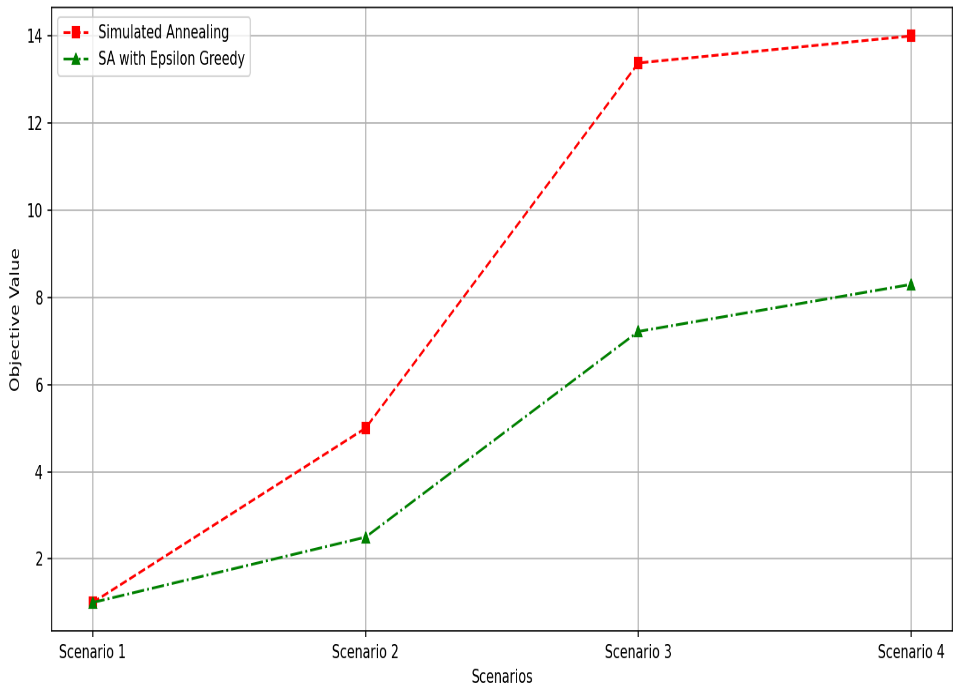

Figure 3.11: Comparison of computational time between SA and SA-Epsilon greedy

can be attributed to the inherent learning phase of SA-Epsilongreedy and the delicate trade-off between exploitation and exploration during move selection in each iteration.

Comparison between Classical supply chain and physical internet

Scenario	Classical	Physical internet
Scenario 01	26247,8	26225
Scenario 02	39395,6	39352
Scenario 03	52494	52447,2
Scenario 04	-	105021,6

Table 3.6: Comparison between physical internet and classical supply chain

The proposed model for the physical internet case was compared with a model for the classical supply chain were hubs can't share their trucks and drivers, and the truck must go back to the starting hub3.6. The results showed that physical internet has better performance than the classical supply chain in term of transportation costs. The results were represented graphically in 3.12, where actually only the transportation costs were considered for the comparison since the opening costs are fixed for both concepts.

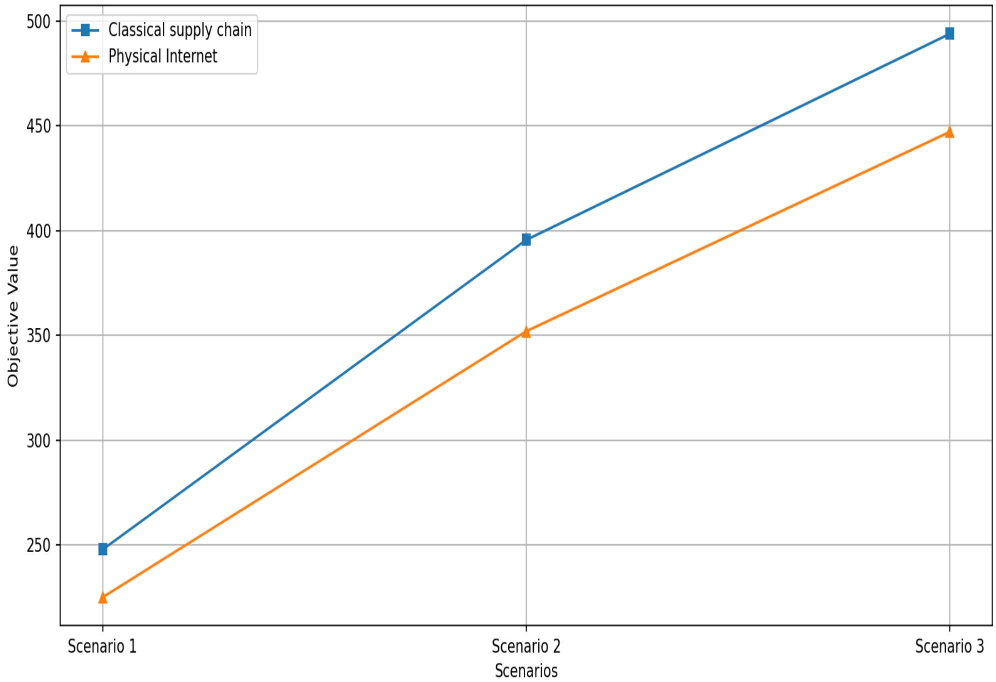

Figure 3.12: Comparison between classical supply chain and Physical internet

Conclusion

In conclusion, this chapter explored a novel approach to solving a logistics optimization problem. We began by outlining the problem and its assumptions, followed by the development of a mathematical model. We then discussed various solution methods, focusing on two main algorithms: classical simulated annealing and simulated annealing combined with the epsilon-greedy strategy.

Both algorithms showed good results. Classical simulated annealing, a widely used optimization technique, provided a solid baseline for our analysis. However, recognizing its extensive use in the literature, we sought to innovate by integrating it with a reinforcement learning strategy. This led us to develop an enhanced algorithm that combines simulated annealing with the epsilon-greedy strategy.

The results from our experiments indicated that both approaches performed well, with the hybrid method demonstrating a slight edge by achieving a small gap of only 1% from the optimal solution. This hybrid approach not only improved the optimization outcomes but also introduced an element of adaptability and learning into the process.

Furthermore, our analysis highlighted the positive economic impact of the Physical Internet framework, particularly in reducing transportation costs. This underscores the potential for advanced optimization techniques to significantly enhance logistics efficiency.

Chapter 4

A sustainable Location routing problem in a physical internet context

Introduction

In this final chapter, we extend our previous work by incorporating an additional objective focused on the environmental aspect: CO2 emissions. This transforms our model into a multi-objective optimization problem, addressing both economic and environmental aspects.

We begin by describing the second objective, which aims to minimize CO2 emissions alongside the initial objective of optimizing transportation costs. This dual focus ensures a balanced approach to logistics optimization that considers both economic and environmental factors.

Next, we proceed to the modeling phase, where we develop a mathematical representation of the multi-objective problem. To solve the multi-objective model, we utilized Gurobi, as CPLEX is not capable of addressing bi-objective problems. Gurobi's robust capabilities allow us to effectively handle the complexities of our dual objectives.

Additionally, we developed an AMOSA (Archive-based Multi-Objective Simulated Annealing) algorithm, a multi-objective version of simulated annealing. This algorithm is designed to efficiently navigate the trade-offs between our two objectives, providing a practical solution approach.
Finally, we tested our model across different scenarios to evaluate its performance and robustness.

4.1 Multi-objective model

Since the physical internet strives to address environmental concerns, we found it valuable to assess our model with an additional objective: minimizing gas emissions in our network.

To achieve this, we examined emissions from hubs and trucks. Hub emissions were influenced by the materials used within them, higher-quality materials typically resulted in lower emissions. Meanwhile, truck emissions during tours were influenced by travel distances.

Incorporating these considerations allowed us to create a more comprehensive model that balances logistical efficiency with environmental sustainability within the physical internet framework.

4.1.1 Problem formulation

Notations:

$\mathbf{H}$	: Set of PI-Hubs
$\mathbf{I}$	: Set of retailers
$\mathbf{T}$	: Set of trucks
$\mathbf{D}_{hi}$	: Distance matrix between hub h and retailer i
$\mathbf{Dist}_{ij}$	: Distance matrix between retailer i and retailer j
$\mathbf{Dem}_i$	: Demand of retailer i
$\mathbf{CAP}_t$	: Capacity of truck t
maxhrs	: Maximum working hours in a day
$\mathbf{S}_t$	: Speed of truck t
TC	: Fixed unit transportation cost per kilometer
$\mathbf{OCh}_h$	: Opening cost of hub h
FE	: Fixed fuel emission rate (g/l)
FC	: Fixed fuel consumption rate (l/km)
BT	: Breakdowns time (maintenance of vehicle, gas stations..)
$\mathbf{I}_h$	: Inventory level at hub h

Decision variables:

$$Q_h : \begin{cases} 1 & \text{if hub } h \text{ is open} \\ 0 & \text{otherwise} \end{cases}$$

$$Y_{hi}^{t} : \begin{cases} 1 & \text{if truck } t \text{ goes from hub } h \text{ to retailer } i \\ 0 & \text{otherwise} \end{cases}$$

$$X_{ij}^{th} : \begin{cases} 1 & \text{if truck } t \text{ goes from retailer } i \text{ to retailer } j \text{ starting from hub } h \\ 0 & \text{otherwise} \end{cases}$$

$$Z_{ih}^{t} : \begin{cases} 1 & \text{if truck } t \text{ goes from retailer } i \text{ to hub } h \\ 0 & \text{otherwise} \end{cases}$$

U_i : to eliminate sub tours

Objective function:

$$
\begin{aligned}
Z1 = \min TC \cdot \Bigg(& \sum_h \sum_i \sum_k D_{hi} \cdot Y_{hik} + \\
& \sum_h \sum_i \sum_j \sum_k \mathrm{Dist}_{ij} \cdot X_{ijhk} + \\
& \sum_i \sum_h \sum_k D_{hi} \cdot Z_{ihk} \Bigg) + \sum_h O_{Ch} \cdot Q_h
\end{aligned}
\tag{4.1}
$$

$$
\begin{aligned}
Z2 = \min FE \cdot FC \Bigg(& \sum_h \sum_i \sum_k D_{hi} \cdot Y_{hik} + \\
& \sum_h \sum_i \sum_j \sum_k \mathrm{Dist}_{ij} \cdot X_{ijhk} + \\
& \sum_i \sum_h \sum_k D_{hi} \cdot Z_{ihk} \Bigg) + \sum_h (1/O_{Ch}) \cdot Q_h
\end{aligned}
\tag{4.2}
$$

4.2 Multi-objective optimization

4.2.1 Introduction

Real-life problems often cannot be adequately represented by a single objective. This is where multi-objective optimization comes into play, aiming to find a trade-off between multiple objectives.

4.2.2 The dominance

According to [Collette and Siarry, 2011] we say that a solution S1 dominates a second solution S2 if:

- S1 is just as better than S2 in all the objectives.
- S1 is exactly better than S2 in at least one objective.

Solutions which dominate others but do not dominate each other are called Pareto optimal solutions (or non-dominated solutions). We actually have two types of dominance : local optimality in the sense of pareto and global optimality in the sense of pareto.

Local optimality in the sense of Pareto

A vector $\vec{x} \in R^n$ is locally Pareto optimal if there exists a real number $\delta > 0$ such that there is no vector $\vec{x}'$ that dominates the vector $\vec{x}$ with $\vec{x}' \in R^n \cap B(\vec{x}, \delta)$, where $B(\vec{x}, \delta)$ represents a ball centered at $\vec{x}$ with radius δ. [Collette and Siarry, 2011].

So a vector $\vec{x}$ is locally Pareto optimal if it is Pareto optimal within a local neighborhood of the set R^n.

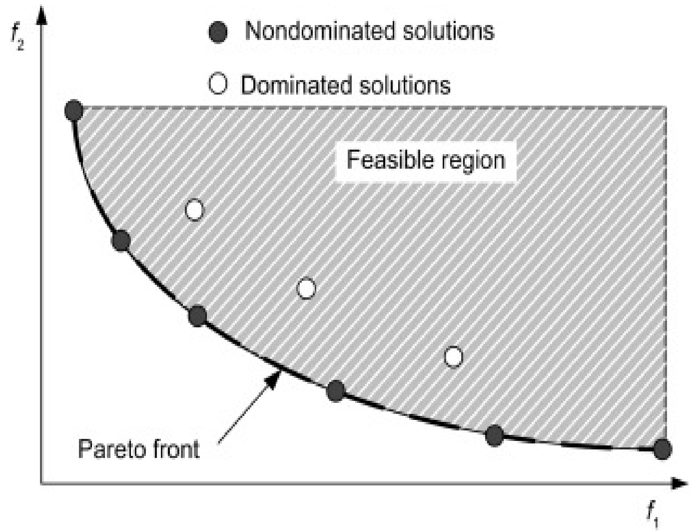

Figure 4.1: Pareto optimility

global optimality in the sense of Pareto

A vector $\vec{x}$ is globally Pareto optimal (or simply Pareto optimal) if there is no vector $\vec{x}'$ such that $\vec{x}'$ dominates $\vec{x}$[Collette and Siarry, 2011].

Actually the difference between the two concepts lies in the fact that we no longer consider a restriction of the set R^n.

4.2.3 Methods for solving multiobjective optimization problems

Many methods have been introduced in the literature that can be classified into five main groups :

- **Scalar methods**: Scalar methods convert a multi-objective optimization problem into a mono-objective problem represented by one objective function by combining the multiple objectives into one scalar objective function. Many scalar methods exists in the literature, for example: The Objective Function Weighting Method and Keeney-Raiffa method.

- **Interactive methods**: These methods include the decision-maker in the process of finding the best solution. The decision-maker gives their preferences and feedback step by step, helping to find a solution that best matches their goals and priorities. Interactive methods aim to find a single solution. They belong to the family of progressive methods, allowing the user to determine their preferences regarding trade-offs between objectives during the optimization process. There is different methods that exists, for example : The Compromise by Substitution Method and Fandel method.

- **Fuzzy methods**: These methods use fuzzy logic to deal with uncertainty and imprecision in decision-making. Unlike traditional methods that require precise numerical inputs, fuzzy methods allow for inputs that are uncertain.

- **Methods using a metaheuristic**: Metaheuristic methods employ high-level strategies to guide the search process for optimal solutions. For example we have : genetic algorithms, simulated annealing, ,particle swarm optimization and ant colony . These methods are typically used for solving complex and large-scale optimization problems where exact methods are ineffective.

- **Decision support methods**: These methods offer tools and systems to assist decision-makers in examining and comparing various alternatives. They frequently use different models and algorithms to help in decision-making, aiming to find the most effective solution given the specific goals and limitations.

4.3 Resolution approach

4.3.1 Gurobi

In a multi-objective optimization problem, we have many objectives that we want to optimize simultaneously. Each objective may represent a different aspect or goal of the problem , and often these objectives are conflicting or competing with each other.

In our problem, we have two objectives as it is mentioned before, the first objective represents the economic aspect: opening and distribution costs while the second one represents the environmental aspect : gas emissions.

To solve this problem, we have used Gurobi solver and employed the:
setObjectiveN (expr, index, priority) function that allows us to solve a multi objective model where

- **expr** : Represents the expression of our objective (Z1 or Z2 in our case)
- index : Represents the indexation of our objectives. It allows us to distinguish between different objectives when defining or modifying alternative objectives.
- **priority** : serves to establish the importance or precedence of the alternative objective in relation to other objectives. In our model, both objectives are important, that's why they have both the same priority (priority =1)

In our model we have :

- setObjectiveN (Z1 ,0 ,1)
- setObjectiveN (Z2 ,1 ,1)

4.3.2 Meta-heuristic

Archive multi-objective simulated annealing (AMOSA) is an optimization algorithm inspired by the annealing process in metallurgy, tailored specifically for multi-objective optimization problems.

Definition

Archive-based Multi-Objective Simulated Annealing (AMOSA) is an optimization algorithm inspired by the annealing process in metallurgy, tailored specifically for multi-objective optimization problems. In AMOSA, the Pareto dominance approach is adopted, utilizing the concept of an archive to store all non-dominated solutions.

AMOSA code

AMOSA Metaheuristic can be divided into two main steps:

- **Step one** :
  Where the initial configuration is built, it consists on introduction the archive, defining the variables of the algorithm :
  - Tmax: the initial temperature.
  - Tmin: the minimal temperature that can not be exceeded and it represents a stop criteria for our meta-heuristic.
  - the cooling rate alpa
  - the number of iterations that will be executed for every temprature.

  We have also to choose a solution randomly from our archive that will represent our current solution (currentsol).

- **Step two** :
  This step forms the core of our meta-heuristic. Starting by assigning the maximum temperature Tmax value to our variable T to initiate the meta-heuristic. We perform the following steps as long as the temperature remains above the minimum threshold Tmin. The temperature is updated after a set number of iterations using the cooling rate. After this, a new solution (newSol) through perturbing our current solution based on the moves previously discussed in Chapter 3 : Swap move(Hub Hub), Swap move(Retailer retailer), Reversion move for the routing part and the location swap move for the location part. This new generated solution must be feasible, if it is not another solution is also generated based on the currentSol. After this the objectives functions (F1 and F2) are calculated for both solutions (Currentsol and newSol) to compare and evaluate them where we can face 3 different situations:
  - **Case 01**: where currentSol dominates Newsol, here newSol is accepteded as Currentsol with a probability :

    $$\frac{1}{1+e^{T\cdot\Delta\text{Dom}}}$$

    where T represents our current temperature and DeltaDom represents the amount of dominance between the two solutions which is calculated as follow:

    $$\Delta\text{Dom} = \sum_{i=1}^{M}\left|\frac{f_i(currentSol) - f_i(NewSol)}{f_{i,\max} - f_{i,\min}}\right|$$

    where M represents the number of objectives (here we have two), f represents the value of the objective function for both solutions, fmax represents the maximal value of the objective function for all the solutions in the population and including the newSol, same for fmin that represents the minimal value.

  - **Case 02**: where currentSol ad newsol don't dominate each other, here we have two sub-cases, in the first one newSol is dominated by k solution from the archive,, here newSol is accepted as currentSol with the same probability in the first case. In the second subcase no solution in the archive dominated newSol, here newSol is always accepted as currentSol, it is also added to the archive and the solutions dominated by newSol are removed from the archive .

- **Case 03**: where newSol dominates currentSol, also in this cases we have two different sub-cases in the first one newsol is dominated by k solutions from the archive, and currentSol is equal to the solution having the minimum amount of domination between newSol and k solutions with a probability equal to:

$$\frac{1}{1 + e^{-\Delta \mathrm{Dom}}}$$

. In the second sub-case newSol is always accepted as currentSol and if no solution in the archive dominates newSol then it is added to the archive, and if it dominates k solutions from the archive then all this solutions are removed from the archive.

Algorithm :

Data: Archive, variables (Tmax, Tmin, Cooling rate, Nbiteration)
currentSol ← random solution from the archive
T ← Tmax
Result: Solution, F1, F2
Function AMOSA (Archive, Tmax, Tmin, Cooling rate)
While T > Tmin do:
for (i = 0; i<Nbiteration; i + +) **do:**
newSol ← Perturbation (currentSol);
if newSol not feasible:
Generate other solution
endif
Evaluate currentSol and newSol by calculating the objective functions F1 and F2

if currentSol dominate newSol **then** : **(Case 01)**
currentSol ← newSol with a probability
probability ← $\frac{1}{1+e^{T*\Delta Dom}}$ and ΔDom ← $\prod_{i=1}^{M}\left|\frac{fi(a)-fi(b)}{fimax-fimin}\right|$
end if
if currentSol and newSol not dominate each other **then : (Case 02)**
if newSol is dominated by k solutions from the archive **then :**
currentSol ← newSol with a probability
probability ← $\frac{1}{1+e^{T*\Delta Dom}}$
end if
if no solution in the archive dominates newSol **then :**
currentSol ← newSol
newSol is added to the archive
Solutions dominated by newSol are removed from the archive
end if
end if

if newSol dominates currentSol **then : (Case 03)**
if newSol is dominated by k solutions from the archive **then :**
currentSol ← solution having the minimum amount of domination between newSol and the k solutions with a probability
Probability = $\frac{1}{1+e^{-\Delta Dom}}$

end if
else:

currentSol ←newSol
if no solution in the archive dominates newSol **then**:
newSol is added to the archive
end if
if newSol dominate k solutions from the Archive **then**:
newSol is added to the archive
The k-dominated solutions are removed from the archive
end if
end
end if
end for
end while
return Solution, F1, F2

Figure 4.2: AMOSA

4.4 Application

4.4.1 Data

The proposed model and data were inspired from the works of [Kantasa-Ard et al., 2021a] and [Kantasa-ard et al., 2023] as mentioned in 3.3.1. In addition to the first objective of minimizing costs, the model incorporates a second objective to minimize gas emissions. This objective uses two additional data parameters: fuel emission, which is set to a value of **2.6 g/l**, and fuel consumption, set to a value of **1 l/km**.

4.4.2 Scenarios

The model was evaluated and tested under four different scenarios, each characterized by different numbers of hubs, retailers, and trucks. The details of these scenarios are summarized in the table below:

Scenario	Nb of potential hubs	Nb retailers	Nb trucks
Scenario 01	3	4	2
Scenario 02	4	8	4
Scenario 03	7	12	6
Scenario 04	10	20	10

Table 4.1: Scenarios

For the different parameters used in the meta-heuristic : Tmax, Tmin, Population size, cooling rate and number of iterations, they are resumed in the next table:

Parameter	value of the parameter
Tmax	50
Tmin	5
Cooling rate	0.5
Population size	20
Number of iterations	1000

Table 4.2: Data

4.4.3 Results

The proposed multi-objective model was also tested under four different scenarios with different numbers of potential hubs, retailers, and trucks. In all the scenarios, AMOSA showed good performance with a small gap of less than 1% compared to the optimal solution obtained using Gurobi for the first objective 4.3. For the second objective, a small gap of 4% was faced, which is showed in 4.4 However, for the fourth scenario, No solution was obtained using Gurobi due to the complexity of the model. For small instances Gurobi provided the results in a shorter time frame, but starting from the third scenario, Gurobi took longer times, while the meta-heuristic gave results in shorter time frames.

Scenario	Gurobi		AMOSA		GAP	
	F1	**F2**	**F1**	**F2**	**GAP F1**	**GAP F2**
Scenario 01	26225	1830.96	26238	1848	$< 1\%$	$< 1\%$
Scenario 02	39352	2765.3	39375.9	2796.13	$< 1\%$	1%
Scenario 03	52447.72	3658.28	52572.23	3821	$< 1\%$	4%
Scenario 04			105120.89	7608.7		

Table 4.3: Results of scenarios

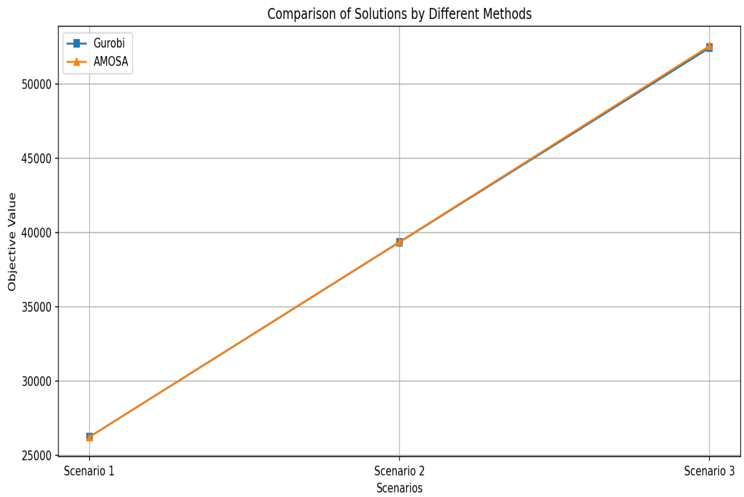

Figure 4.3: Comparison of solutions using Gurobi and AMOSA for the first objective

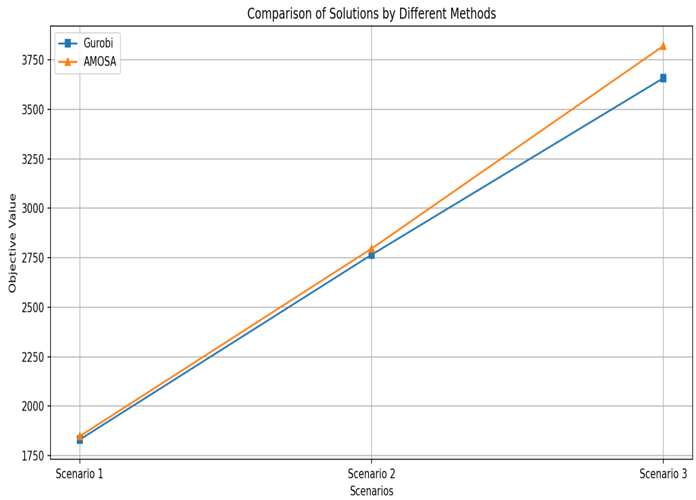

Figure 4.4: Comparison of solutions using Gurobi and AMOSA for the second objective

Computational time

Comparison between physical internet and classical supply chain for both objectives

The proposed model for the physical internet case was compared with a model for the classical supply chain where hubs can't share their trucks and drivers, and the truck must go back to the starting hub 4.5. The results showed that physical internet

Scenario	Gurobi	AMOSA
Scenario 01	0,1 s	1,5s
Scenario 02	1s	3,9s
Scenario 03	118,42s	5,5s
Scenario 04	6360s	9,9s

Table 4.4: Comparison of computational time between Gurobi and AMOSA

demonstrated better performance than the classical supply chain for both objectives in term of transportation costs and gas emissions.

Scenario	**Physical internet**		**Classical**	
	F1	**F2**	**F1**	**F2**
Scenario 01	26225	1830.96	26247.8	1860.60
Scenario 02	39352	2765.3	39395.6	2821.97
Scenario 03	52447.72	3658.28	52494	3719.12
Scenario 04			-	-

Table 4.5: Comparison between Physical internet and classical supply chain for both objectives

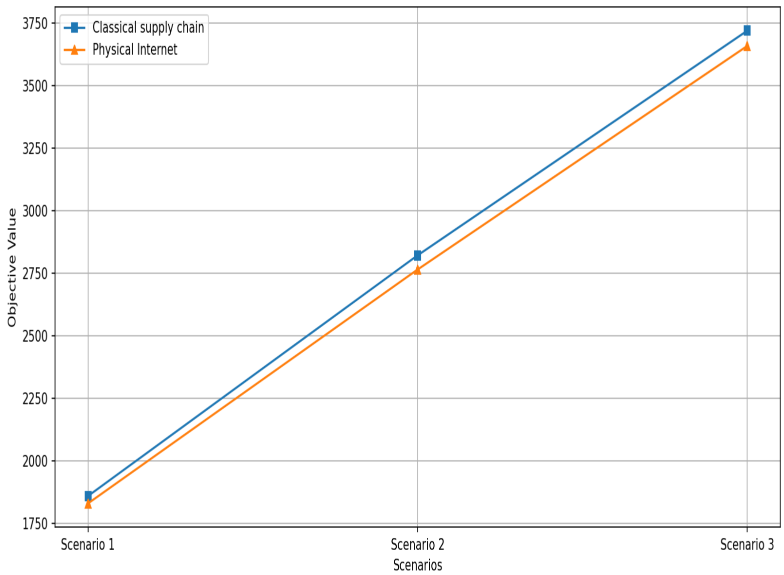

Figure 4.5: Comparison of physical internet and classical supply chain for the second objective

Conclusion

In conclusion, this chapter extended our logistics optimization work by incorporating an environmental objective, specifically CO2 emissions, transforming our model into a multi-objective problem. We described the second objective, developed a comprehensive mathematical model, and solved it using Gurobi due to its capability to handle bi-objective problems. Additionally, we implemented the AMOSA algorithm.

The results demonstrated that AMOSA performed well for both objectives. For the first objective of minimizing transportation costs, it maintained a small gap of only 1% from the optimal solution. For the second objective of reducing CO2 emissions, it achieved a maximum gap of 4%. These outcomes highlight the effectiveness of our approach in balancing economic and environmental goals.

Furthermore, the Physical Internet framework showed strong performance in addressing environmental aspects, further underscoring its potential to enhance logistics operations sustainably.

General Conclusion

In conclusion, this thesis explored how to improve logistics within the Physical Internet framework by addressing both economic and environmental aspects. We began by explaining the basics of logistics challenges and the need for new solution which is the Physical Internet .

We focused on the Location Routing Problem (LRP), which combines the Vehicle Routing Problem (VRP) and the Facility Location Problem (FLP). By examining these problems, we aimed to understand how to better manage logistics in a PI-network.

We began by developing a mathematical model representing the different proposed hypotheses of our problem. Initially, we aimed to minimize transportation costs using mono-objective optimization. We implemented the model using CPLEX but found that it was limited when handling larger data sizes. To overcome this, we employed metaheuristic approaches: the Simulated Annealing algorithm and a Simulated Annealing-Epsilon Greedy hybrid algorithm. These methods allowed us to obtain good results for larger instances. We tested the model on small instances using both CPLEX and the metaheuristics to evaluate the efficiency of the metaheuristic approach. The results showed that the metaheuristics performed well, with a gap of around 1% for all scenarios.

Later, we included environmental factors such as CO2 emissions, making it a multi-objective problem. We started by testing the model using Gurobi, which can solve multi-objective models. We then developed another multi-objective metaheuristic: AMOSA. The results demonstrated good performance of AMOSA for the first objective, with a small gap of around 1%, and a maximal gap of 4% for the second objective.

Our findings show that the Physical Internet framework performs better in terms of both economic and environmental aspects. Economically, the Physical Internet improves logistics efficiency by optimizing transportation routes and facility locations, which reduces overall transportation costs. This optimization leads to significant cost savings, enhancing the economic viability of logistics operations. Environmentally, the Physical Internet reduces CO2 emissions through more efficient routing, contributing to lower environmental impact. By combining economic and environmental benefits, the Physical Internet framework offers a comprehensive solution that addresses both the financial and ecological challenges of modern logistics.

List of Figures

List of Tables

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