Javad Rouzafzoon

Development of transportation and supply chain problems with the combination of agent-based simulation and network optimization

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Tiivistelmä

Tuotteiden kysyntä ohjaa erilaisia toimitusketju- ja logistiikkasijaintipäätöksiä, ja agenttipohjainen mallinnusmenetelmä (ABM) tuo innovatiivisia ratkaisuja toimitusketjun ja logistiikan ongelmien ratkaisemiseen. Tämä väitöskirja keskittyy agenttipohjaiseen mallinnusmenetelmään ja verkon optimointiin tällaisten ongelmien ratkaisemiseksi, ja sisältää kolme tapaustutkimusta, jotka voidaan luokitella kuuluvan yleisiin toimitusketjun hallinta- ja logistiikkaongelmiin.

Ensimmäinen tapaustutkimus esittelee kuinka käyttämällä väestötiheyksiä Norjassa, Suomessa ja Ruotsissa voidaan määrittää strategioita jakelukeskusten (DC) sijaintiin käyttämällä matkan etäisyyden minimoimista. Kullekin skenaariolle kehitetään matka-aikakartat. Lisäksi analysoidaan näistä kolmesta maasta koostuvaa pohjoismaista aluetta ja esitetään viisi mahdollista sijaintia optimointituloksena. Toinen tapaustutkimus esittelee kuljetuskustannusmallintamisen prosessissa, jossa puutavaraa kerätään useilta alueilta ja kuljetetaan lähimpään keräyspisteeseen. Tämä tutkimusprojekti esittelee agenttipohjaista mallinnusta (ABM), joka yhdistää kattavasti noudon ja toimituksen toimitusketjumallin keskeiset elementit ja suunnittelee komponentit keskenään kommunikoiviksi autonomisiksi agenteiksi. Mallinnuksessa yhdistetään erilaisia komponentteja, kuten GIS-reititys, mahdolliset tilojen sijainnit, satunnaiset puunhakupaikat, kaluston mitoitus, matkan pituus sekä monimuotokuljetukset. ABM:n avulla mallinnetaan noutojen ja toimituksien koko ketju ja tuloksena saadaan aikasarjoja kuvaamaan käytössä olevat kuorma-autot, sekä varastomäärät ja ajetut matkat. Lisäksi arvioidaan erilaisia simuloinnin skenaarioita mahdollisten laitosten sijainnista ja kuorma-autojen lukumäärästä sekä tunnistetaan optimaalinen toimipisteen sijainti ja tarvittava autojen määrä. Kolmannessa tapaustutkimuksessa agenttipohjaista mallinnusstrategiaa käytetään ratkaisemaan ajoneuvojen aikataulujen ja kaluston optimoinnin ongelma. Ratkaisumenetelmää käytetään dataan, joka on peräisin todellisesta organisaatiosta, ja ratkaisun tehokkuuden arvioimiseksi luodaan lukuisia keskeisiä suorituskykyindikaattoreita.

ABM-menetelmä, toisin kuin monet muut mallintamismenetelmät, on täysin räätälöitävissä oleva menetelmä, joka voi sisältää laajasti erilaisia prosesseja ja elementtejä. Autonomisia agentteja soveltava ABM voi integroida erilaisia komponentteja, jotka ovat olemassa monimutkaisessa toimitusketjussa ja luoda vastaavan järjestelmän toimitusketjun tehokkuuden arvioimiseksi yksityiskohtaisesti.

Asiasanat: Agenttipohjainen simulointi, sijaintiongelma; kaluston optimointi; toimitusketjun hallinta ja logistiikka; maantieteellinen tietojärjestelmä (GIS); sijainti – jako; ajoneuvojen aikataulut; liikenteen optimointi.

Abstract

Demand drives a different range of supply chain and logistics location decisions, and agent-based modeling (ABM) introduces innovative solutions to address supply chain and logistics problems. This dissertation focuses on an agent-based and network optimization approach to resolve those problems and features three research projects that cover prevalent supply chain management and logistics problems.

The first case study evaluates demographic densities in Norway, Finland, and Sweden, and covers how distribution center (DC) locations can be established using a minimizing trip distance approach. Furthermore, traveling time maps are developed for each scenario. In addition, the Nordic area consisting of those three countries is analyzed and five DC location optimization results are presented. The second case study introduces transportation cost modelling in the process of collecting tree logs from several districts and transporting them to the nearest collection point. This research project presents agent-based modelling (ABM) that incorporates comprehensively the key elements of the pick-up and delivery supply chain model and designs the components as autonomous agents communicating with each other. The modelling merges various components such as GIS routing, potential facility locations, random tree log pickup locations, fleet sizing, trip distance, and truck and train transportation. The entire pick-up and delivery operation are modeled by ABM and modeling outcomes are provided by time series charts such as the number of trucks in use, facilities inventory and travel distance. In addition, various scenarios of simulation based on potential facility locations and truck numbers are evaluated and the optimal facility location and fleet size are identified. In the third case study, an agent-based modeling strategy is used to address the problem of vehicle scheduling and fleet optimization. The solution method is employed to data from a real-world organization, and a set of key performance indicators are created to assess the resolution's effectiveness.

The ABM method, contrary to other modeling approaches, is a fully customized method that can incorporate extensively various processes and elements. ABM applying the autonomous agent concept can integrate various components that exist in the complex supply chain and create a similar system to assess the supply chain efficiency.

Keyword: Agent-based simulation, Facility location; Fleet optimization; Supply chain management and logistics; Geographical information system (GIS); Location – allocation; Vehicle scheduling; Transportation optimization.

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I feel fortunate that I was able to take the Ph.D. journey at the University of Vaasa. During this path, I could learn how to think critically, expand my knowledge, read other researchers' publications, collaborate with amazing colleagues, and finally publish academic articles. This journey also required countless hours spent alone to develop tailored solutions and overcome obstacles; I am very glad that I was able to achieve all those steps.

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Lastly, yet most profoundly, I would like to thank my family for believing in me and walking this path with me.

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Javad Rouzafzoon

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Abbreviations

ABM	Agent-Based Modelling
GIS	Geographic Information System
DES	Discrete Event Simulation
H&S	Hub and Spoke
FLP	Facility Location Problem
DC	Distribution Center

1 INTRODUCTION

This dissertation focuses on supply chain and logistics problems and how agent-based simulation and network optimization tools can be utilized to resolve those problems. First, the supply chain interconnected network is described briefly, and second, the research motivation and background are discussed. Third, the research questions and objectives are presented. Fourth, the importance of the study is explained and in the last section, the research structure is defined.

1.1 Complex problems in supply chain

Providers, producers, carriers, vendors, and consumers are all part of a supply chain that provides consumers with items that are delivered quickly and at a competing price. A supply chain is not just one chain anymore, yet a network interconnected with some chains, referred to as a supply chain network, after expanding its original idea. As a result, the conventional linear supply chain has evolved into an interconnected supply chain. All of the participants in the network have distinct functions to play, and their relationships are more complex. (Long, 2014)

Supply chains have been vital for companies, and managers are constantly working to increase resilience, efficiency, and client delivery performance. The COVID-19 pandemic and consequent disruptions revealed the significance of supply chains to the public and the necessity of optimization because of factors such as inflations, increasing geopolitical unpredictability, constant pandemics, and an uncertain economy.

For instance, Amazon expanded its distribution networks in 2021 to fulfill the increased demand and half of the total capital was invested in fulfillment and logistics capacity. Furthermore, by optimizing warehouse operations and fulfillment capacity, the cost was decreased from 6 billion dollars in Q1 to 4 billion in Q2, 2022. In addition, Amazon plans to open 21 multi-story distribution centers with a total size of 62 million square feet in 2022. These facilities are considered first-mile where commodities are transported to middle-mile and last-mile sites for last delivery to customers. Decisions on the location of those facilities could affect supply chain performance and transportation costs.

United Parcel Service, UPS, is piloting a plan to reduce transportation cost by combining the pickup and delivery routes. The plan is to pause an order until another order is matched with the same delivery address. The hold periods could be between 9 and 12 hours. This approach would improve parcel volume delivery on driving routes and more packages are delivered with fewer stops.

Considering the complexity of today's supply chain and the various components involved, it is necessary to create comprehensive background information by extensively examining the system's dynamic behavior in order to optimize supply chain architecture, organizing, scheduling, and systems for monitoring and activities. In general, decisions by incorporating various hierarchical levels in order to improve the efficiency of the entire supply chain can be challenging.

1.2 Background and motivation

There are various methods available in the literature to optimize supply chain design and logistics; however, these studies lack an efficient approach to incorporate a comprehensive list of major elements in supply chain and logistics optimization.

Agent technology enables the entire supply chain to be integrated as a networked system of autonomous tiers and has its own set of rules for making decisions (Gjerdrum et al., 2001). Agent-based models are specifically effective for simulating complicated processes in which a large number of agents or dynamic elements communicate with one another based on specific intrinsic features to build functional relationships, allowing for automated rationalization and problem-solving (Abar et al., 2017).

1.3 Research objectives and questions

The objective of this dissertation is to present how an agent-based approach can be employed to resolve supply chain and logistics problems. To conduct detailed research within this field, three case studies data that each has its own research problems and solution methods are discussed in this paper. The cases are focused on facility location and logistics modelling and optimization in supply chain management. Three case studies include DC locations in Nordics, Wood collection, and Transportation design.

1.3.1 DC locations in Nordics

The research project goals are as follows and Nordic countries' population data is utilized to develop and analyze the solution method:

1) How DC locations can be allocated by using geographical population data and optimization in Sweden, Norway, and Finland and at the Nordic level?

2) How several service zones can be defined depending on the selected facility locations at each country and Nordic level?

In the case of DC locations in the Nordics, the demographics of Nordic countries are used to find distribution center locations. The analysis' purpose is to look at a theoretical case in which the customer's location is a major component in the final delivery and evaluate how optimum locations and the growing number of distribution sites affect shipping periods. (Helo, Rouzafzoon, Solvoll, et al., 2018)

Distances and travel times between facilities and demand locations are calculated using population location data to analyze distribution center location scenarios. Potential distribution center sites are analyzed by using optimization methods. The goal is to evaluate how enhanced facility sites and an increase in fulfillment facilities affect shipping times. Potential facility locations are evaluated in this case by taking into account lengths and trip durations between request points and centers based on demographic data.

1.3.2 Wood collection

The research problem goals are defined as following and the solution method is implemented on the Wood collection case company data.

1) How ABM can be used to model the transportation structure of collection operations and evaluate the number of fleets required for each facility location?

2) How ABM can analyze the impact of selecting a certain facility location setting on the transportation cost?

The Wood collection case company provides picking up and delivering tree logs service in various parts of Finland. Logs can be sent to mainly two collection sites, and logs are received from seven different areas. Since tree locations are scattered in each area, there is no predetermined point of pickup, but the case company provides the average number of pickups per day for each region. The Wood collection case introduces an agent-based framework technique and discusses the solution method utilizing data from a real-world organization.

1.3.3 Transportation design

The key research questions include as following and the solution method is implemented on the Transportation design case company data;

1) How ABM can solve fleet size and scheduling of periodic cargo transportation?

2) How departing and arriving periods of vehicles impact on truck resource pool numbers?

The Transportation design case presents a "vehicle scheduling problem" and optimization of fleet size for a set of vehicles dispatched to collect perishable products. Commodities are available at a set of defined locations, and they must be delivered to the central facility. (Rouzafzoon & Helo, 2018)

An "agent-based simulation (ABS)" is used as a modeling tool to address fleet scheduling and vehicle sizing optimization in the Transportation design case.

The final purpose of the research is to provide a simulation technique for firms facing VSP and fleet optimization obstacles, mostly to identify the number of trucks needed for the least price and to assess the influence of fleet arriving and departing timeframes on vehicle number optimization. Table 1 provides a summary of case titles and research questions.

Table 1. Case titles and research questions

Case Number and Title	**Research Questions**
1. DC locations in Nordics	1) How DC locations can be allocated by using geographical population data and optimization in Sweden, Norway, and Finland and the Nordic level?
	2) How several service zones can be defined depending on the selected facility locations at each country and Nordic level?
2. Design of wood collection network	1) How ABM can be used to model transportation structure of collection operations and evaluate the number of fleets required for each facility location?
	2) How ABM can analyze the impact of selecting a certain facility location setting on the transportation cost?
3. Transportation network design and scheduling	1) How ABM can solve fleet size and scheduling of periodic cargo transportation?
	2) How departing and arriving periods of vehicles impact on truck resource pool numbers?

1.4 Justification for the research importance

The design of logistics network architecture is one of the most challenging tasks in supply chain management. The concept of creating a transportation network was presented by Hitchcock (1941). The goal was to create a cost-effective solution to convey items from several origins to various endpoints. According to Tilanus (1997), the ability to deliver the appropriate volume of correct items to the valid location at the proper time so that the supply chain's efficiency can be considerably improved is referred to as logistics.

Various research projects have focused on supply chain design and logistics, and researchers have suggested a wide range of solutions to the problem. Simulation modeling has been demonstrated to be an important mechanism for determining complex dynamics including supply chains and transportation systems. Agent-oriented software, or multi-agent frameworks, on the other hand, takes a step ahead of object-oriented programming by combining the most recent advances in artificial intelligence, parallel computing, and telecommunications (Serova, 2013).

The significance of this research lies in how the ABM concept can be employed in complex supply chain and logistics networks to resolve problems. The supply chain and logistics networks, and their research problems are a broad domain when considered within different industries; in order to provide a complete picture of ABM capability in resolving supply chain challenges, problems such as distribution center location-allocation, vehicle scheduling and routing problem, and fleet management are considered in this paper.

The significant challenge of supply chain design for firms is deciding where to establish facilities such as industrial facilities or depots to lower the expense of fulfilling demand. Fixed expenses exist along with locating facilities, as well as logistic costs associated with distributing between facilities and demand locations.

Optimally locating facilities while considering factors such as fleet number optimization, random demand point location, and the number of required facilities could add further complexities to these problems. Various mathematical optimization methods for facility location problems have been introduced in scientific research projects; however in this research ABM and network optimization tools are used to solve this problem.

Logistics efficiency is vital to supply chain performance. In addition to location-allocation problems, vehicle routing and scheduling improvement have been shown to increase logistics operations performance in recent studies. When time factors are added to a basic "vehicle routing problem (VRP)", it becomes a "vehicle scheduling problem (VSP)". VSP is primarily concerned with allocating fleets to complete all deliveries in the best efficient method possible. (Rouzafzoon & Helo, 2018)

The goal of VSP is to reduce costs such as fixed expenses for each operational truck as well as variable costs such as deadheads, downtime, and travel length. On the other hand, establishing the number of fleets required to achieve optimal supply chain operation can be challenging. Effective vehicle sizing can assist companies to save money while also increasing consumer loyalty.

Mathematical optimization methodologies are mostly used to resolve and formulate the VSP; however, in this paper, other key factors such as facility locations and fleet sizing optimization have been included to analyze vehicle scheduling problems by using ABM method.

1.5 Research structure

In this dissertation, agent-based simulation, distribution center's location, hub and spoke, GIS systems for distribution centers, optimization approaches, and possibilities of ABM in supply chain are discussed in section 2. In section 3, the problem is described as well as the solution technique. The findings and key performance metrics are presented in Section 4. The research discussion and conclusion are described in sections 5 and 6, and the research references are mentioned in section 7.

2 LITERATURE

Supply chain planning and logistics strategies have received much interest in order to minimize costs and improve demand fulfillment. The goal of expenditure reduction requires centralization of inventories, but the goal of demand fulfillment responsiveness involves having goods as close as possible to the demand location. To bridge this gap and achieve these two conflicting goals, decisions on distribution centers' location play a critical role. (Nozick & Turnquist, 2001)

Supply chain networks must be treated not just as a system, but also as a complicated adaptive system to address the absence of awareness of the structural, operational, and evolutionary characteristics of supply chains(Surana et al., 2005). Large-scale supply chain networks are complex dynamic systems, in which the integrated structures of various entities adapt to changes in the environment as well as the system itself (Choi et al., 2001). Agent-based methods, incorporating independent entities strategy, can be an efficient method to resolve supply chain problems and recent studies of the ABM method are reviewed in the Agent-based simulation sub-section of this chapter.

The distribution center location challenge entails determining how to select distribution centers from a variety of options in order to lower overall operational costs. The hub-and-spoke system, on the other hand, has been vastly applied in a range of industrial technologies, including supply chain network designs for shipping and telecommunications. It is a densely connected system with material and data streams between any two points being analyzed at a limited number of crucial nodes (i.e., hubs) as then operators can consider taking benefits of economies of scale by combining streams from and to spoke blocks and intensifying hardware and staff efficiency at those edge node (An et al., 2015). Different approaches for optimizing distribution centers and the hub location-allocation problems have been developed which are discussed in the following subsections of distribution center location, hub/spoke problems, and optimization approaches.

GIS has also played a critical role in electronic navigation, logistics, electricity, communications and other fields. The aggregation of huge entity geospatial databases is now possible and economical because of recent advances in location-aware systems; thus, GIS systems can be utilized efficiently in supply chain location-allocation and spatial analysis. Recent studies on GIS application in supply chain problems and logistics are reviewed in the GIS systems for DC subsection in this chapter.

2.1 Agent-based simulation

Agent-based simulation such as systems dynamics, time-stepped, discrete events, and several other types of simulation entails modeling all the interactive events of agent interaction repeatedly through time. A system in which agents interact frequently is known as an agent-based model. While agents enhance their aggregated activities using simple information transfers, such as in particle swarm or ant colony algorithm, the goal is to reach the intended conclusion, i.e., the optimal approach, rather than modeling a complicated process. (C. M. Macal & North, 2009a)

ABM is an efficient mechanism to analyze the behavior of various distributed networks like the Internet of Things, with the capacity to absorb components of the model structure, embrace new constraints, add human behavior information, and simulate a system's encounters and structures. (Borshchev & Filippov, 2004)

Furthermore, ABM can be a useful method for gaining valuable information about a potential solution and exploring the model's dynamical behaviors. It also helps in the testing of the reliance of results on-premises and variables for a method with a mathematical model that can be established but not fully resolved, or with a large number of equations. (Axtell, 2000)

We live in a rapidly changing complicated world, which is one of the factors why agent-based modeling (ABS) has become more common. In terms of interconnections, the structures we have to investigate and model are becoming more complicated at first. Traditional modeling methods can no longer be as effective as they have ever been. The restructuring of the previously regulated electric power industry is an example application field where agents are immediately permitted to create investment and cost control decisions based on their parameters. (C. M. Macal & North, 2009a)

Certain structures, on the other hand, have always been too complicated for us to properly model. Long-term stability, ideal economies, and homogeneous agents have historically been used to model economic markets since these premises enabled the challenges analytically and quantitatively manageable. Via ABMS, we're starting to be able to relax these kinds of presumptions and develop a more practical look at these economic structures. As a result, information is gathered and structured at finer classifications into databases. Entity simulations are now possible with microdata. Then there's the fact that computing power is increasingly improving. We can now perform massive microsimulation models that were previously unimaginable. (C. M. Macal & North, 2009a)

Previously, some of the first agent-based simulations had their type, duration, and mechanisms for state advancement established by the sector of cellular automata. ABS emerged and evolved regardless of conventional "Monte Carlo" and "Discrete Event Simulation" techniques (DES). (C. Macal et al., 2013)

ABM is used to explore people's social, cognitive, ethnic, and physiological processes among other things. Simulating historical cultures that were extinct for millennia, as well as constructing a new marketplace for items that do not yet live, are just a few of the features. (C. M. Macal & North, 2009a)

Research on agent-based simulation models was released by Heath et al. (2009). According to these researchers, agent-based simulation has been employed since it is the best way to directly integrate the ambiguity that emerges from human activities and experiences in the real world. Network agents are characterized by the association for the development of systematic data principles as a model for coordinating and employing dispersed capacities that may be handled by multiple ownership domains (Oluwole, 2008).

In computer engineering, a network agent is characterized as a network element that is independent to achieve its design goals, regarded as a part of a broader mission, via the assumption of integration and collaboration with other agents, according to Gilbert (2008). An application agent is described as a software application that conducts tasks in order to achieve a certain objective in a study (Nienaber & Barnard, 2007). A mobile agent is a system agent which is autonomous and can travel inside networks to act on a user's or some other person's behalf (V. A. Pham & Karmouch, 1998).

ABM is an efficient approach when various participants are acting independently, interacting with each other, and responding to system alteration collectively. In addition, when the total activity of system participants is multidimensional, and it is not obtained from the accumulation of each entity's actions, ABM can be utilized as a concrete modelling method. Agent-based frameworks are composed of units called Agents that communicate with one another in a given context.

Agents are self-contained and exist in a system where they can interact with many other agents, make decisions, and set goals based on their actions. Each agent in the system acts as if it were a self-aware organism with its own goals and conditions, capable of making decisions given a set of principles. (Rouzafzoon & Helo, 2018)

Modeling actors are represented by agents, who are a unique element of the operation and persons, companies, and entities like nation-states can all fall within this category. Agents have the following unique features, according to pragmatic modeling.(Helo, Rouzafzoon, & Gunasekaran, 2018; C. M. Macal & North, 2009b)

- Agents are communicative creatures who interact with one another.
- Agents are self-administered and autonomous.
- Agents are identifiable, distinctive, or decentralized entities, each with a combination of traits and principles governing their activity and decision-making abilities.
- Agents exist and operate in a place where they communicate with one another.
- Agents may have objectives and plans based on their actions (not specifically maximizing goals).
- Agents are adaptable, and they can develop from their mistakes and alter their actions accordingly.

The following are characteristics of agent-based modeling:

- "Ontological correspondence": The framework algorithmic agents and actual actors have a direct relationship, which makes model creation and analysis easier.
- "Diverse agents": Every agent behaves based on its own set of values and interests.
- "Environment representation": An agent-based framework can reflect the world in which agents are engaging. It can also involve physical characteristics like physical or geological obstacles, the influence of other agents on the adjacent region, and the effect of issues like congestion and resources limitation.
- "Agent interactions": It is feasible to simulate agent-agent exchanges.
- "Bounded rationality": People's intellectual capacity and the extent to which they can maximize their behavior are limited, and it is able to develop confined intelligent agents in an agent-based paradigm.
- "Learning": Individual, adaptive, and communal learning may all be simulated using agent-based models, which can be used to model training at both the personal and community level. (Gilbert, 2008)

An agent-based simulation is a beneficial strategy for decision assistance in supply chain planning since it uses a bottom-up simulation paradigm. Because all objects can operate as perceptive agents, take actions, and interact with other intelligent agents in the development and management of a supply chain, multi-agent simulation is well suited to the problem of modeling supply chains. (Gunasekaren et al., 2000; Helo, Rouzafzoon, & Gunasekaran, 2018)

Every component in a system operates as an intelligent agent with its own range of priorities and circumstances, as well as the ability to make decisions based on predetermined rules. The behavior of an agent can range from simple responsive decision criteria to sophisticated adaptable artificial intelligence. (Bonabeau, 2002; Helo , Rouzafzoon, & Gunasekaran, 2018)

Figure 1 illustrates how each component of a real supply chain can be modeled with an individual agent and Figure 2 displays how each agent can consist of sub-agents representing tasks to be completed or elements within that agent.

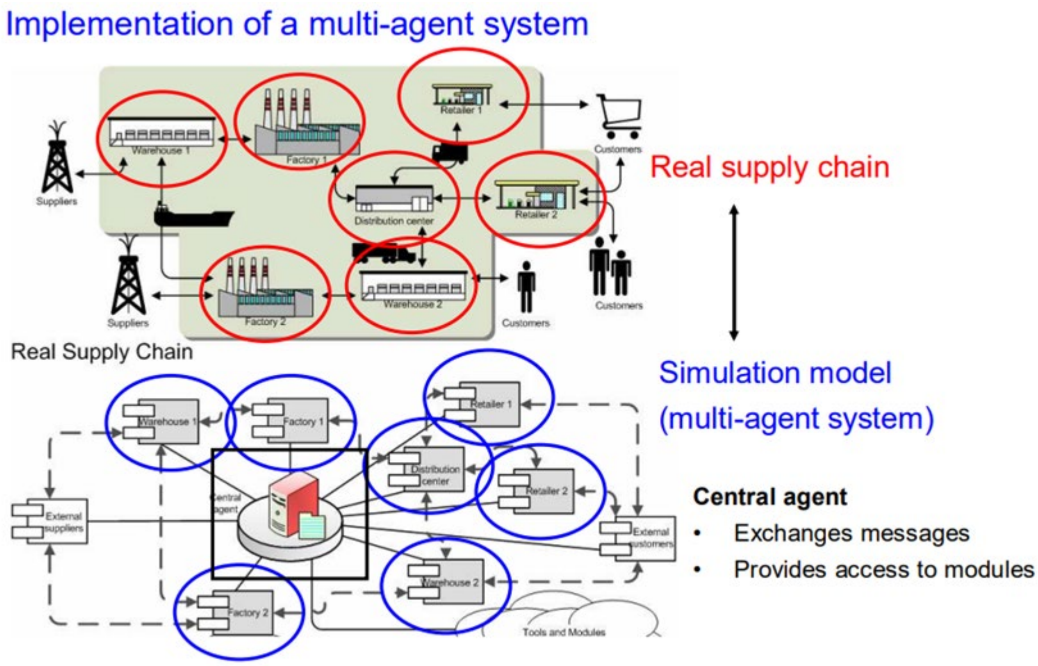

Figure 1. ABM structure in the supply chain (Fernando D. Mele, 2007)

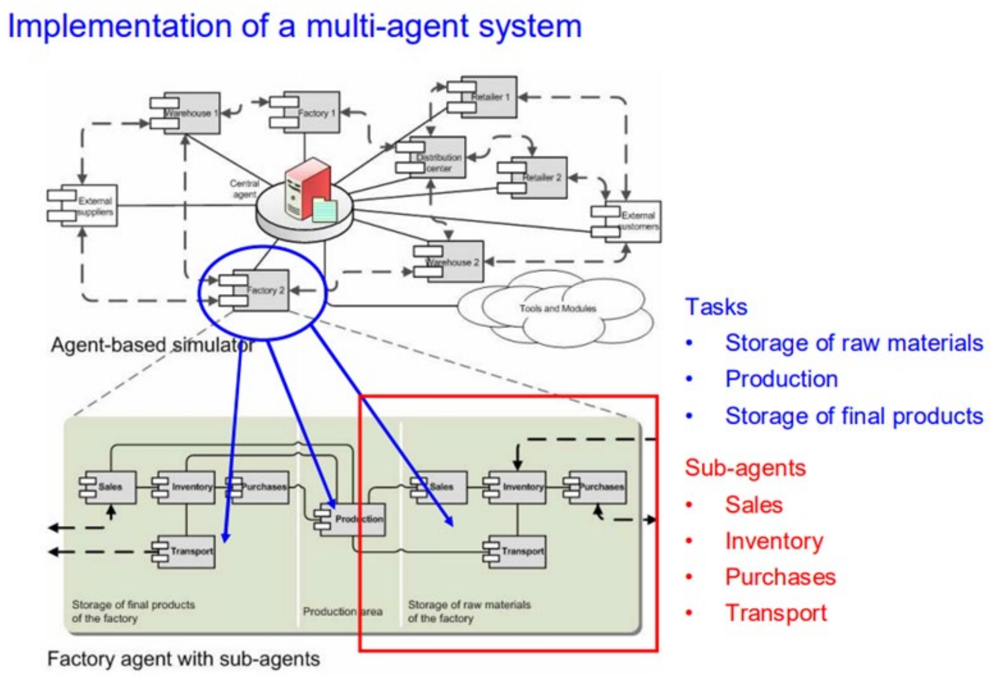

Figure 2. ABM structure with sub-agents (Fernando D. Mele, 2007)

ABM is applied in extensive domains and some of its applications in supply chain management and logistics are as follows; based on the movement of customers, geographical locations, and service prices, Rouzafzoon (2016) presented an agent-based strategy for simulating the supply chain and distribution of services. In a multicenter chemical distribution network, Sha and Srinivasan (2016) used the agent-based model technique to estimate the fleet size. The simulation modeling took into account the autonomy of every agent's choice, restocking management, and ordering allocation.

Karttunen et al. (2013) investigated the profitability and competitiveness of intermodal container supply chain compared to multimodal one in transportation over a vast distance of forest chips by rail and trucks. Availability analysis and agent-based simulation methods were utilized to estimate and compare logistics costs in different scenarios.

Kohout et al. (1999) modeled shipping and truck orders as agents, with a resolution generated by a series of announcements of allocated orders through auction procedures. Abdul-Kader and Haque (2011) discussed the ecological impact of tire retreading using agent-based modeling. The "tire agent, the remanufacture agent, the recycler agent, and the collector agent" are the four agents in the framework. Each agent's activity and decisions were outlined. The findings revealed that retreaded tires can satisfy 25% of the renewal market, and this amount may be increased by raising the retread grade.

Garro et al. (2015) employed agent-based simulation to analyze a deploying approach for the straddle carrier sharing problem. Vojdani et al. (2017) put negotiating techniques to the test in order to provide decentralized manufacturing control, which is reliant on the engagement of fewer agents. Lima et al. (2015) examined a process by ABM that enables port logistic systems to organize and control shipping flows more quickly.

Akanle and Zhang (2008) suggested a framework for optimizing supply-chain configurations over time to satisfy consumer demand. This approach employs a multi-agent framework to design resource choices in a supply chain, and also various modifications that occur at the sources and their operational conditions. A timeframe-bound set of orders are placed that are treated progressively by the supply chain defines demand. Under the framework of an iterative bidding process, supply chain agents communicate with the duties in each customer order to find the best resource arrangement to fulfill each order. Individual order resource mixtures are then structured to determine commonly used resource classes, which are then optimized more based on the qualitative standards to identify a potential chain structure.

Amini et al. (2012) investigated how alternate supply chain strategies affect the spread of a new product. The method considers the adoption patterns of 3,000 distinct customer service agents. It is important to note that every agent determines whether to accept or refuse the new product on their own, based on dynamic connections and a changing context.

Chenglin and Xinxin (2008) introduced a multi-agent approach to address the supply planning problem by taking into account three distinct agents: "manufacturing agent (MA), supplier agent (SA) and collector agent (CA) ". A numerical framework for each one of the agents is developed, with the goal of lowering operating costs and, in turn, decreasing the chain's entire operational costs.

Serrano-Hernandez et al. (2018) developed an agent-based model to assess the impact of horizontal cooperation in logistics and transportation. The negotiation process, coalition forming, trust-related problems, and level of integration are included in the modeling. The result indicates that significant savings can be achieved with cooperation, and a higher degree of collaboration, more than the number of companies, can yield higher savings.

Fragapane et al. (2019) applied agent-based modeling to evaluate the automated guided vehicle (AGV) operation in hospital logistics. Various scenarios such as equalizing transportation volumes, increasing demand for hospital items, and increasing logistics capacity were assessed to help hospital planners and to forecast the needs.

Naghavi et al. (2020) created agent-based modelling for a milk supply chain to investigate the behavior of agents, dairy farmers, against the policy of increasing the raw milk price. The modeling showed that increasing prices resulted in lower dairy products because of the processing industry's reactions to that policy. In addition, the bullwhip effect can be decreased or removed using centrality in decision-making and information sharing between agents.

Sakai et al. (2020) introduced a new agent-based model approach for simulations of metropolitan logistics in "SimMobility" which takes into account factors such as location and truck number, without reliance on financial information such as "make-use" and "input-output" tables, and forecasts commodities streams, truck performance, and traffic patterns.

Because "SimMobility Freight" is a completely sectoral system due to its agent-based structure, it may be used to measure operating effectiveness at the highest sectoral layers such as individual firms, commodities agreements, deliveries, and commercial vehicles. Sakai et al. (2020) used the agent-based simulation platform for policy research, and the platform's usefulness demonstrations.

2.2 Distribution center location

Distribution center location can significantly impact supply chain and logistics performance as there are constant flows of materials between these centers; therefore, in the supply chain design and network optimization, DC location decisions are critical and can lead to cost reduction and improved operational performance.

The implementation of "Facility Location Problems (FLP)" can be used in a variety of situations, including the location of a distribution hub in a supply chain, the storage site for a product manufacturer, recreational facility location for an urban architect, and even databases site in computer systems. (Boloori Arabani & Farahani, 2012; Rouzafzoon, 2016)

There are two features that distinguish FLP problems; Time and Space. The term "space" pertains to the region in which facilities are placed, while "time" corresponds to the period when the facility was established. FLP elements can also be described in terms of discrete and continuous characteristics. Facility with discrete attributes, for instance, can be located only at certain points inside the project area, whereas in continuous space, they can be located wherever within the proposed site. Furthermore, discrete-time implies that adding new sites or changing existing ones is only allowed at pre-determined times, but continuous time does not have this constraint. (Boloori Arabani & Farahani, 2012; Rouzafzoon, 2016)

Because the space aspect is more important than the time aspect in "FLP problems," the space component is addressed in "Static Facility Location Problems, SFLP," whereas the time attribute is emphasized in "Dynamic Facility Location Problems, DFLP" . (Boloori Arabani & Farahani, 2012; Rouzafzoon, 2016)

Boloori Arabani and Farahani (2012) defined the "Continuous Facility Locating Problems, CFLP", as a subclass of the "SFLP" principle. Models are influenced by two primary factors in these problems: Firstly, in a continuous space, the facilities can be placed at any point in the planned space; Secondly, the length between facilities and clients is estimated using measuring indices. ReVelle et al. (2008) provided examples of using these methods to monitor the surroundings, such as installing recording devices and pollution controls.

There are three different types of "CFLP" problems;

"Single Facility Location Problems":

Boloori Arabani et al. (2012) indicated in this class that the site is situated on a spot where its length to other facilities is reduced, and length can be determined using "Euclidean" or "Manhattan" approaches. Wesolowsky (1973) developed the first and most basic form of these problems, which included an objective function that reduced overall cost. In research by Diaz-Banez et al. (2004), more improved forms of these models such as " half-line facilities, hyperplanes, and spheres, polygonal curves, the location of single line and multiple lines in the plane" are composed.

"Multi-Facility Location Problems":

According to Boloori Arabani and Farahani (2012), "MUFLP" problems are comparable to "SIFLP" problems in that "SIFLP" considers the optimal site of only one new plant, whereas "MUFLP" considers the location of numerous additional facilities. Daneshzand and Shoeleh (2009) developed a "MUFLP" model that includes weights for lengths between new sites.

"Facility location-allocation problem":

In these approaches, an efficient resolution is sought for two targets: the place of facilities and assigning them to customers to meet demand. ReVelle and Swain (1970) presented the first edition of this concept, in which the overall expenditure resulting from clients' facility assignment is minimized.

Other types of these frameworks may include capacity constraints on facility distribution to customers, such as expense, timing, and so on. There are also multi-product facility assignment problems, in which many commodities are regarded rather than a single product. (Boloori Arabani & Farahani, 2012; Rouzafzoon, 2016)

"Discrete Facility Location Problems":

In "DFLP" problems, demand and locations are classified into two main groups. Because most demands are expected to happen within specified geographical areas, this parameter is assumed to be a discrete one. The "*quadratic assignment problem (QAP)*" and the "*plant location problem (PLP)*" are two key "DFLP" problems. Allocation problems, in which clusters of people are allocated to tasks, are similar to "QAP" problems; however, facilities are allotted to consumers in the "FLP" setting. (Boloori Arabani & Farahani, 2012; Rouzafzoon, 2016)

The cost of allocating a facility to a client is minimized in the integer form of "DFLP" models and one of the key limits is that only one facility can be assigned to one client; in other words, only one client or facility can be allocated to another. (Koopmans & Beckmann, 1975; Rouzafzoon, 2016)

"Plant location problems, (PLP)," is composed of a set of facilities, each of which can be a depot, a manufacturing plant, or a shipping site and it has a wide range of applications. It's also frequently regarded as a problem in the absence of capacity constraints. (Boloori Arabani & Farahani, 2012; Rouzafzoon, 2016)

"Network Facility Location Problem":

"Network facility location problem" is integrated with a network component made of Nods and interconnections dependent on that demand can exist. These problems are divided into five categories, each of which is detailed below. (Boloori Arabani & Farahani, 2012)

"Median Problems":

The "P median problem" is an enlarged variant of the first median problem in which the best appropriate spots for P facilities are sought and the weighted interval aggregate for each demanding node to its adjacent facilities is minimized, so facilities that meet the demand node are specified as well. There are also multiple types of this problem, such as those with or without capacity limits.(Boloori Arabani & Farahani, 2012; Rouzafzoon, 2016)

"Covering problems":

Toregas et al. (1971) was the first to propose this sort of problem, and in "covering problems", each client can be supplied by any facility when the only length between the facilities and the customer is less than the permissible distance, which is known as the "coverage distance".

"Center Problems":

Center models, as opposed to "covering problems," look for a potential position on the proposed site that can adapt to all demand, but facilities should keep a minimal distance from demand locations. The "vertex p-center problem", in which plants are only permitted to be provided on network points, is also regarded to be among the most common classes of these problems. (Boloori Arabani & Farahani, 2012; Rouzafzoon, 2016)

"Hub Location Problems":

O'Kelly (1987) provided the first version of this problem, in which the optimization problem is focused on total cost reduction. O'Kelly (1987) also noted that elements such as discount, circulation, and hub transit costs are considered.

"Hierarchical Location Problems":

There are several categorized facilities within a distribution network framework in "HILP problems", and the higher hierarchy tier of a facility can select sites separately from the bottom tier. It is important to remember that in these situations, processing and transportation expenses are computed according to the quantity of goods moved. (Boloori Arabani & Farahani, 2012; Rouzafzoon, 2016)

Also, Sahin and Sural (2007) described the basic "HILP problem", which consists of one stream and two hierarchical tiers. The" SFLP problem" was addressed in the preceding sections, and "Dynamic Facility Location Problems (DFLP)" will be presented in the following.

Two key criteria determine the placement of the optimal facility in "DFLP problems".; 1) choosing on a trade-off depending on the cost of constructing a new facility or enhancing a current one 2) the facility's shutdown or opening time from the standpoint of planning. (Boloori Arabani & Farahani, 2012; Rouzafzoon, 2016)

There is a second standpoint on how to classify "DFLP problems." In "Explicit Dynamic problems", facilities will be opened or shut at designated time periods and locations while facilities in "Implicit Dynamic models" start functioning at a particular schedule and remain open for the duration of the predefined timeframe. (Boloori Arabani & Farahani, 2012)

There are several forms of "DFLP" problems, which are classified in the subsequent sections:

"Dynamic deterministic facility location problem":

Other beneficial criteria such as environmental parameters, the population of the state, request trend, market dynamics, and so on are adjusted across various periods in static models that majorly seek for an optimized location in the terms of expenditure. These developments are brought about by real-world challenges, necessitating the need to alter, change, and shift facilities. As a result, dynamic models are needed to cover the gaps in these types of challenges. (Boloori Arabani & Farahani, 2012; Rouzafzoon, 2016)

Wesolowsky (1973) claimed that "single facility location problems" might be shifted to "Dynamic Deterministic Problems". Rather than a unique solution for the entire time period, the optimum result for each P time period is considered in these situations.

"Facility location–relocation problem":

As a result of the convergence of components such as customers, vendors, laws and policies, and the work environment, criteria for situating facilities vary, and organizations ponder relocating or changing existing ones. (Boloori Arabani & Farahani, 2012; Rouzafzoon, 2016)

When it comes to facility relocation, there are three elements to consider: quantity, timeframe, and expense of relocation. Facilities can be shifted in continuous or discrete time periods. Facility locations are modified on a definite, pre-specified, and distinct particular time in "discrete-time" periods, but there are no predefined time points in "continuous-time" periods, and adjustments can be made at any moment within the planning horizon. (Boloori Arabani & Farahani, 2012; Rouzafzoon, 2016)

In addition, in regards to the relocation numbers, R. Farahani et al. (2009) stated that there is a single relocation classified as a "Server", as well as multiple relocations. Finally, the cost of relocating is determined by the current and prospective location of the plant.

Some factors, such as the cost of procuring a property, bordering authorization, shifting equipment, employees, immediate delivery to customers and availability, ease of access to vendors, ease of accessing transportation locations, tax incentives, employment circumstance, and employment relationship building, have a major impact on relocation decision making. Additionally, one of the really applicable domains of "FLRPs" is "Emergency Medical Services", which ensures a reasonable response time to healthcare crises. (Min & Melachrinoudis, 1999)

"Multi-period (discrete time) vs. single-period (continuous time) facility location problems":

Using multiple period facility locations, three findings can be derived. First, an appropriate timeframe for facility location choices; second, identifying the perfect site; and third, in multiple period development plans, a chance for firms to analyze the preferable/unpreferable demand volatility in the enterprise market, which that opportunity does not occur in "single period facility location" problems. Additionally, dynamic models allow organizations to operate more effectively on amending parameters in each time frame, as opposed to a single period in which employees are seldom able to deal with unlimited aspects. (T. C. Miller et al., 2007)

Wesolowsky and Truscott (1975) proposed a system in which the target function is cost-minimizing, and the model considers three types of costs: The first is the expense of assigning facilities to the corresponding demand point; the second is the expense of removing facilities from the current node, and the third is the expense of establishing new facilities at the corresponding demand point.

"Time-dependent facility location problems":

Drezner and Wesolowsky (1991) developed a model that is comparable to dynamic models but operates well in real-world scenarios with periodic fluctuations. The majority of "TDLP" challenges revolve around identifying two variables: the timing of facility site change and the location of the new unit in each time frame.

"Stochastic, probabilistic, and fuzzy facility location problems":

Although dynamic models are typically used to schedule facility locations, determining an optimal location that meets all characteristics is a difficult task for decision-makers because elements such as costs, demand, and transportation time are likely to be unpredictable over the construction phase. (Boloori Arabani & Farahani, 2012; Rouzafzoon, 2016)

Lack of certainty can arise from two factors: new circumstances may produce uncertainties, or a lack of information about how to define the variable's value may result in ambiguities. (Owen & Daskin, 1998)

Two strategies have been utilized to deal with ambiguous situations. Elements of the model are specified by probability distributions in a probabilistic or stochastic methodology and the development of a scenario (robust) strategy that takes into account the most likely values for every component or parameter. In the second version, variables are assumed to be unspecific, and there is no information on probability. (Boloori Arabani & Farahani, 2012)

In addition, the first form of the problem was proposed by (G. Chen et al., 2006; Owen & Daskin, 1998) and in this case, stochastic planning is used in conjunction with a scenario method.

In addition, the Fuzzy method has been used in facility locating problems that can be divided into two categories: 1) deciding on a plant's location, "Decision Making Problem" 2) "Location-Allocation problem" and "Optimization Problem". For the first level, the following techniques could be used; "Fuzzy Analytic Hierarchy Process (AHP), Fuzzy TOPSIS (the technique for order preference by similarity to ideal solution) method, and Fuzzy information Axiom". (Boloori Arabani & Farahani, 2012; Rouzafzoon, 2016)

In addition, Boloori Arabani and Farahani (2012) inferred from a comparison of different facility location papers that in most circumstances, cost reduction target functions are employed, with operational, logistic, and materials processing expenses taken into account, and revenue-maximizing is a less commonly utilized objective function.

ReVelle et al. (2008) emphasized two elements that should be specified before developing the specifics: first, pre-identified client locations, and second, facilities should be established based on the objective function.

Zhang et al. (2012) stated that the importance of methodology and strategies for enhancing long-term home health care is becoming increasingly vital as the population ages. Contacting for service, preadmission assessing for defining clients' requirements and assistance needed, deciding the recurrence of service, length of service for each appointment, and service duration (weekly, monthly, etc.) are all steps of Homecare Service. The ideally appropriate caregiver is allocated to the patient when the abovementioned criteria are defined. (Maya Duque et al., 2015)

Maya Duque et al. (2015) defined two objectives; accommodating the patients' and carers' demands to the fullest extent practicable and decreasing trip distance since the firm reimburses caregivers for travel expenditures. The following modeling constraints have been considered: for patients who require more than one session each week, visits should be evenly distributed throughout the week. Attributing patients who require more than a single weekly appointment to different caregivers to lessen the consequence of service providers' unavailability. To make scheduling easier for patients, appointment planning should be consistent across the time frame. The maximum number of hours a caregiver can spend in order to offer health assistance.

In terms of the simulations, three choices must be taken: The sequence of various visits that caregivers should deliver for patients, organizing sessions according to patients' time slots, allocating service vendors to patients for every session, and scheduling appointments based on patients' time slots. (Maya Duque et al., 2015; Rouzafzoon, 2016).

A two-staged strategy is used to solve the bi-objective problem rather than a weighted technique. The first level of care was optimized without consideration for the second objective, while the second stage focused on minimizing total travel distance while allowing for a certain degree of service quality reduction. The resolution method entails calculating all possible visit patterns and then selecting the best one for both goals. (Maya Duque et al., 2015)

Based on conventional three-level procedures, a "decision support system (DSS)" was also created for care planning. The design step includes the general design of a structure, the specification of a problem, and the development of a solution approach.

Validation includes reviewing the simulation using ANT/OR Simulation software programmers, discussing and reporting the outcomes to the team lead, conducting the simulations over two months, and comparing the outcomes to the prior manual design procedure. The phase of execution, during which the program will be implemented with the help of the county's ICT division. (Maya Duque et al., 2015)

Ross and Soland (1980) majorly solved facility location problems using linear programming, in which authors specified the optimum solution while taking into account constraints.

A research project on the Taiwanese healthcare system was conducted in order to pinpoint the facility's placement among 17 medical fields. Because of elderly demographic trends in this region, according to World Health Organization data, and an extremely competing service and health industry, choosing the wrong site could lead to cost increases and uncertain future expansion. (Wu et al., 2007)

Wu et al. (2007) used the "Diamond paradigm", which was established by Porter (1990) in which four major and two outer variables are proposed for investigating the benefits in competition. Wu et al. (2007) proposed the elements as factor circumstances, demand status, company policy, hierarchy, and competition, linked and assisting sectors, opportunity, and politics.

The following sub-criteria for every Porter's modeling element were also described: Element conditions (resources, labor, government), demand circumstances (habitants number, congestion, age group), business strategy, structure, and rivalry (management objectives, level of competing facilities, executives' conduct), sponsoring and affiliated organizations (the healthcare section, the medical services and pharmaceutical section, and the research and development segment Managers of health institutions), Politics (Clinic construction requirements and regulations, Health policy made by the government, Efforts to enhance the medical system, creating guideline that necessitates a hospital assessment) and Opportunity (a significant alteration in market demands, a significant change in manufacturing costs, a significant change in the exchange value and element in economic). (Wu et al. 2007)

Saaty (1980) developed the Analytic Hierarchy Process (AHP), which disintegrates complex multi-criteria problems into a structure and evaluates pair-wise alternatives. Wu et al. (2007) used AHP in their research, and AHP Eigen ratings, reliability tests, component weight, and scenario analysis were generated for three indicated places, with the top score picked as the ideal position.

The research concentrated on an organ's transplantation procedure where duration, instead of capacity or stock, serves as a buffer. Demand and supply parameters, as well as two restrictions, were used to define the procedure. The first constraint is freezing ischemia duration, which is the greatest amount of time an organ can be outside the body. The second constraint is fixed capacity since the organ will be ready for transplanting demand by the time the giver dies, which is why there are long lines for it (Beliën et al., 2013). The methodology was created to reduce waiting times by identifying the best transplant locations for every organ as it became accessible. In order to modify the significance of elements, various weights are analyzed for every time element (Beliën et al., 2013). This problem was resolved using mixed-integer linear programming in the setting of facility location.

The model's outcomes include costs associated with setup and transplant surgeries, as well as sensitivity in terms of reducing the time from donor notification and organ insertion (Beliën et al., 2013).

Between 2004 and 2009, Beliën et al. (2013) used the modeling in a Belgian case, encompassing several circumstances on real data, and the below findings were observed; If the goal is to reduce the ischemia period, then consolidation with a limited number of locations should be taken into account; if the goal is to reduce the hours between donor notification and organ transplantations, then dispersion with a large number of sites should be defined.

Beliën et al. (2013) also noted that decreasing ischemia time will result in more links across donor clinics and institutions. Budget restrictions would also lead to a reduction in the number of centers and, as a consequence, a reduction in levels of service.

Mestre et al. (2015) conducted research on medical strategy development, which is the process of deciding where a hospital should be built and how much capacity it should have.

Clinics can manage potential demand and supply with a choice on the two factors. Because of the large capital in hospital construction and the inability of changing the site in the coming years, a selection of hospital sites is especially important.

Management must evaluate a range of outcomes while building health systems, which often encompass enhancing accessibility to health centers and reducing costs. These goals are incompatible; for example, to enhance spatial connectivity to hospitals, health centers should develop smaller facilities closer to the people, resulting in higher costs and inefficiency. (Mestre et al., 2015)

Mestre et al. (2015) conducted research using the NHS framework, in which legislators must allocate medical supplies adjusted for population requirements while working with restricted funding.

Kall (1994) and Birge (1997) claimed that there are actions that should be made without full information and undetermined variables, referred to as first-stage selections, and choices that should be made once ambiguity has been revealed, referred to as second-stage choices.

As a result, two approaches of location-allocation have been recommended: one in which site is determined first, and then selections about the distribution of resources are made when ambiguity is discovered in the second step. The second version is that the locations of the plant and the allocation of resources are both determined at the beginning stages. In more depth, there are two categories of medical services: DH has lesser levels of service and is nearer to the community, while CH has an increased service facility but a fewer number. In addition, the researcher has considered the demographic's proximity to the closest clinic. (Mestre et al., 2015; Rouzafzoon, 2016)

Royston (2009) mentioned that style of living, personal ambitions, population expansion, technologies, labor, connectivity, and data have all impacted the unpredictability of hospital demands. Mestre et al. (2015) forecasted healthcare service rates largely on demographics and utilization rates, whereas she evaluated both favorable and unfavorable initial possibilities for medical demand. The accessibility and expense targets were presented in two objective functions in the optimizing modeling. To estimate modeling variables, healthcare data from three locations in Portugal was used. The problem constraints were capacity facilities, travel length, and request fulfillment, and modeling was completed using the mathematical equation in "GAMS" software. When the findings were compared, the second version was presented to have better flexibility for medical management systems.

Based on the perspectives of transportation service suppliers, T. Y. Pham et al. (2017) developed a benchmarking system for the facility location of distribution centers in Vietnam. A combination "Fuzzy-Delphi-TOPSIS" model was applied in this context to assess factors and alternatives in an unpredictable information setting. The findings indicated that cargo demand, shipping costs, and accessibility to market, manufacturing location, and consumers are the most important aspects to take into account when deciding where to locate logistics facilities.

For the capacitated facility location problems, Rahmani and MirHassani (2014) proposed a composite firefly genetic algorithm. To address the single-source capacitated facility location problem, Ho (2015) introduced a recursive tabu search heuristic that combined tabu search with perturbation operators to avoid complexities in local optimization. To address a multi-objective, resource, and staged location-allocation problem, Thongdee and Pitakaso (2015) proposed a revised "differential evolution algorithm".

To manage a logistics distribution center location problem, Chi et al. (2019) introduced a novel mixed optimization technique known as "cuckoo search-differential evolution (CSDE)". The "CSDE" method takes advantage of the differential evolution method and combined that with cuckoo search algorithms. To address the multiple goals restricted optimization method for a distribution center location problem, Jun et al. (2016) introduced an enhanced particle colony optimization approach.

Dou et al. (2020) proposed an "immune wolf swarm hybrid" method to resolve a cold network transportation distribution center location problem. Because of the multi-objective nature of this problem, a single heuristic algorithm was not an ideal approach.

Addressing the placement of DCs, Sun et al. (2008) devised a "bilevel programming" technique. Requests arriving at a DC may not surpass its limit since DCs have restricted capacity. The goal is to reduce costs as much as possible, and the problem is solved using a customized "heuristic" technique. For the location of a transportation distribution hub, Hua et al. (2016) utilized particle swarm optimization (PSO) methods.

Distances are considered as the shortest route in a diagram in-network location model. Potential facility locations refer to a cluster of points on arcs, while points serve demand nodes. In order to develop network location systems, the majority of location decisions could be constructed through "mixed-integer programming" techniques that provided a set of possible facility locations (Boffey et al., 2003). A genetic algorithm method was used by Zhou et al. (2002) to address balanced customer assignment to several distribution centers.

To improve the placement of capacitated distribution hubs, Gutjahr and Dzubur (2016) introduced the "Frank–Wolfe" method. Several current algorithms are constrained by one of the hypotheses, according to these researchers; (i) the premise that clients will always choose the facility that is closest to their residence; or (ii) the idea that centralized management can control the allocation of consumers to centers by the supply-providing company.

Gutjahr and Dzubur (2016) introduced a more realistic model based on user equilibrium, characterized by the compromise between travel costs and possible losses by uncovered demand, and that led to a bi-objective bilevel optimization problem to minimize total cost and total uncovered demand, including the equilibrium behavior of the customers.

Facility location approaches, which include the location and choice of distribution facilities, storage facilities, sanctuaries, health clinics, and other places, are an important part of disaster planning (DM). (Boonmee et al., 2017; Rouzafzoon, 2016)

Facility position modeling is a robust managing methodology for before and after disaster processes that can be essential for successful and practical disaster management. Techniques for optimizing immediate humanitarian operations have been emphasized as a major factor in emergency facility location problems in past research. To resolve these problems, a heuristic algorithm and then an "exact algorithm" could be applied.(Boonmee et al., 2017; Rouzafzoon, 2016)

Many humanitarian aid distribution facility locating situations are "NP-hard", and several scientific research have used a "heuristic" method to solve them because it requires minimal time to develop and can tackle complicated situations, but the results are of uncertain quality in comparison to the "exact algorithm". (Boonmee et al., 2017)

Although the first strategy can outperform the second, the latter is necessary because it may be used to verify the heuristic approach, and in some practical scenarios, an exact algorithm could be used to solve the issue. As a consequence, using an exact algorithm is critical and inevitable. (Boonmee et al., 2017; Rouzafzoon, 2016)

Mihajlović et al. (2019) used multi-criteria decision-making (MCDM) approaches to select the best logistics fruit distribution center in Serbia. "An Analytic Hierarchy Process (AHP) and a Weighted Aggregated Sum-Product Assessment (WASPAS) " were used to assess the location selection. Criteria such as "land price, Infrastructure access, number of registered agricultural holdings, number of citizens, delivery time, presence of competitors, and orchards and soil under the berry fruits" were considered in the problem formulation.

Guo (2020) proposed a bi-level programming model for route selection and distribution service center selection within the service network of e-commerce logistics. The genetic algorithm was employed in C# to resolve and optimize the problem.

Wang et al. (2022) introduced a new method of combining "K-means clustering algorithm" and "Dempster–Shafer evidence theory" for distribution center location decisions. Factors such as traffic degree, rules and policies, business surroundings, resource conditions, expenses and information clarity, and natural conditions were included in the problem formulations.

In recent research, various optimization methods have been developed for distribution center location problems in supply chain management and logistics such as hybrid Fuzzy-Delphi-TOPSIS, mixed-integer linear programming, and several algorithms including genetic, heuristic and combinatory ones.

2.3 Hub/spoke

Hub and spoke have been employed in supply chain design networks and can be applied in traffic management, materials flow congestion, and logistic type selection. Similar to distribution center location, various methods have been employed to improve supply chain and logistic performance by focusing on the hub and spoke location and flow optimization.

Onstein et al. (2019) identified seven categories of elements that influence distribution hub location decisions. Request degree, service scale, goods qualities, logistical expenses such as transportation, inventory, and storage expenditures, personnel and site availability, proximity, and environmental variables are all aspects to consider.

Delta Airlines is often regarded as being the first airline to introduce the Hub and Spoke model in 1955 (Delta, 2013). The term Hub and Spoke comes from a bicycle wheel with a single spoke connecting each point on the outside rim to the hub. In practice, the notion allows any point on the wheel to connect to another by routing flow through the wheel's single hub. (Oti, 2013)

Because of the economies of scale that could be acquired by routing through the hubs, this became a huge operational benefit for the airline industry. Instead of multiple low-utilization flights from point to point, Delta may fly fewer flights to its initial hub site in Atlanta, GA, and then smaller numbers of commonly implemented flights to the ultimate destinations. The approach is best illustrated in Figure 3. (Oti, 2013)

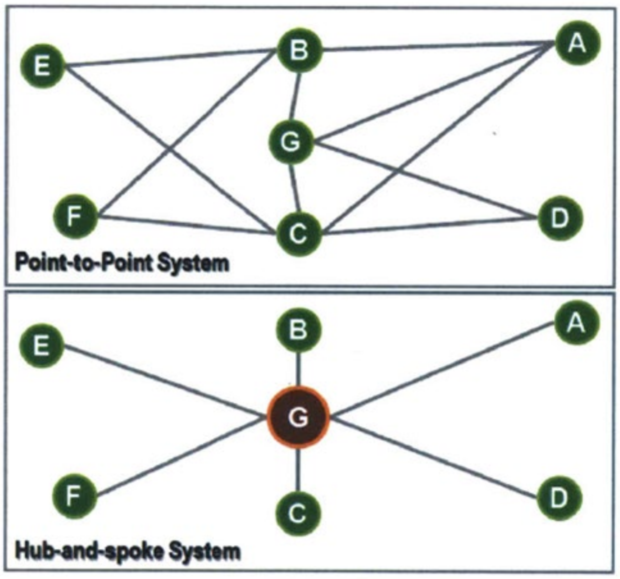

Figure 3. Hub and Spoke vs. Point to Point Network

In the early 1970s, Frederick Smith, the founder of FedEx, introduced the use of the Hub and Spoke in air transport industries (Coyle et al., 1994). Several logistics companies and carriers, including UPS, Wal-Mart, and Lowes, have embraced the model to run their distribution networks since FedEx implemented it in the logistics and shipping market. (Oti, 2013)

Because of the enhanced alternatives numerous hubs can offer, a larger number of navigation hubs/nodes offers more control and receptiveness in the system. It also enables arcs with a high use rate to connect these nodes, allowing for lower-cost constructions. Small parcel zone skipping and load consolidation are two approaches that can be used with the network of hubs and spokes architecture. (Oti, 2013)

Zone skipping is a cost-cutting tactic used by some small parcel shippers to decrease long-distance hauls in their network. To reduce costs and enhance transit times, the approach uses a hub-and-spoke system and numerous ship methods. (Oti, 2013)

In the early 1990s, a small parcel consolidator (SPS) developed a tactical agreement with CRST, a long-haul trucking company, to transport goods from SPS's central distribution center to destination hubs at great distances before being delivered by UPS to the ultimate destination, indicated in Figure 4. (Oti, 2013)

Because CRST used a group of drivers for the long-distance portion of the route, this operation resulted in a 10 to 15% cost savings for SPS's customers, as well as a 2 to a 3-day reduction in overall transit time in some situations (Andel, 1992).

Figure 4. Zone skipping method

Load consolidation is a broader concept than zone skipping, which is a more precise method. The term refers to both inbound and outbound operations, to lower transportation costs and increase trailer usage by mixing products produced and consumed in several places at various times into loads carried by a single vehicle. (Baykasoglu et al., 2011)

United Parcel Service (UPS) has expanded its operations to encompass road and railways deliveries. UPS began as a package provider employing air transportation. UPS has extended its utilization of road, rail, and air transportation to the point that it is now the country's largest intermodal customer. (Yang et al., 2016)

Intermodal transportation, in which cargo is transported utilizing many modes of transportation, is a cost-effective form of freight transportation. Multimodal transportation is not the same as intermodal transportation. Multimodal transportation refers to the selection of one mode of transportation from a range of alternatives. (Yang et al., 2016)

Almost all logistics providers use the strategy across air, land, and rail transit; yet, in the dynamic context of real-world business situations, it becomes a very difficult challenge to solve. (Yang et al., 2016)

Load consolidation solutions rely on cross-dock operations' efficiency. Within the hub and spoke distribution design, cross-docks are the hub nodes or "pool points." These hubs act as network routing and aggregation sites, allowing freight to be transferred from trailers arriving at outgoing trailers without any need for storing. Cargos are rarely kept in a cross-dock facility for more than 24 hours and are occasionally transferred in less than an hour. (Oti, 2013)

To support the inbound transportation organization in saving costs and increasing transit time performance, Oti (2013) used a "mixed-integer linear program (MILP)" to determine optimal freight transit and consolidate hub locations in the AmazonPay network.

The traditional hub location problem entails identifying hub infrastructure and assigning hubs' demand to direct flow between the starting point and the final destination combinations. In the hub location literature, it is typical to assume that every hub pair has a link, that there may be no direct route between non-hub nodes, and that leveraging inter-hub connections saves time (Alumur & Kara, 2008). Non-hub nodes are assigned to hub facilities in two ways, resulting in two types of networks: single and multiple allocations (Azizi et al., 2016).

Hub location problems can be classified based on how demand points are distributed or assigned to hubs. Single allocation is one option, in which each demand point is assigned to a single hub and can only send and receive via that hub. Multiple allocations are a second option, in which a demand point sends and receives data through multiple hubs. Examples of hub-and-spoke networks with single and multiple allocations are shown in Figure 5 below. (Ghaffari-Nasab et al., 2015)

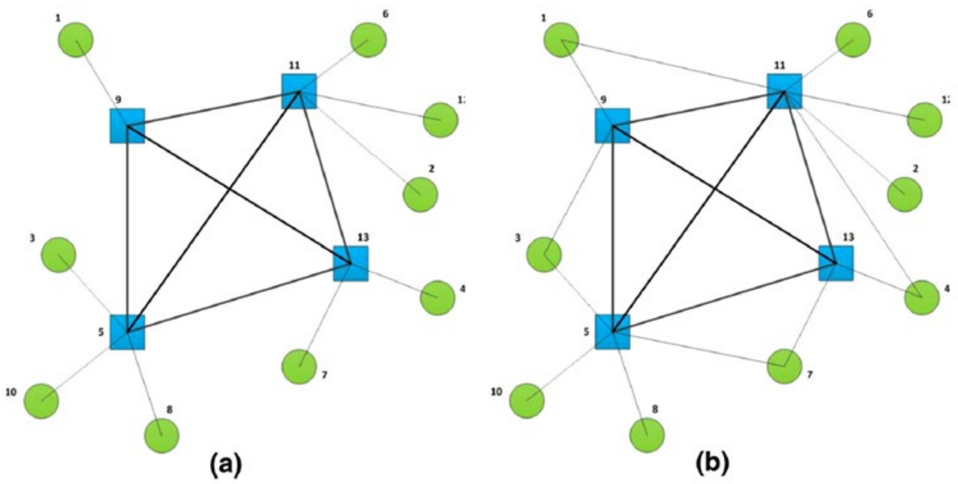

Figure 5. Typical hub and spoke networks: (a) single allocation; (b) multiple allocations

Hub location approaches have traditionally assumed that facilities are always available. In reality, although, one or more of these centers may be temporarily inaccessible due to factors such as weather and/or natural catastrophes. In air carriage, responsive (e.g., canceling, halting, rearranging, etc.) and constructive methods (e.g., investment in improving the reliability of current facilities) are commonly used to manage hub failure. However, a hub interruption can have a substantial effect on service levels and result in excessive transportation costs because customers (demand) that were previously served by such facilities must now be covered by other hubs. (Azizi et al., 2016)

The traditional H&S network design (HSND) issue has been extensively researched by (Alumur & Kara, 2008; R. Z. Farahani et al., 2013), which primarily consists of the hub center and hub median topics. O'kelly (1986, 1987) introduced a quadratic integer programming for the hub median problems.

J. F. Campbell (1994) formulated the first quadratic programming model to solve the hub center problem. Skorin-Kapov and O'Kelly (1996) established fitted linear relaxations of the formulation for the hub median problem. Kara and Tansel (2000) offered several linear formulations for the hub center problem.

Ernst and Krishnamoorthy (1998) reformulated the "HSND" with reduced constrictions and variables. In addition to identifying hubs and delegating O-D nodes to hubs, like in the traditional "HSND problem", the researchers analyzed the use of different modes of transportation over cross-hub flows.

The standard "HSND" problem has been investigated in the past literature under probabilistic uncertainty. For example, T.-H. Yang (2009) proposed a two-stochastic programming formulation for determining the best site for an air freight hub and aircraft routes in the face of periodic demand fluctuations.

Sim et al. (2009) addressed "HSND" using mutually independent normal distributions and stochastic travel times. Contreras et al. (2011) examined stochastic uncapacitated "HSND" in which transportation costs are related to uncertainty.

Mohammadi et al. (2013) suggested a novel stochastic multi-objective transport formulation for the "HSND" problem when travel times are subject to stochastic uncertainty. Despite the fact that these models broaden the conventional HSND problem to include random events, they fail to account for both shipping costs and journey times (Yang et al., 2016).

Another aspect of the "HSND" problem is figuring out how to account for fuzzy sets. For instance, for evaluating and choosing a cargo transit point hub terminal, Chou (2010) proposed a "fuzzy multi-criteria decision-making" approach. To lower network transportation costs, Taghipourian et al. (2012) suggested a "fuzzy integer programming" method to dynamic simulated "HSND".

By including the valuation parameter in the construction of the objective module, a revised risk avoidance "HSND" with fuzzy trip times was created by Yang et al. (2013). Mohammadi and Tavakkoli-Moghaddam (2016), by implementing the "fuzzy M/M/1 queuing" method, developed a "fuzzy HSND" problem.

However, uncertainty can manifest as both fuzziness and randomness. For the "HSND", Mohammadi et al. (2014) demonstrated a combined probabilistic-stochastic programming paradigm. For the "HSND" problem, in which journey times are dictated by a fuzzy stochastic process, Yang and Liu (2015) presented three new optimizations of equilibrium strategies.

These concepts are basic variations on the "fuzzy HSND" problem. In order to depict the interplay of financial and service challenges, these studies are unable to incorporate service and financial elements into their formulations. (Yang et al., 2016)

In comparison to traditional "HSND", the "IHSND" problem has received a lot more attention. It may be because intermodal transportation is a newly developing area and has not been thoroughly explored yet. (Bontekoning et al., 2004)

A few types of research have been conducted in order to solve the issue. For the "IHSND" problem, Arnold et al. (2004) presented an integer programming approach. For example, Racunica and Wynter (2005) proposed an ideal hub locations approach to increase the rail mode's share of the market in an H&S structure. Meng and Wang (2011) developed a mathematical model for the layout of a multi-type container transportation intermodal hub network.

While some methods extend the traditional "HSND" problem to include some aspects of intermodal freight processes, they lack the multi-criteria character of the "IHSND" problem. Furthermore, these models fail to depict the "IHSND" problem in the presence of coupled unpredictability, and that is a common occurrence in real-world logistics. An essential part of "HSND" is how to resolve them efficiently, considering that they are "NP-hard" problems. (Alumur & Kara, 2008)

Several heuristics strategies have been widely used to resolve "HSND" in publications. J.-F. Chen (2007) presented two ways to establish the maximum bound for the hubs number, as well as a mixed heuristic based on tabu list, the simulated annealing process, and enhancement techniques to solve the proposed incapacitated "HSND".

Azizi et al. (2016) proposed a "genetic algorithm-based heuristic" to solve the case of configuring H&S systems with a concern of hub failure. To solve a finite capacity central distribution HSND, Randall (2008) used an "ant colony algorithm". Calık et al. (2009) offered a "tabu search algorithm" for the "HSND". Saboury et al. (2013) presented two algorithms based on hybrid "heuristics" that merged "simulated annealing" and "tabu search" with a dynamic neighborhood search algorithm. Martí et al. (2015) presented the NP-hard version of the traditional HSND with a scattered search configuration.

Among these strategies, simulated annealing has been particularly effective in identifying relatively close to optimal solutions for a wide range of problems. The classic SA method, to our understanding, is slow to the concurrence, and the "SA algorithm" application is problem-dependent. As a result, a variety of researchers have been working on how to enhance the standard "SA algorithm". (Yang & Liu, 2015)

Almost all HLP studies presumed that the selected hubs will always work as predicted; However, hubs can fail for a variety of reasons. Bad weather, as is typical in the aviation sector, can drastically impair a hub airport's capacity, leading to significant interruption expenses.

Facilities, such as hubs, play a vital role in facility and customer-based supply chain and logistics networks, and their potential sites are measured employing facility location frameworks. The difference is that there is no inter-facility transit in such schemes, unlike hub-and-spoke designs. To deal with facility disruptions, (Snyder & Daskin, 2005;Yang & Liu, 2015) devised a facility location strategy with a contingency option, known as the robust facility layout method.

Kim and O'Kelly (2009) developed SA and MA methods to construct an optimum network layout that improves the expected system flow without the need for alternative hubs or paths, as long as every hub or arc is reliable.

Kim (2008) proposed a "p-hub" security model with main and secondary links, based on a single allocation system. The authors then solved the real-world cases with approximately 20 nodes using a "heuristic approach (tabu search)".

Aboytes-Ojeda et al. (2020) introduced a hybrid model to find the optimal number and location of depots in a biomass-to-biorefinery hub-and-spoke network problem. The Simulated annealing-simplex approach was utilized to identify an initial solution and a tabu search-simplex technique to improve the result.

Huang et al. (2022) investigated an extended version of the hub and spoke network problem in the maritime supply chain after encountering disruptions in the Covid-19 period. The extended version works based on a single allocation p-hub location problem, considering the possibility of hub failure and congestion. Asia-Europe data and particle swarm optimization (PSO) were used for the problem, and it was shown that backup hubs can maintain a reliable global container shipping network in the case of disruptions.

Aranguren et al. (2021) completed a research project on biomass supply chain network design which is an alternative to fossil fuels. Hub and spoke networks have been applied as a modeling approach for these problems to select the depot locations and compute the operation cost. The simulated annealing metaheuristic approach including uncertainty in weather conditions and biomass quality parameters was utilized to resolve the problem.

Researchers, in the recent hub and spoke scientific articles, have employed primarily optimization methods such as integer programming, fuzzy multi-criteria decision-making model, mixed possibilistic-stochastic programming, and heuristic-based algorithms.

2.4 GIS systems for DC

GIS-based tools have long been utilized in infrastructure design and are increasingly being employed by organizations that operate supply chain operations. A "geographical information system (GIS)" is a technology which can collect, retain, retrieve, interpret, and visualize spatially related data representing the position and qualities of spatial objects on the earth's surface. GIS tools are efficient since they have a great capacity for visualizing complex phenomena. (Helo, Rouzafzoon, Solvoll, et al., 2018)

The application of "geographic information systems (GIS)" for economic analysis is becoming more popular, and it was first used to improve the predictability of trip costs and benefits distributions. (Bateman et al., 2002)

As a consequence of a variety of interconnected variables, the use of GIS has evolved. To begin, there are various GIS software products on the market from vendors as well as universities. Second, computer workstations can now address several computing, collection, and storing complications in a practical time period and for a decent price. (Church, 2002)

Third, graphical displays and plotters have progressed to the point that they can deliver high-quality, high-resolution output in a limited period of time. Fourth, providers of geographic data as well as federal agencies including the US Census Bureau have made vast volumes of geographic data accessible at a fair rate. (Church, 2002)

Fifth, the use of satellite data has increased, particularly in environmental monitoring, necessitating the creation of systems that can manage large amounts of data while also serving as a key resource of data on land coverage. (Church, 2002)

Sixth, the satellite-based "Global Positioning System (GPS)" has rendered it extremely convenient to collect datasets as well as its place at an affordable price and even with great accuracy. (Church, 2002)

GIS allows for the study of heterogeneity in spatial elements such as Levels of people, transportation systems, and regional components (Metters & Marucheck, 2007). One of the most significant advantages of a GIS is that data collected and kept for one function could be easily allowed access to various functions, such as location model, allowing data gathering and storage costs to be shared (Church, 2002).

In recent years, the integration of transportation demand simulation with Geographical Information Systems (GIS) has received a lot of attention from the GIS and transportation sectors. (Greaves & Stopher, 1998; Kwan, 1997; H. J. Miller, 1991)

Because GIS encourages the illustration and processing of geographic information, it is useful in defining the geographical contexts of activity types and the interaction of time and space properties. In the last ten years, it has also been aided by the effective integration of GIS and transportation "(GIS-T)". "GIS-T", like GIS in general, progressed from hardware components advancements to information system and backend operations. (Waters, 2005)

Crossings, connections, sidewalks, trace quantities, and incident sites have all been managed using GIS. GIS application was created to aid the development of the four-step public transit modeling framework in terms of transportation demand modeling. (Shaw & Wang, 2000)

Even though the majority of scholars believe that GIS can contribute significantly to the convincing achievement of the activity-based approach by providing capabilities for the gathering, storage, modification, evaluation, and visualization of geo-referenced data, they all acknowledge that existing GIS methodologies must be further developed to meet the needs of activity-based modeling. (D. Wang & Cheng, 2001)

GIS is highly useful for activity-based modeling because most activity data has location features (georeferenced). GIS will be used more frequently as a geographic decision-making tool enabling activity-based modeling in data gathering, data warehousing, data processing, data presentation, and visualization, according to Greaves and Stopher (1998).

GIS can help with demand modeling by assisting with information gathering, displaying cross-classification of operations by category, duration, position, and socio-demographic status of a person, representing space-time figures, and defining a person's geographic and temporary occasion for organizing tasks. (D. Wang & Cheng, 2001)

The accessibility of open geospatial data, such as map data, geo-tagged position data, demographic statistics, and public data from government agencies, has given data analysts new tools for modeling and displaying information. GIS innovation can help public service firms better understand their sector, where their users are located, and how to deploy supplies in the region to meet requests. (Davenhall & Kinabrew, 2011)

GIS has also been used in macroeconomic assessments to improve the precision of trip costs and incentive distributions (Bateman et al., 2002). Open data may be leveraged to find trends, resolve issues, and take data-driven actions. For example, transportation service assessments can be carried out utilizing "OpenStreetMap (OSM)" datasets, which contain a range of information such as road categories, speed restrictions, path directions, and distance. (Helo, Rouzafzoon, Solvoll, et al., 2018)

By employing maps, route data, and identifying the service provider representative on a map, a viable service area can be determined. The amount of time required to go to a service center can be considered to assess the accessibility of each prospective location. Consumer population information is typically paired with accessibility and outreach services. (Helo, Rouzafzoon, Solvoll, et al., 2018)

In service-oriented operations, demographic data can be very useful. With open-source services, population data is becoming increasingly comprehensive. At the very least, data is easily obtainable at the zip code level. Several countries, such as Finland, share demographic data in square kilometers grid, providing highly accurate data at a regional scale as shown in Figure 6 and 7. (Official Statistics of Finland, 2016)

Client agents can be generated using population data, also including age and gender information. The density of the population can influence the likelihood of a client having a service requirement in a particular spot. (Helo, Rouzafzoon, Solvoll, et al., 2018)

GIS has been extensively used in several applications, including assessing a client's position, resource allocation to regions to meet customer demand, and measuring logistics efficiency and trip costs. For example, for logistics research, the "OpenStreetMap (OSM)" data source can be used to retrieve data such as road types, directions, speed limits, and distances. (Westin et al., 2020)

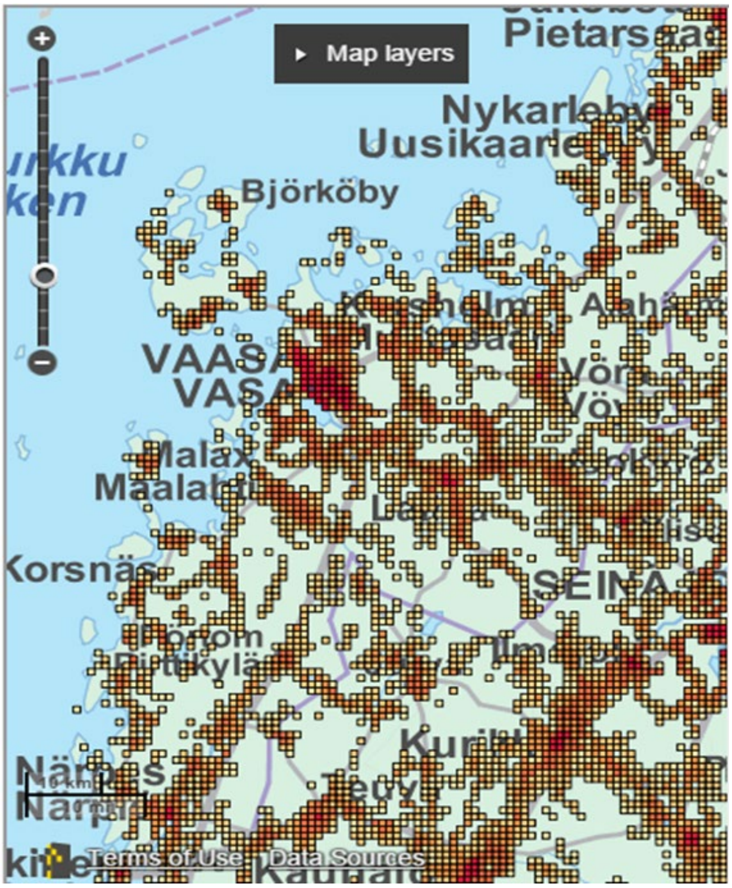

Figure 6. GIS Population (5 Km Sq) in Finland (Official Statistics of Finland, 2016)

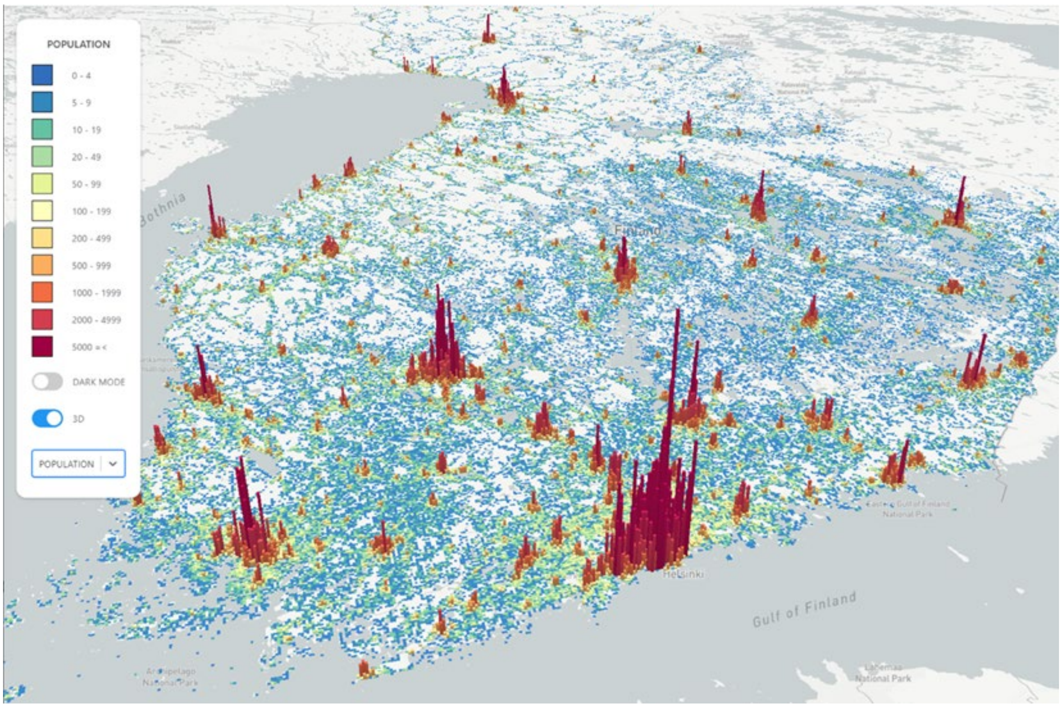

Figure 7. Finland population density in 3 dimensions

One of the great early instances of GIS-based siting investigation is that of Dobson (1979). The issue entailed deciding which sites in Maryland could be used to construct a power plant. The utilization of MapInfo in a position analysis has been demonstrated in interesting research by Camm et al. (1997).

Camm et al. (1997) separated their problem into two sections: warehousing and merchandise collection and delivery. The storage location component, they claimed, was less susceptible to products supply than the customer location element. Simpler models could be used if the problem was split into two main components. They built a software decision-making framework that used mixed "integer-linear programming and MapInfo GIS" method. Their method of operation resulted in a proposal to decrease Proctor and Gamble's centers by 20%, reducing $200 million per year.

Tahvanainen and Anttila (2011) proposed a GIS-based model to estimates the cost of ten different forest supply chains and developed an additional eleven modified supply chains for sensitivity analysis. The cost calculation modelling was split into distance-dependent and distance-independent cost factors.

Similarly, Kinoshita et al. (2009), using a geographic information system, conducted a geographical analysis of forestry biomass utilization. Operational costs for various stands were estimated using GIS and paired with the total demand of the subject region.

Yu et al. (2012) suggested a new location selection methodology for the biomass supply chain that included GIS modeling and a road distribution system, as well as a mathematical model of straight-line delivery. The models were combined to improve optimization efficiency.

GIS technology enables social service agencies to understand their market reach, where their customers are located, and how a district should distribute capital to meet service requests (Davenhall & Kinabrew, 2011).

In a regional evacuation project planning analyzed by Esmaelian et al. (2015), a hybrid of geographic information systems and the decision-making based on multiple parameters methodology of "Preference Ranking Organizational System" for "Enrichment Evaluation IV (PROMETHEE IV)" were used to make decisions on shelters and emergency service sites.

For assessing earthquake-vulnerable areas, open data sources are used to look at three main attributes: population size, building age density, and resilience density. Geographic information system software and open data were used in a research project to display and evaluate the association between distance to clinics and the extent of cardiac mortality. (Yamashita & Kunkel, 2010)

Human actions that have an impact on the environment, including property use, can have a negative impact on the development of products and services. Field coverage data from remotely scanning, field registry, and GIS were linked with surveys, analytics, simulation, and observation in the research project by Burkhard et al. (2012) to assess environmental service supplying and demand, and to convert to various temporal and spatial dimensions. Furthermore, the research findings reveal characteristics of human activity depending on location and time, as well as the supply and demand for ecosystem resources and the quantification of data contained within maps.

In service-oriented operations, population statistics can be very useful. Masters et al. (2013)) analyzed strategies to reduce maternal and neonatal fatalities in Ghana, focusing on remote regions. To measure transit times between residents and medical centers, geospatial methods were used. Transportation durations to healthcare services were measured as population data was split into 1 sq. km blocks.

Leung et al. (2015) conducted a pilot study in human services planning with the use of GIS technologies and analyzed the demographic and locations of food assistance service consumers in Hong Kong to demonstrate various ways in neighborhood service planning.

The fact that GIS and technical decision support are complementary methods is the secret to their success. GIS enables a group of decision-makers or a decision-maker to perform geospatial data analysis, planning, storage, and visualization.

The "Multi-Criteria Decision Making method (MCDM)" includes a series of techniques and practices based on those features that help to model decision-making challenges and evaluate the options that have been considered. (Malczewski, 1999)

The goal or major objective of a "Multi-Criteria Decision Making" technique is to investigate a variety of options in presence of various parameters and competing aims, and the GIS–MCDM has already been utilized in several regional planning studies, including town development, public infrastructure, and so on. (Joerin et al., 2001)

Currently, the GIS–MCDM hybrid is being used in energy-related applications. Mari et al. (2011) utilized "GIS and MCDM" in conjunction with an online platform to coordinate the construction of wind farms in Tuscany (Italy). Due to a solar energy peak in the Granada region of southern Spain, Carrión et al. (2008) conducted research into the best place for new solar installations linked to the power source by incorporating GIS and AHP.

Önden et al. (2018) proposed a multi-step method combining fuzzy-AHP and GIS statistics to assess the level of propriety of logistics centers in Turkey. Shahparvari et al. (2020) introduced an integrated two-stage approach to resolve a multidimensional hub location decision problem with a combination of Linear Programming (LP), Multiple-criteria decision-making (MCDM), and GIS methods. The location selection process was generated by a "GIS-embedded heuristic clustering" approach to measure and link the suitability index within the whole grid.

Abd El Karim and Awawdeh (2020) proposed the "GIS-based multicriteria decision analysis (GIS-MCDA) " to generate a spatial propriety map of the standard of living in the different regions in Buraidah city. Then, "analytic hierarchy process (AHP) " technique was applied to establish the factor weights. The location-allocation model was employed to provide new service locations to enhance the geographical allocation of services and improve the conditions of life in the regions.

2.5 Optimization approaches

Supply chain operations and logistics efficiency can be enhanced by employing various optimization methods. These methods can consist of different quantitative, qualitative, simulation, or combination methods. A review of several studies on supply chain and logistics optimization approaches, particularly targeting distribution center location and transportation, are mentioned in this section.

Managerial, analytical, administrative, and collaboration decisions are made by all layers of leadership in logistics. While reconsidering and adjusting their transportation tactics and, as a result, rearranging the related operating procedures, corporations are confronted with vital decision-making conditions. (Bartolacci et al., 2012)

On logistics network architecture, several researchers collaborated. To maximize overall net profit, Park (2005) developed unified production and delivery planning methodologies and assessed the feasibility of integrating them in a multi-retailer, multi-plant transportation architecture.

Lejeune (2006) used a mixed-integer programming (MIP) strategy to minimize expenses in a three-stage supply network that included suppliers, manufacturers, and distribution hubs.

Liang (2008) established a "linear programming model" for supply chain problems with combined production-logistics planning that reduced shipping costs, total production, and the overall number of returned goods. Aggregate Manufacturing and Distribution Plans for a two-tier supply chain network were discussed by Fahimnia et al. (2012) who used the "MINLP" structure.

Facilities, distribution centers (DCs), and retailers are strategically located and scaled according to network infrastructure. When deciding where to build DCs that serve as intermediate inventory and distributing hubs connecting existing facilities and shops, the simplest layout of the network structure problem can be presented.

A "mixed-integer linear program (MILP)" can be used to solve this problem. Annual cumulative demand for the product category at each retailer, plant capacity, unit delivery fees among each set of locations, and the yearly static cost of managing a DC at each feasible location are all data required. The volume to transfer across sites and binary parameters that determine whether each DC must be closed or open are among the deciding factors. (Souza, 2014)

The target function seeks to reduce overall freight and fixed DC expenses. Constraints ensure that request is met across the board, that enterprises only transfer product from a DC while it is operational, and that all plant capacity is maintained. The resolution specifies the region (i.e., where the DCs will be opened), and also the facilities that will be assigned to the DCs, the retailers who will be assigned to the DCs, and the size of each DC. (Souza, 2014)

Multiple commodities, transporting capacity between sites, multiple delivery types between points, a multi-year planned outlook, several tiers (i.e., supply chain echelons), request variability, supply unpredictability, and inverse flows (e.g., the remanufacturing and recycling of discarded products) are all versions of this simple MILP model. (Souza, 2014)

When a problem involves numerous products, the analysis outputs the product combination for each plant as well. When several variations are combined and the problem is extensive (e.g., hundreds of retailers and prospective DC and facility sites), off-the-shelf optimizing algorithms may not be able to tackle the problem to optimal solutions. As a result, a group of scholars has proposed high-performing heuristics, such as "genetic algorithms", to ensure acceptable—and potentially optimal—solutions. In contrast to optimum branch and bound techniques, which are sequential in character, "genetic algorithms" use a split and conquer (the achievable zone) strategy to find an appropriate resolution to the MILP. (Souza, 2014)

Most of the data required for these kinds of analytics requires preliminary processing so that it may be collected, filtered, and integrated from ERP systems. Each company only performs network design on rare occasions, such as through acquisitions and mergers. As a result, it is not included in mainstream ERP software. Especially for large projects, customized software makes it easier to input data, establish constraints, conduct the optimization, and display the result. (Souza, 2014)

Powers (1989) outlined how computerized modeling and optimizing began to challenge the corporate logistics' complex challenges. Since then, and especially in recent years, the application of optimizations for transportation management and planning has advanced dramatically. For coordinating and managing shipping and supply chain operations, approaches that depended solely on the technical knowledge of competent workers have given way to considerably more sophisticated optimization strategies.

Logistics and supply chain applications, as well as vertical market software tailored for a specific industry area, have become common components in big, widely used enterprise asset management computer systems. (Bartolacci et al., 2012; Helo & Rouzafzoon, 2021)

Transportation planning is a component of supply chain management that designs, executes, and monitors the optimal, efficient forward as well as reversal flow and warehousing of products, processes, and information between the source of production and the location of consumption in order to meet customer needs. (Council, 2012)

Clients, retailers, producers, transportation services, and even competitors can now engage and collaborate in diverse networks with exchanging and cooperating partners. These components form a double-dimensional supply chain with a horizontal element for collaborations with new rivals or similar organizations (e.g., substitutors, indirect rivals, noncompetitors, partners, etc.) and a vertical aspect for conventional supply chain participants including raw resources distributors and retailers. (Bartolacci et al., 2012)

Over the last few decades, logistics optimization has progressed as computational power and code complexity have increased. As a result, optimized algorithms are implemented in software that can address problems of increasing complexity and breadth. Bixby (2007) claims that between 1988 and 2004, the resolution performance for linear algorithms decreased by a ratio of more than 5 million. In addition, improvements to optimization tools and algorithms are being made on a daily basis to assist ever-more computationally intensive devices. To place Bixby's remark in context, an algorithm that required two months to process to optimal solutions in 1988 may be done in under a second in 2004.

Surprisingly, as the ability to use increasingly intricate equations and technology for logistical challenges grew, so did the range and character of the problems that could be optimized. Conventional transportation challenges were narrowly tailored, with examples including the typical traveling salesman delivery problem, the distribution center DC location problem, and the shipments problem, just for a single organization.

As software and hardware improve their capacity to solve problems of growing complication and scale, the range and sophistication of logistical optimization frameworks expand. Due to greater computational power and more powerful algorithms, elements such as suppliers and consumers were added to the modeling formulations. From an optimization standpoint, this transformation integrates what was originally regarded as independent units within a firm: Outgoing logistics (distribution/transportation/client deliveries and services) and incoming logistics (acquiring/procurement/raw supplies stock management). (Bartolacci et al., 2012)

In past years, logistics simulation has been concerned with the so-called "softer" aspect of supply chain operations. Today, terms like "collaboration," which encompasses much more than oral commitments from decades earlier, may be incorporated into optimization methods. In past years, 3rd logistics companies have also become a more involved entity in supply chain operations. (Zacharia et al. 2011)

Furthermore, optimization provides a number of advantages that ease the pressure on individual decision-makers. Decision-making that is repetitious but complex can now be made quickly, enabling decision-makers to respond more quickly. Decisions can be made without the input of humans, and if the technology is sufficiently trustworthy, without human supervision. (Bartolacci et al., 2012)

This can significantly reduce the burden of logistics managers and analysts, allowing them to focus on other important responsibilities. Additionally, decision automating provides a tool to evaluate fresh opportunities. For example, when discussing new expenditure structures, managers with an optimization method can rapidly assess potential negotiated results to see how she or he will make various choices and finally try to find the best solution. (Bartolacci et al., 2012)

The common characteristics of logistics challenges include a dependency on prediction accuracy for effectiveness, a focus on stock management, and the coordination of strategies and goals across entities. With regard to developing exact modeling for optimization, such similarities give both benefits and new downsides. The so-called "bullwhip effect," in which failures in forecasting at one tier in a supply chain result in inefficiency and even worse failures elsewhere as the repercussions spread across the business and its external suppliers. (Bartolacci et al., 2012)

When developing and integrating models for optimization objectives, it's important to make sure that such an outcome isn't overlooked or amplified by the design and optimization process. One example of a benefit is that supply chain parties involved usually have similar broad aims, which might be modeled hierarchical or similarly to provide for some flexibility in the overall analysis and modeling process. If done effectively, transportation optimization can help a company achieve productivity gains and can be used to make logistic decisions at several levels. (Bartolacci et al., 2012)

Mathematical optimization approaches are used to discover the ideal allocation of supply chain resources, which is usually based on the net present value. The transportation optimizing can be assessed using three different decision-making models: operational (short-term and real-time), tactically (medium-term) and strategically (long-term), all of which are based on the decision-making timeframe. (Bartolacci et al., 2012)

Decision-making about strategic logistics management is critical because they often involve significant financial investment and also includes a long-term influence on the firm. The appropriate number of additional facilities or DCs, as well as their capacity and site, is a generic strategic logistics challenge. These strategic choices dictate the tactical planning stage for each site's interior design features, as well as the supporting equipment, transportation, and associated required resources for its operation.

Biswas and Narahari (2004) created an object-oriented architecture to keep operational, tactical and strategic decisions in perspective. Whenever a simulation was used for narrower tactical decision-making, a collective degree optimizer was used for strategic and tactical evaluations.

The strategy used by consumer goods giant P&G is an example of the actual world application of these optimizations. P&G uses the add-in package, What is the Best, to run a major optimization technique in Excel and to tackle supply chain challenges such as plant location, scale, and other comparable decisions. (Anthes, 2005)

Timpe and Kallrath (2000) provide strategic logistical frameworks for manufacturing, delivery, and sales forecasting with multiple temporal spans for business and industrial elements using a mixed-integer linear modeling approach.

To develop supply chain manufacturing and distribution management, Dogan and Goetschalckx (1999) presented a "mixed-integer linear programming" methodology. Goetschalckx et al. (2002) developed a multi-system that included key supply chain layout considerations.

The strategic sub-outcomes systems flow into the operational sub-modeling that includes request fluctuation, production, and delivery, and whose results flow back into the strategic sub-model in a continuous loop. LeBlanc et al. (2004) investigated time-cost exchange in logistics using linear programming. A model for manufacturing and distribution facilities that integrates planning and coordination and was established by Jayaraman and Pirkul (2001) applies the "Lagrangian relaxed approach" and "heuristic" solutions techniques to address the problem.

A method that combines network structure, output, and delivery planning and that was introduced by Jang et al. (2002) is resolved by the Lagrangian relaxation approach and genetic algorithms.

Tactical transportation methods are frequently used to distribute production and delivery capital in a more efficient manner than strategic logistics approaches across a smaller time frame. Workforce size, stock policies, service agreements, carrier method allocation, methods of sourcing, networks of delivery, and other decisions are common tactical problems. In a two-level unified strategy, such models are often paired with a company's strategic models. (Goetschalckx et al., 2002)

The three steps in the decision-making procedure are problem definition, problem model construction, and solution optimization. Figure 8 shows how to create and resolve decision-making problems using a variety of optimization models. Mathematical programming and constraint programming approaches are the most successful in this area. (Koopialipoor & Noorbakhsh, 2020)

Figure 9 depicts the various optimization methods. Because of the problem's intricacy, it is resolved using either exact or approximation methods. Exact approaches guarantee optimality and give optimal solutions. Although approximate methods give desirable and near-optimal outcomes, they do not guarantee that the resolution is ideal. (Koopialipoor & Noorbakhsh, 2020)

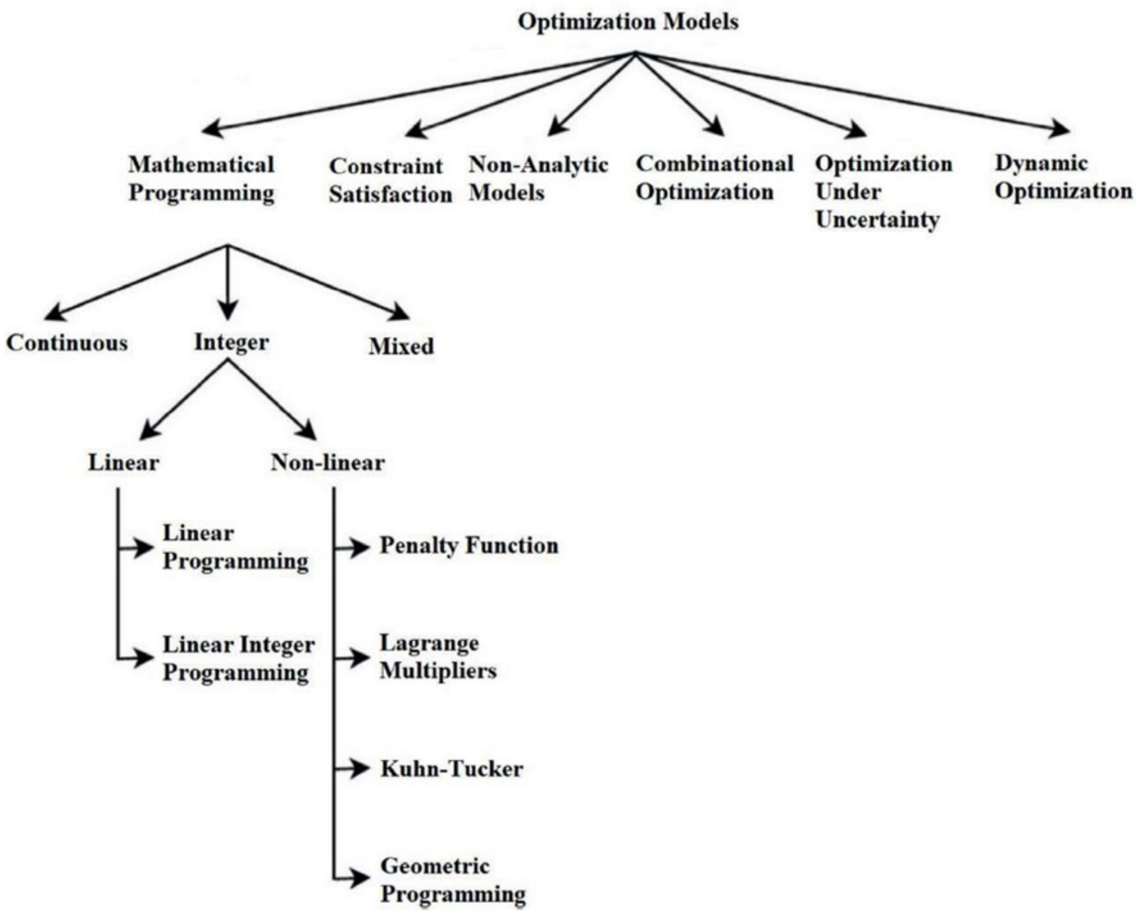

Figure 8. Optimization models (Koopialipoor & Noorbakhsh, 2020)

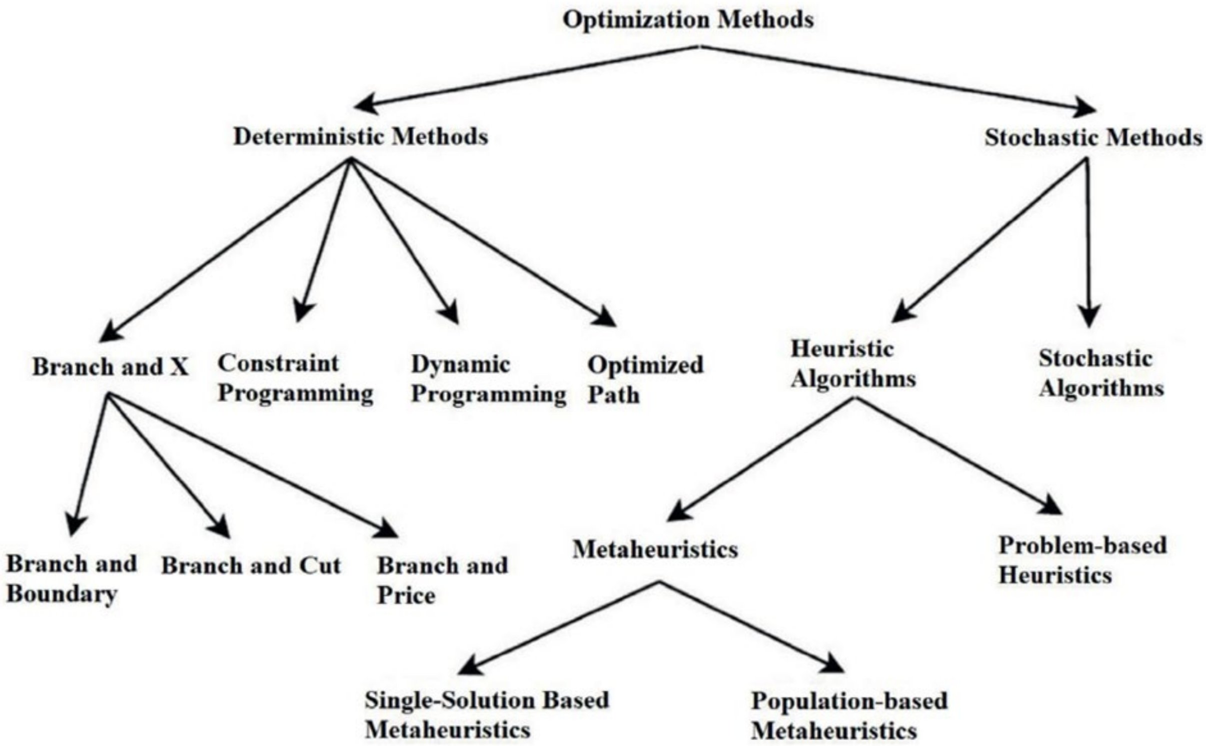

Figure 9. Optimization methods (Koopialipoor & Noorbakhsh, 2020)

Hybrid methods including linear modeling and simulation have been developed to optimize overall system performance in the case of several products, division, and procurement production delivery methods (Lee & Kim, 2002). Transport modes design, which would be a tactical decision procedure, was also accomplished utilizing mixed-integer programming and simulations combination frameworks (Cordeau et al., 2006).

Carlsson and Rönnqvist (2005) proposed branch-and-bound integrated logistics optimization methodologies for deciding the forest products sector, involving problems of routing and travel modes selection. Eskigun et al. (2005) developed an optimization method for strategic supply chain networks relying on a Lagrangian heuristic, taking into account lead times, distribution center location, and mode of transportation.

Planning loading dock services is an instance of operational logistics. Other functions entail assigning customer requests to vehicles or transport trucks, vehicle cargo management, freight route managing, deploying, and order processing and accelerating. All of these issues reflect a collection of transportation and operational management limitations in logistics. The temporal existence of the decision-making separates models of logistics at the organizational level from the preceding two groups. (Stank & Goldsby, 2000)

With these styles of optimization techniques, more real-time data is needed to maintain stable and productive operations. For example, if a truck is loaded with multiple client orders, the routes must be optimized, especially if the journey is a routinely planned and repeated "tour". (Ergun et al., 2007)

Evers et al. (2000) introduced AgileFrames which is a communication-focused operational level logistics modeling system. The three operational management layers in this system are the application level, the disagreement handling layer, and the implementation piece. A solution for creating an agile transportation component for a cargo container port is included with that model structure.

Hung et al. (2006) proposed an object-oriented architecture-based operational dynamic supply chain modeling system to allow the creation of a scalable supply chain configuration, as well as the operational policies and decisions that go with it. The system is built by connecting generic nodes and defining each supply chain member's structural and company attributes. In addition to this optimization technique, to estimate the effect of supply chain unpredictability, a "Monte Carlo" simulation is performed. A case study including a vertically integrated global pharmaceutical corporation was used to illustrate this framework.

Correll et al. (2014) applied a simulation approach and metaheuristic optimization to redesign the supply chain by adding multiple crops to save on logistics and inventory costs. F. Zhang et al. (2016) employed an integrated multistage, mixed integer programming model to manage multimodal logistics, trucks, and trains in the context of a biofuel supply chain. The model's goal is to reduce overall cost, which includes equipment, shipping, feedstock purchase harvesting, warehousing, and processing.

Gautam et al. (2017) assessed the advantages of including a terminal to address the problem of delivering high-quality feedstock in the forest supply chain. The mixed-integer programming structure was utilized to quantify the gains, integrating information on biomass quality, harvest schedule, and seasonality in supply and demand.

The discrete-event simulation was used by Lesyna (1999) to optimize the rail car fleet for product delivery to end customers. Shi et al. (2014) utilized the simulation approach to create a model of the product collection and delivery process to distribution facilities. The sequential bifurcation (SB) was used to define the most important factors on cycle time and throughput such as truck number, loading, and unloading time. To find the most efficient level of key performance indicators in the post-screening phase, the "response surface methodology (RSM) "is used.

Larson (1988) conducted research to reduce the size of the shipping fleet used to transport debris from water purification plants. The problem limitations were inventory size, vehicle capacity, and transportation limitations such as waterways and water depth. He used the "SIRSA" heuristics conserving technique, which divides consumers into regions and supplies all of them via one route.

Campbell and Hardin (2005) performed a research study on minimizing the fleet size required to make strictly periodic, single destinations deliveries to a set of customers under the assumption that each vehicle can carry out one trip a day. A greedy algorithm was used as a solution approach. In addition, for the assumption of a truck can make many journeys per day, the modified algorithm using a "first-fit rule" in the same way as the framework of the method "bin-packing heuristic" is applied.

In the "Pickup and Delivery Problem (PDP)", the transportation fleet collects products from locations of origins and delivers them to destinations without any transshipment. Li and Lim (2003) proposed the "tabu-embedded simulated annealing" algorithm to solve a PDP with time windows and several vehicles. The objectives of the research were defined as minimizing the distance, waiting time, vehicle fleet number, and total schedule duration.

Al-Khayyal and Hwang (2007) applied the node-arc (NA) formulation approach to solving the ship scheduling problem with deliveries between origin and destination ports. Calvo and Colorni (2007) suggested a heuristic approach to resolve a PDP problem with time windows and a homogenous vehicle fleet. The problem goal was to maximize the linear combination of served customers and service level. Corso and Wallace (2015) address a multiple-day "pickup and delivery" with demand uncertainties. A new algorithm was proposed to generate a minimum logistics cost plan that meets a specific degree of competence. The reliability of a candidate solution is measured against a large number of scenarios through the genetic algorithm.

Wang et al. (2020) have addressed a two stages problem of "pickup and delivery" and "location routing". The initial phase involves massive eco-package delivery, which is simulated in the shared resources state–space-time (SST) system using temporal partitioned and transit-centered network stream programming. The expense-minimization synchronization centered location routing approach, which reduces the overall generalized expenditure, is used in the second phase to solve micro eco-package "pickups and deliveries".

Wang et al. (2020) applied a Gaussian mixture clustering algorithm to allocate customers to their respective service providers and a Clarke–Wright saving method-based non-dominated sorting genetic algorithm II to optimize pickup and delivery routes and improve their cost-effectiveness and degree of synchronization.

Optimization approaches have been compared in the terms of efficiency and computation time within several recent research; for instance, Aranguren et al. (2021) utilized simulated annealing (SA) to resolve a biomass hub and spoke network design problem. The optimization approach was compared with Bender's Decomposition (BD) method and the SA result was better by 7.71 % difference, and the computation time of SA method was reduced by 91.4% compared to BD method. Aboytes-Ojeda et al. (2020) compared the result of the hub and spoke network optimization between meta-heuristic, combining simulated annealing and tabu search, and the standard L-shaped (LS) method. The metaheuristic approach produced 2.48% lower costs and 96.57% less computation time in comparison with LS method.

Li et al. (2020) evaluated the performance of several optimization methods to resolve a logistics distribution center location problem. The effectiveness of " Cuckoo search (CS), improved cuckoo search algorithm (ICS), modified chaos-enhanced cuckoo search algorithm (CCS), immune genetic algorithm (IGA) and dynamic step size cuckoo search algorithm (DMQL-CS) " for scenarios of 6 and 10 distribution centers was examined. DMQL-CS algorithm exceeds the other methods in a majority of scenarios.

The logistical distribution facility site problem entails determining the best spot for distribution facilities in order to save money on shipping. To solve the problem, various algorithms have been suggested and can be divided into " quantitative and qualitative" approaches. Expert collection, comparative analysis, fuzzy assessment, and the analytic hierarchy process are all examples of qualitative techniques. These approaches can help solve the problem in part, however, they are subject to a variety of factors. (Esnaf & Küçükdeniz, 2009)

Quantitative approaches contain mixed-integer, gravity methods, and Bi-level programming. Due to the NP-hard framework, solving the problem using quantitative techniques becomes more difficult as the problem size grows (Manzini et al., 2006). To solve complex optimization problems, heuristic techniques such as genetic and Tabu algorithms are commonly used.

When the research streams are compared, it is clear that there are variations in research and concentration methodologies. Logistics and SCM are concerned with the distribution network, which covers DC choice of location, while Geography is solely concerned with DC site decision. To determine DC locations, SCM mostly uses OR techniques. Since it is impractical to represent all aspects of decision-making, the applicability of SCM models is debatable, and it is unidentified if organizations make reasonable site selections according to SCM paradigms. Logistics frameworks have the same flaws similar to SCM systems. The geography line of research excels in analyzing DC's geographical characteristics. (Onstein et al., 2019)

In the facility location problem (FLP), the space element is more essential than the timeframe component. In "Static Facility Location Problems (SFLP)", the space aspect is considered, while in "Dynamic Facility Location Problems (DFLP)", the time component is emphasized.

FLP components can also be described in terms of "discrete and continuous "characteristics. Infrastructure with discrete features, for instance, can be located only at certain locations in the planning scheme, whereas in the continuous domain, they can be located wherever within the planning framework. Additionally, discrete-time implies that adding new sites or changing current ones is limited to pre-determined time intervals, but continuous-time does not have this limitation.

Static facility location problem (SFLP) is comprised of two categories: "Discrete facility location problems (DIFLPs)" and "Continuous facility location problems (CFLPs)".

"Continuous facility location problems (CFLPs)" and "Discrete facility location problems (DIFLPs)" are two subsets of Static facility location problems. CFLPs include three problem types; "Single facility location problem (SIFLPs)", "Multi-facility location problem (MUFLPs)", and "Facility location-allocation problem (FLAP)". SIFLPs and MUFLPs problems are mainly resolved similar to the total cost incurred minimization problems by considering the distance between facilities as assigned weights and FLAP are optimized in the same method because it allocates such facilities to consumers in the most efficient way possible in order to meet their requests.

"Discrete facility location problem (DIFLPs)" consists of "Quadratic assignment problem (QAP)" and "Plant Location Problem (PLP)". In the FLP setting, QAP problems are similar to allocation problems in that groups of people can be assigned to tasks, however in QAP, facilities are allocated to consumers. PLP refers to a group of facilities, each of which can be any type of facility. The optimization method follows the same total incurred cost minimization.

Demands often exist on nodes when a location problem is arranged as a collection of nodes and connections; however, demands may be on both connections and nodes at the same time. Based on this description, "Network facility location problems (NFLPs)" can be categorized into five major groups: "covering problems", "median problems", "hierarchical location problems (HILPs)", "hub location problems (HULPs)" and "center problems". Median problems mainly optimize the weighted length between potential location demand nodes. Such a method could be utilized to accomplish expense or profit-maximizing objectives. Nevertheless, such an optimization approach is not of relevance in the covering and center problems, where entirely other parameters are applied.

Apart from the Static facility location problem (SFLP), there are Dynamic Facility Location Problems (DFLP) in which two factors affect choosing the facility location. The first factor is the cost which is the difference between the expenditure of opening or revising a facility and the potential profit that could be obtained. The second factor is the length of time that facilities will be open and closed across the planned horizon.

DFLP is comprised of dynamic "deterministic facility location problem", "Time-dependent facility location problems", "facility location–relocation problem", "multi-period (discrete-time)" and "single-period (continuous-time) facility location problems" and "Stochastic, probabilistic, and fuzzy facility location problems". Moreover, any kind of Static facility location problem (SFLP) can be converted to DFLP.

Facility location problems have been vastly investigated and major optimization methods at a general level include mixed-integer linear programming, a hybrid Fuzzy-Delphi-TOPSIS, hybrid firefly genetic algorithm, heuristic merged tabu search, an innovative combination optimization technique named "cuckoo search-differential evolution (CSDE)", "particle colony optimization algorithm", "immune wolf swarm hybrid algorithm", "heuristic algorithm", "Frank–Wolfe algorithm", and "exact algorithm".

Hub and spoke problems are considered as the continuation of the facility location problem. Methods of zone skipping and load consolidation have been introduced in Hub and spoke. Load consolidation relies more on cross-dock operations' efficiency.

There are two kinds of problems with hub and spoke allotment. Demand is just allotted to a single hub in a "single allocation problem", but demand can be distributed to numerous hubs in a "multiple allocation problem". Researchers have introduced various approaches to optimize freight routing and hub locations.

Traditional Hub and spoke problems have been formulated mainly by the hub median and hub center problems, while recent research projects have applied mainly mixed-integer linear, fuzzy multi-criteria decision-making model, mixed possibilistic-stochastic programming, and equilibrium optimization techniques.

In HSND problems, the intermodal transportation in which cargo is transported using a different type of transportation has also attracted a lot of attention. Optimization methods such as integer programming model, heuristic based on a "simulated annealing ", "ant colony optimization", "genetic algorithm", and "tabu search" have been used in recent research.

GIS has been used as a practical tool in facility location analysis. GIS also can support demand modelling by applying information gathering, presenting cross-categorization of activities by kind, duration, site, and individuals social demographic factors, representing space-time figures and defining a person's spatial and temporal context for carrying out tasks.

Data scientists now have additional resources for modeling and displaying data because of the accessibility to public spatial information including maps, georeferenced location data, population distribution, and information sharing from government agencies.

Researchers have used GIS beside other optimization techniques, for instance, "integer-linear programming", "sensitivity analysis", "multiple-criteria decision-making methodology of Preference Ranking Organizational System for Enrichment Evaluation IV (PROMETHEE IV)", "Multi-Criteria Decision Making method (MCDM)" to optimally assign tasks or locate facilities in supply chain and logistics.

Researchers have applied various optimization methods in the domain of supply chain networks and logistics to identify the best value for various parameters such as distribution, sale and production planning, facility location, facility capacity, transportation costs, plant assignment to DCs, network design and capital distribution.

Techniques such as mixed-integer programming, Lagrangian relaxation method, heuristic solution, genetic algorithms, hybrid models incorporating linear programming, discrete-event simulation, branch-and-bound, Monte Carlo simulation, metaheuristic, Gaussian mixture clustering algorithm have been used in recent research.

Since supply-chain operations are becoming extremely relevant to manufacturing performance, OEM manufacturers are engaged in optimizing their supply chains to fulfill consumer demand at the lowest potential expense. While a new adaptive supply chain, in which the optimum hybrid of resources is discovered and employed for every client order, may be adequate in some circumstances, others require a more robust supply network that evolves gradually in reaction to modifications.

Individual design activities benefit from optimization approaches in particular. A holistic assessment, on the other hand, is questionable. The simulation can be used to conduct an integrative assessment of particular scenarios using a key performance indicator framework, illustrating the target values' interrelationships. On the other hand, identifying acceptable scenarios and choosing criteria for ecological and economic control parameters within the supply chain can be challenging. In the scope of sustainable supply chain design, integrating optimization and simulation is a powerful tool to completely leverage the benefits of both methods. (Schreiber, 2019)

Mathematical optimization approaches and simulation can be used as techniques in the solution process to be outlined. Analytical mathematical approaches are especially well suited to modeling and dealing with complex design challenges. The simulation is a valuable method for evaluating the interrelationships that exist in a supply chain in detail. Simulation and optimization combinations can decrease a simulation's design complexity by creating preliminary resolutions for specific design tasks by employing multiple optimization models in advance. (Schreiber, 2019)

To overcome the limitation of individual design application of mathematical optimization and to obtain more efficient solutions, the systematic direction of the supply chain concept is introduced in which the goal is to include a comprehensive set of critical factors into the analysis.

Selecting the best approach to optimize supply chain design and logistics systems, particularly distribution centers' location, and fleet management decisions can be a challenging task for companies. Considering the systematic direction of the supply chain, the purpose of this research is to how to combine concepts of supply chain, transportation and geography models and find better solutions to supply chain management challenges.

2.6 Possibilities of ABM in supply chains

Supply chain problems with parameters such as unpredictable pickup points, trip time, routing, fleet number, and inventory levels are considered as a complex supply chain since various dynamic variables are involved. On the other hand, agent-based modelling is an efficient method to model supply chains since each entity can be represented as an intelligent agent interacting with other agents and making decisions based on a set of guidelines. (Helo, Rouzafzoon, & Gunasekaran, 2018)

Agent-based modelling and optimization is a useful technique for decision-making in supply chain management since it employs a bottom-up simulation approach. Multi-agent simulation is particularly adapted to the task of modeling supply chains since all entities can function as observant agents, take actions, and communicate with other intelligent elements in the planning and implementation of a supply chain.

ABM can be merged with spatial data that is available to the public such as mapping, georeferenced site data, and demographic data, creating new opportunities for researchers to model and visualize data. ABM and GIS have been immensely utilized in various scopes such as analyzing the client's location, allocating resources to regions to fulfill the customer demand, and assessing logistics performance and trip costs. For instance, the "OpenStreetMap (OSM)" source of data, retrieving data including road types, directions, distances and limits of speed can be employed for logistics analysis.(Helo, Rouzafzoon, Solvoll, et al., 2018)

3 METHOD

When multiple participants operate autonomously, interact with one another, and collectively adapt to a system change, ABM is an efficient approach to tackle problems. Furthermore, ABM can be used as a practical modelling technique when the overall activity of network participants is multidimensional and not acquired from the aggregate of each entity's actions.

ABM can be also combined with optimization methods in supply chain and logistics problems to include both interactions between supply chain components and target parameters optimization. GIS and spatial information can be merged into the modelling to create more precise modeling and optimization, and supply chain components can interact according to time and location parameters.

Major supply chain management and logistics challenges are linked to domains such as distribution center locations, demand location, transportation cost, vehicle scheduling and routing, policies of task assignment, fleet sizing, inventory management, and product characteristics. These problems are mainly focused on in this paper.

To conduct detailed research within the domain of supply chain and logistics networks, research problems and optimization methods in this paper are discussed with three case studies data including DC locations in Nordics, Wood collection, and Transportation design. In this section, the research problem and proposed method are provided and Figure 10 presents an overview of the research method steps. The outcome of the methods is presented in section 4, results and discussion.

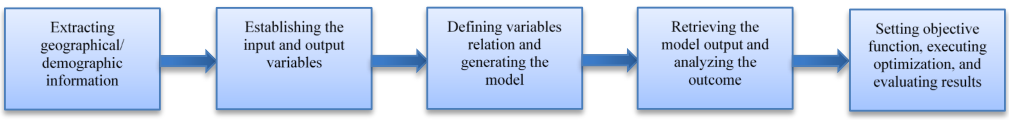

Figure 10. Overview of Method steps

3.1 DC locations in Nordics

The demographic information of Nordic countries is used to locate distribution hubs in this case. The analysis' major goal is to investigate a theoretical situation in which a consumer's spatial location is used as input for ultimate shipments and to evaluate how optimal locations and an increase in the numbers of distribution centers affect delivery times. (Helo, Rouzafzoon, Solvoll, et al., 2018)

As per demographic location data, distances and travel times between facilities and request points are used to analyze distribution center location scenarios. In detail, the research seeks to:

1) Identify the most optimal locations for 5 distribution facilities nearby customers in Sweden, Norway, and Finland, and the Nordic level.

2) Create separate service zones depending on chosen facility locations at the Nordic level.

In the first step, population information which are extracted from Finland's government statistical website is modelled as demand points. Population data is available at numerous scales including the number of inhabitants per one square kilometer, 5 square kilometers, and county level. (Helo, Rouzafzoon, Solvoll, et al., 2018)

The next step is computing travel length between the uploaded population points and facilities according to current roads. Open data sources have been utilized in a large proportion of facility location research. These datasets are open data that may be used to find trends, resolve problems, and take data-driven actions. For logistics analysis, for example, the OpenStreetMap (OSM) dataset which offers a variety of information such as road types, speed restrictions, routing directions, and length can be used. (Helo, Rouzafzoon, Solvoll, et al., 2018)

Furthermore, the number of additional details that may be extracted from solutions is affected by the volume of detailed data in the demographic and road datasets. As a result, marine paths between regions are also formed and incorporated in the optimization procedure at the Nordic level. Demand locations and prospective distribution locations should be entered into the program to determine the most efficient distribution locations. For location-allocation problems, there are a variety of potential solution options such as "Minimize impedance, Maximize capacitated coverage, Minimize facilities, Maximize coverage, Maximize market share, Maximize attendance and Target market share".(Helo, Rouzafzoon, Solvoll, et al., 2018)

The goal function of this research is to minimize impedance, which is defined as the total of all weighed costs between demand points and facility locations. For location-allocation problems, the impedance class can be also specified.

When the impedance is set to distance, the analysis considers the shortest path between demand locations and facilities. If the chosen impedance is time, the location-allocation problem is addressed via the shortest travel time. Minimize impedance, as chosen for this case, decreases the overall distance traveled by individuals to reach the chosen distribution center in this analysis. Moreover, the demand point weight is determined by the number of individuals who live in each location. (Helo, Rouzafzoon, Solvoll, et al., 2018)

A location-allocation problem is a form of a combinatorial optimization problem, with a large number of alternative resolutions. As a result, exhaustive search approaches are impractical for finding optimum solutions in a reasonable amount of time. Therefore, heuristic algorithms are used to speed up the searching.

According to the route dataset, an origin-destination matrix of shortest-path cost connecting facilities and demand points is constructed throughout the facility location optimization phase. Hillsman editing is a mechanism used by the algorithm to produce a modified version of the matrix. After that, the location-allocation algorithm provides a set of semi-randomized solutions and uses a "vertex substitution heuristic (Teitz & Bart)" to enhance results by generating a set of upgraded resolutions. (Helo, Rouzafzoon, Solvoll, et al., 2018)

After that, a metaheuristic technique is used to integrate these collections of solutions to produce improved results. When no additional improvement is feasible, the metaheuristic technique delivers the best result. The integration of these techniques results in near-optimal solutions. (Helo, Rouzafzoon, Solvoll, et al., 2018)

Travel time zones or service areas are created in this research. Only when a location-allocation problem is solved, optimum facility locations may be utilized to create trip time regions. In the configuration, variables like impedance, direction (away, from, or toward the facility), permitted or not permitted U-turns at intersections, and limitations like one-way streets can be specified. (Helo, Rouzafzoon, Solvoll, et al., 2018)

There are also combining polygons choices for creating service regions with several distribution centers, including "Overlapping, Not Overlapping, and Merge by break value". A service area is a zone surrounding a designated site in which all roadways are reachable within the given impedance range. For example, a distribution center's 1-hour service area includes all roadways within 1 hour's driving distance. The service area impedance variable can also be configured as a timeframe or length from a facility. (Helo, Rouzafzoon, Solvoll, et al., 2018)

The service zone solver traverses the network using "Dijkstra's algorithm". The goal of the algorithm is to provide a selection of linked edge elements that are inside the network length or expense threshold. The service area algorithm can draw straight lines, polygons around straight lines, or both. (Helo, Rouzafzoon, Solvoll, et al., 2018)

The traditional Dijkstra algorithm finds the shortest route from an originating location s to a target point d by keeping track of a set of junctions, S, where the ultimate shortest path from s has already been calculated. The algorithm discovers a connection in the collection of junctions with the lowest shortest-path estimation, brings it to the series of junctions S, and updates the shortest path computation of all those neighboring to this junction that is not in S. The procedure iterates across the junctions till it finds the final junction and adds it to S. (Helo, Rouzafzoon, Solvoll, et al., 2018)

After producing the location-allocation analysis tier, specifying the appropriate network analysis components, and establishing proper analysis attributes, a solution for a location-allocation problem can be produced. (Helo, Rouzafzoon, Solvoll, et al., 2018)

3.2 Wood collection

One of the most difficult tasks for businesses is deciding where to locate facilities such as manufacturing sites or depots in order to reduce the cost of serving product demand.

In general, there are static costs associated with situating facilities, as well as logistic expenses associated with transporting between facilities and demand places. Fleet management and facility location are critical disciplines in supply chain management and logistics and they can result in financial gains and higher consumer service quality for businesses.

The research goals are considered as following and the resolution approach is employed on the Wood collection case company data.

1) Determining the minimum transportation cost for different facility location scenarios

2) Defining the optimized number of fleet required for each facility location

3) Evaluating how choosing a certain facility location setting affects the transportation cost

The forest-based supply chain (FbSC) is comprised of a sequential series of spatially referenced activities from the forest to the customer, converting the woody raw materials to forest-based output.

The case company operates in tree log pickup and delivery within several regions in Finland. There are two scenarios in which a company requires logistics analysis to make a decision. In the first scenario, there are two potential collection points to which tree logs are transported and there are seven regions from which logs are collected. Tree locations are dispersed randomly within each region, therefore, there is no pre-set point of pick up but the average number of pickups per day for each region is determined by the case company.

The transportation trucks are stationed at collection points. Based on the number of picks up per day and per region, an arbitrary geographical location point of tree logs is dispatched to the closest factory based on driving routes.

```
Order.setLocation(TreeLocation);

Center= getNearestAgentByRoute(Facilites);

Distance=DistanceByRoute(OrderLocation);

Send(order,center);
```

Code snippet 1. Finding the nearest center based on Tree location

If there is any truck available, a truck will be directed to the tree log location to load and transport the trees to the collection locations. Additionally, in scenario one, logs are transported from two collection points to the factory only via train. To assess and minimize the transportation cost, three forms of expenses are included: truck fixed cost calculated according to the number of trucks allocated to each location, train trip cost, and truck distance cost calculated from the total driving distance in kilometers between tree collection points and facilities.

In the second scenario of modelling, there are three train stations to which trucks carry tree logs from regions. In addition, the factory collects the logs from three train stations by rail transport or directly from regions by trucks. The other parameters of the second scenario are as same as the first one. The goal of the modelling is to identify the minimum transportation cost for each scenario and to assess how the selection of facility location influences the logistics cost. Figure 10 presents the potential facility locations, regions, and the main factory location for both scenarios.

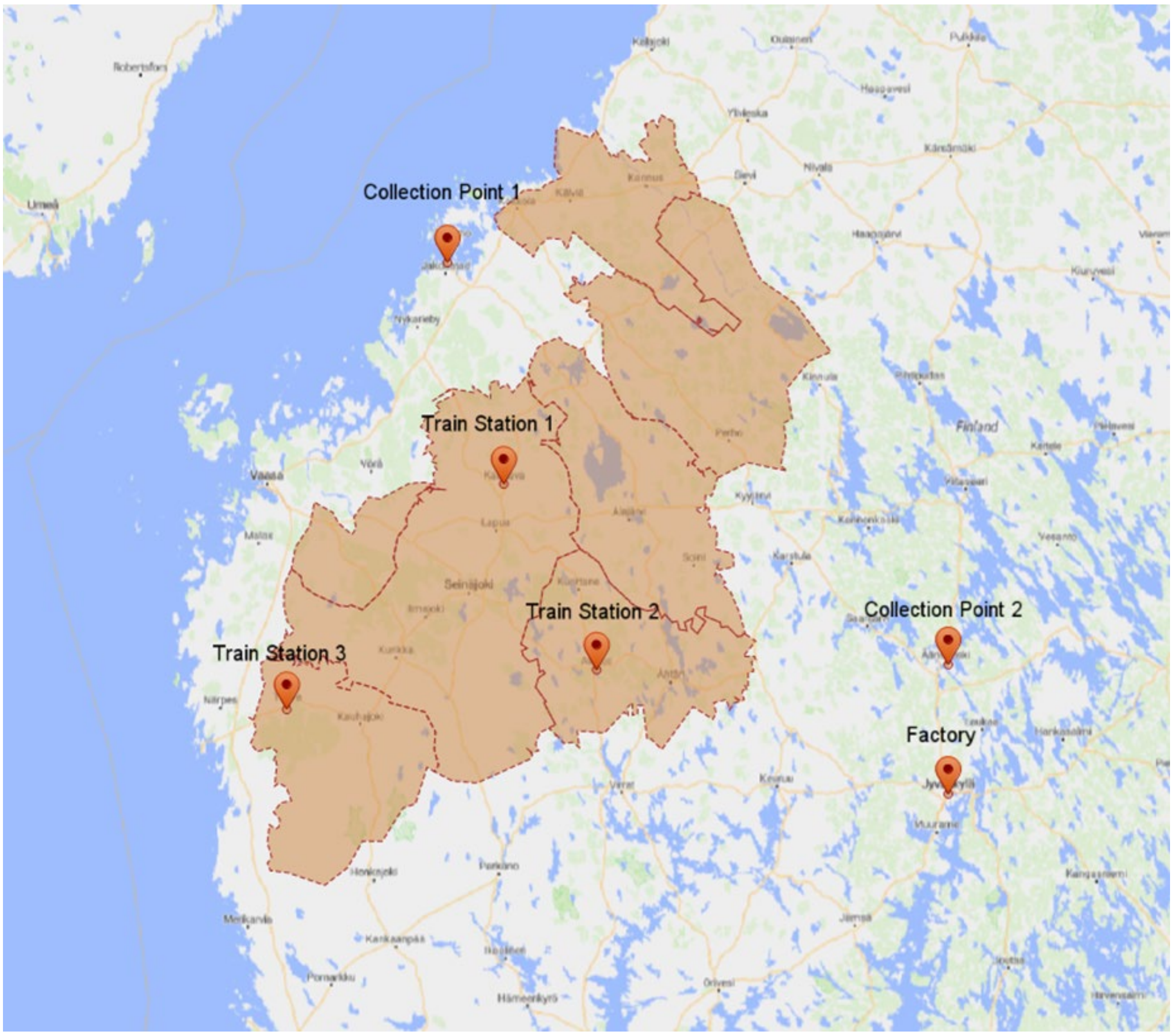

Figure 11. Facilities location

In this case study, the agent-based modeling method with the application of GIS is proposed to resolve the problem. Collection points for tree log delivery are represented as Facility agents and are located on particular points through the GIS map. Seven instances of Region agents are generated to represent each particular region. The region agent consists of a Shape parameter storing the region name, a Center parameter presenting the assigned facility agent, and an Event object scheduling the Order agent creation time.

The Event object generates an Order agent based on the number of pickups per day for each region. The Order agent contains the TreeLocation parameter which stores pickup point geographical information. When the Event object creates an

Order agent, a random point within the specific region is assigned to the TreeLocation parameter of the Order agent. The random point generation method is utilized since the location of tree logs for pickup is arbitrary within every region.

Orders are allocated to facilities and trucks based on the nearest neighborhood assigning policy. According to the geographical location of facilities and orders, the GIS map ,utilizing the most recent routing information and geographical location of facilities and orders, detects the closest facility to the order by calculating route distances between two agents. Then the order agent is dismissed to the facility.

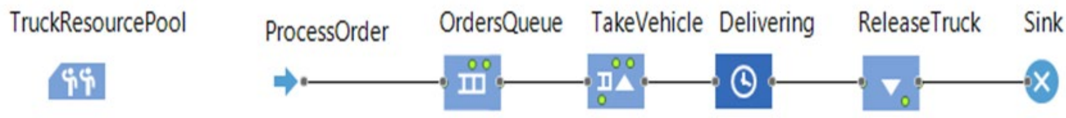

Figure 12. Facility agent simulation blocks

The facility agent operations are created by discrete event simulation, Figure 11. Orders captured by the ProcessOrder block are positioned in OrdersQueue which proceeds orders according to "the first-in-first-out (FIFO)" structure. The TakeVehicle block takes one truck from the TruckResurce pool which contains the total truck number and connects simulation blocks to the Truck agent. If there is a truck free for transportation, the TakeVehicle block delivers the Order agent to the Truck agent, Figure 12.

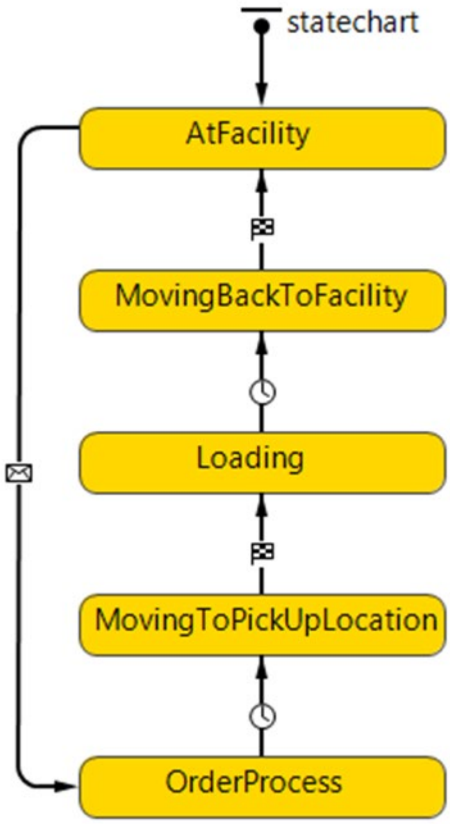

Figure 13. Truck agent state chart

Trucks are located initially at the facilities. When an Order agent is seized by a truck agent, the OrderProcess phase starts and directs the truck to the Order agent location or the pickup point. The routing approaches can be chosen as shortest which identifies the route between two points with minimum distance or as fastest which determines the route with the least travel time. In this case, the shortest routing method is chosen and the GIS map providing the most updated route and traffic data is employed to determine the driving path.

When the truck reaches the pickup point, the process of loading tree logs is conducted. A probability distribution is used to determine the loading time and is calculated from the case company's raw data. In the next stage, the returns to the original facility to unload the tree logs, and the truck agent sends the Order agent to the Delivering block of the Facility agent, Figure 11.

The Delivering block conveys the Order agent to the Release block which releases the tuck for the next trips. Since the tree log transportation for a particular pickup location is accomplished at this phase, the order agent instance is discarded through the Sink block.

Tree logs are also required to be gathered from facility locations and carried to the factory. The train transportation is modelled by discrete event simulation, Figure 13.

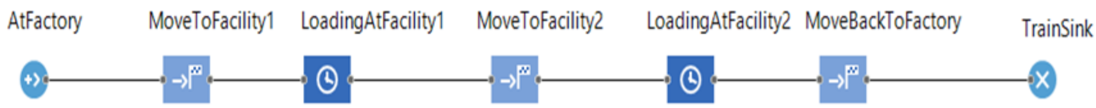

Figure 14. Train transportation simulation blocks

Train travel once a day from the factory to facility locations and complete the trip with returning to the factory. Trains perform trips through real-world railroads by using the GIS map.

Dynamic factors such as tree log pick up location, pick up time in a day, routing, and trip time in supply chains can create complexity in supply chain management; therefore, optimization methods are utilized to minimize the logistics cost according to facility locations and the number of trucks in each scenario.

In addition, there was no empirical cost model for the train transportation; hence, the estimation approach adopted by Tahvanainen and Anttila (2011) for the modelling of Finland forest transportation is utilized in this research project, Eq. (2). The train trip cost is estimated based on an average of five wagons and the distance parameter is calculated by GIS railway routing between the train stations and factory.

In addition, the problem constraint is considered as the average time between a tree log pick-up request and truck assignment should be less than sixty minutes, Eq. (4). The objective function is presented in Eq. (3) and the total driving distance within each simulation run is presented in Eq. (1). In addition, table 2 provides the modelling parameters.

$$TD=\sum Kij \quad (1)$$

$$TW= 160 + 0.89 \times DW \quad (2)$$

$$TC = (FC \times NT) + (DC \times TD) + RC \quad (3)$$

$$\sum(TPkj - TAkj) / TN <= 60 \quad (4)$$

Table 2. Cost model parameters

Modeling Parameter	Description
TC	Total transportation cost (Euro)
FC	Truck fixed cost (Euro)
NT	Number of trucks assigned to a facility
DC	Truck driving cost per kilometer (Euro)
TD	The total truck driven distance in Kilometer within a time period
RC	Train transportation cost of five wagons (Euro)
Kij	Driving distance between facility i and tree pickup location j
TPkj	Pickup request time for pickup request k and tree log location j
TAkj	Fleet assignment time to pickup request k at location j
TN	Total number of trips in each simulation run
TW	Train cost per wagon (Euro)
DW	Total train driven distance in kilometers

3.3 Transportation design

As time factors are incorporated, the "vehicle scheduling problem (VSP)" is an adaptation of the standard "vehicle routing problem (VRP)". VSP is concerned mostly with distributing vehicle fleets in order to complete all trips in the most efficient manner possible. The purpose of the VSP is to reduce expenditures such as the fixed cost of every working truck as well as the indirect cost of deadheads, downtime, and travel durations. (Rouzafzoon & Helo, 2018)

In logistics, determining the size of fleets required to achieve the desired degree of supply chain efficiency can be a complex task. For businesses, optimal vehicle sizing can result in increased profitability and client satisfaction. (Rouzafzoon & Helo, 2018)

Mathematical optimization methodologies are mostly used to address and design the VSP. Numerous research initiatives aimed at reducing delays have been carried out, and they can be divided into three groups; 1) establishing more exact journey timings for vehicle scheduling systems 2) modifying or rearranging timetables in real-time procedures and 3) increasing a vehicle timing's consistency (Bunte & Kliewer, 2009; Rouzafzoon & Helo, 2018).

The length of a trip has a significant influence on the likelihood of a truck arriving on time. According to Kittelson (2003), the average of observed journey times can be used to establish a planned trip time in empirical methods. In order to plan a journey, Zhao, Dessouky, and Bukkapatnam (2006) presented an awaiting optimization framework with the goal of reducing the estimated wait period for passengers.

An agent-based modeling method is used to investigate vehicle size optimization and vehicle scheduling in this case. The following are the most important research questions and tasks;(Rouzafzoon & Helo, 2018)

1) What is the required fleet number to perform the logistics operation with the minimum cost?

2) What effect do vehicle arrival and departure times have on vehicle numbers?

The research's overall goal is to provide a modeling methodology for firms facing VSP and fleet efficiency concerns. Furthermore, the modeling allows managers to customize the program to fit their individual business needs. By adjusting order timetables, manufacturing plans, and fleet sizes, managers can test multiple business operating scenarios. The necessary data was acquired from a shipping firm in Finland in order to perform the analysis and evaluate the recommended method's result in this case. (Rouzafzoon & Helo, 2018)

There is a single processing plant and four manufacturing units distributed around the country. Each manufacturing unit produces four different product categories and runs on a weekly schedule; however, the processing facility is open 24 hours a day, seven days a week. The production rate per hour is fixed in manufacturing units. Products must be transferred from the manufacturing units to the processing plant. (Rouzafzoon & Helo, 2018)

Manufacturing facilities are subject to specific limitations;

1) During 24 hours, the items must be transported to the processing facility

2) Every product in every manufacturing plant has a capacity limitation

3) On Fridays, all goods must be transferred to the plant, and nothing can be held for shipping the following week.

Raw data including production rates for every item in each facility, operative hours of manufacturing sites, warehousing capacity of producing facilities, and vehicle containers size are acquired from case company management in order to analyze transportation procedures. (Rouzafzoon & Helo, 2018)

Modules of modeling are developed in order to generate agent-based simulations. The succeeding agent classes were created; "a processing factory agent", four distinct "production unit" agents (as every piece has its own set-up), an "order" agent, and a "truck" agent. (Rouzafzoon & Helo, 2018)

Several order sequences, factors, and criteria are used in each production unit. The "Order schedule" sends an order agent to the "Processing factory" to dispatch vehicles to the relevant manufacturing unit for product loading and distribution. Once a week, the order schedule is repeated. Utilizing the application platform, orders are transmitted according to a predetermined timetable at specific times and days of every week, Figure 14. (Rouzafzoon & Helo, 2018)

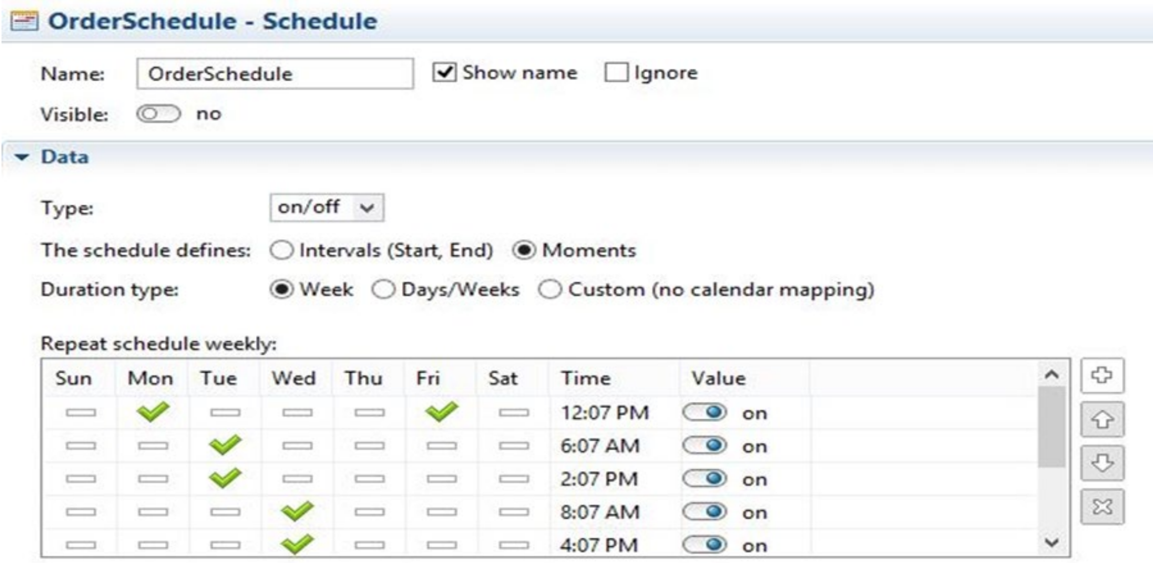

Figure 15. Requesting schedule for delivery to the factory

Due to limits such as manufacturing unit inventory and vehicle capacities, the order schedule is launched with a static order point. The script for creating order agents from a production plant to a processing factory is provided below. (Rouzafzoon & Helo, 2018)

```
Order order= new Order ();

Send (order, main.factory.EnterProductionUnitA);

main.factory.EnterProductionUnitA.take (order);
```

Code snippet 2. Order transfer to the factory process

Java programming defines how agents collaborate and communicate with one another. The production timetable is intended to generate consolidated production volumes on an hourly basis for every manufacturing unit. When the processing facility receives an order, a vehicle is deployed to the corresponding manufacturing unit to carry the materials. After loading, the storage level of the manufacturing unit is deducted from the loading quantity. The GIS component of the Anylogic application is leveraged to create an effective model, Figure 15. Vehicles move to locations based on the most recent route data, traffic, and speed restrictions, and manufacturing facilities and the factory are plotted on a map. Furthermore, routing data is acquired from the "Open Street Map" service, and the fastest route is picked. (Rouzafzoon & Helo, 2018)

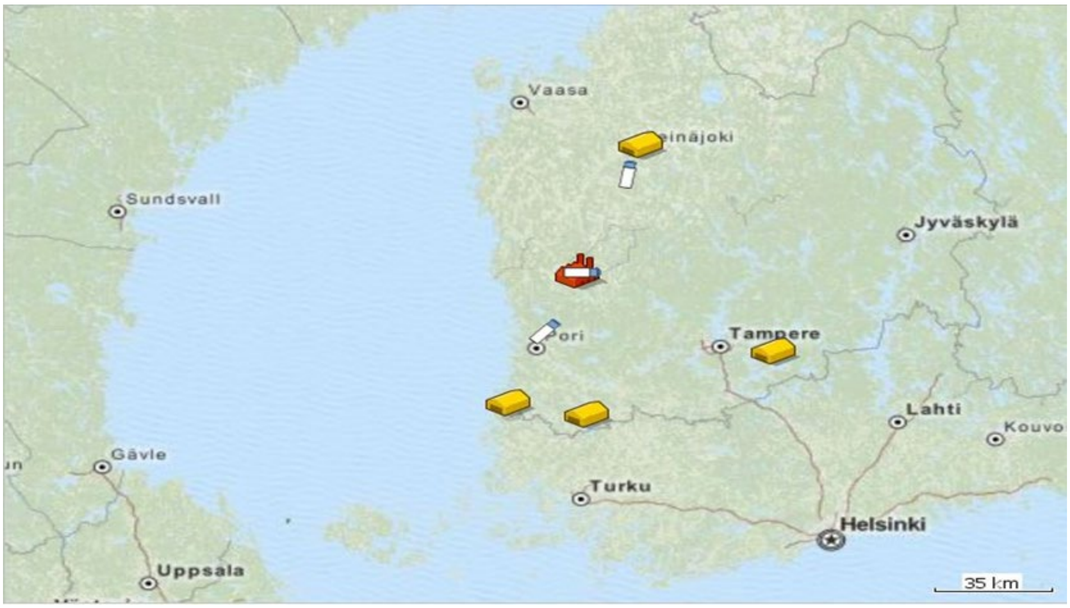

Figure 16. Facilities are located on the GIS map.

Vehicles collect the raw materials according to a predetermined loading schedule and then depart to the processing plant. The procedure is simulated as a discrete event simulation (DES) for every manufacturing block. The unloading procedure is started after the vehicle returns to the factory, and the vehicle is therefore released for another journey. (Rouzafzoon & Helo, 2018)

The factory inventory is raised with the unloading material quantity with each product shipment. The simulation elements for a manufacturing unit operation are shown in Figure 16.

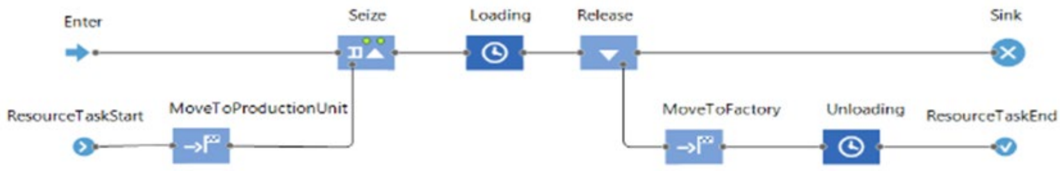

Figure 17. Trucks delivery procedure

Since raw material cannot be stored over the weekends, identical simulation blocks and a collection timetable are used for the final day of every week. Due to problem constraints, the initial site of vehicles is specified at the factory, and an operating timetable for vehicles is defined between 6 a.m. and 9:00 p.m. Furthermore, the quantity of operating vehicles for the truck resource pool is defined by a truck number parameter. (Rouzafzoon & Helo, 2018)

Table 3 presents the case studies selected in the transportation and supply chain problems domain for this paper. The Scenarios column provides research question scenarios and the Analysis column presents methods utilized for each case to resolve the problem. Table 4 provides data sources utilized to complete cases. The case studies and solution approaches are covered extensively in the following chapter.

Table 3. Case studies, scenarios, and analysis tools

Case Number and Title	**Case information**	**Scenarios**	**Analysis**
1. DC locations in Nordics	Locating the most optimal distribution centers location based on Nordic countries population number and geographical location	1) Determine the optimal points in the Nordic region for 5 distribution centers nearby customers.	Network Optimization methods/ GIS
1. DC locations in Nordics	Locating the most optimal distribution centers location based on Nordic countries	2) Create separate service zones depending on chosen facility locations at the Nordic level	Network Optimization methods/ GIS

	population number and geographical location		
2. Wood collection	Collecting tree logs from forests and delivering logs to the main factory, collection points or trains stations.	1) Facility location and fleet optimization in collecting trees from seven regions, delivering to two potential collection points, and transporting trees by train to the main factory	ABM/DES/GIS
2. Wood collection	Collecting tree logs from forests and delivering logs to the main factory, collection points or trains stations.	2) Facility location and fleet optimization in collecting trees from seven regions, delivering to three train stations, and transporting trees by train or trucks to the main factory	ABM/DES/GIS
3. Transportation design	Collecting decaying products from production units and transporting them to the main factory	1) Fleet number and vehicle schedule optimization in perishable products pickup and delivery process with two trucks	ABM/DES/GIS
3. Transportation design	Collecting decaying products from production units and transporting them to the main factory	2) Fleet number and vehicle schedule optimization in perishable products pickup and delivery process with four trucks	ABM/DES/GIS
3. Transportation design	Collecting decaying products from production units and transporting them to the main factory	3) Fleet number and vehicle schedule optimization in perishable products pickup and delivery process with six trucks	ABM/DES/GIS

Table 4. Population and source datasets information

Case Number and Title	Case Information	Country	Year of Data	Dataset Source	Road Dataset Source
1. DC locations in Nordics	Locating the most optimal distribution centers location based on Finland demographic and spatial information	Finland	2016	Official Statistics of Finland	Digiroad, OSM
1. DC locations in Nordics	Locating the most optimal distribution centers location based on Sweden demographic and spatial information	Sweden	2016	Official Statistics of Sweden	OSM
1. DC locations in Nordics	Locating the most optimal distribution centers location based on Norway demographic and spatial information	Norway	2017	Statistics Norway	Kartaverket, OSM
1. DC locations in Nordics	Locating the most optimal distribution centers location based on Denmark demographic and spatial information	Denmark	2018	Statistics Denmark	OSM
2. Wood collection	Picking up tree logs from forests and transporting logs to the main factory, collection points or trains stations.	Finland	2020	Forest case company	OSM

3. Transportation design	Collecting perishable products from production facilities and delivering them to the main factory	Finland	2019	Transportation case company	OSM

4 RESULTS AND DISCUSSION

Research problems and proposed methods for DC locations in Nordics, Wood collection and Transportation design cases are discussed in the Method section. The outcome of those methods applied to case companies' data is presented in this section.

4.1 DC locations in Nordics

After resolving the location-allocation step by the goal function of shortest distance impedance, the outcome can be analyzed by considering the request nodes, attributes of facilities, and lines. Furthermore, by designating the facility ID identical to the desired facility ID, every request point associated with a distribution center can be evaluated. Facility location and assigned request number are extracted from facility parameters. (Helo, Rouzafzoon, Solvoll, et al., 2018)

The outcomes are utilized to generate service zones after identifying the optimal resolutions for the location-allocation problem. Impedances are selected for service zone planning according to traveling time in hourly intervals, the flow is selected "away from the facility," U-turns are permitted at intersections, and one-way routes are prohibited. Figures 17 to 24 present DC locations and service areas generated for those top 5 distribution centers. Tables 5 to 8 provide the location detail and allocated demands for each scenario. (Helo, Rouzafzoon, Solvoll, et al., 2018)

In addition, if the result shape class attribute is defined as straight lines after the resolving procedure, the location-allocation algorithm generates lines that link the solution distribution centers to their assigned demand nodes. It also updates the facility class attribute of a Candidate facility to Chosen if that is included in the solution, however only chosen facilities are presented in the following figures.(Helo, Rouzafzoon, Solvoll, et al., 2018)

Table 5. Finland 5 DC Information

Location	Allocated Demand
Helsinki	2,119,991
Oulu	748,918
Tampere	1,155,869
Kuopio	808,218
Turku	583,801

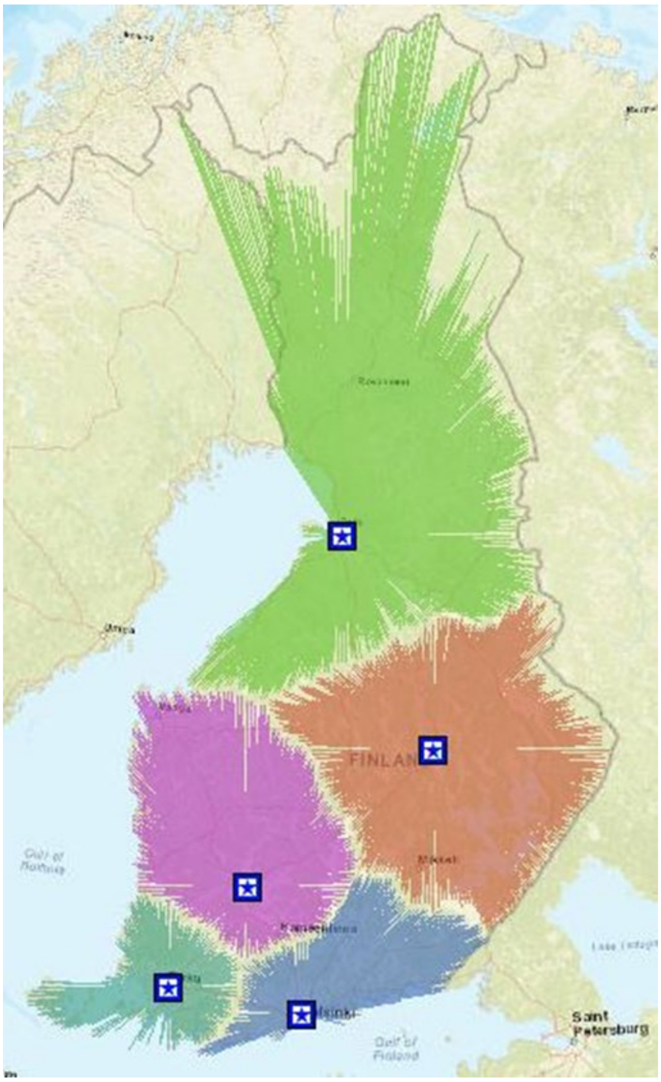

Figure 18. Finland 5 DC locarions

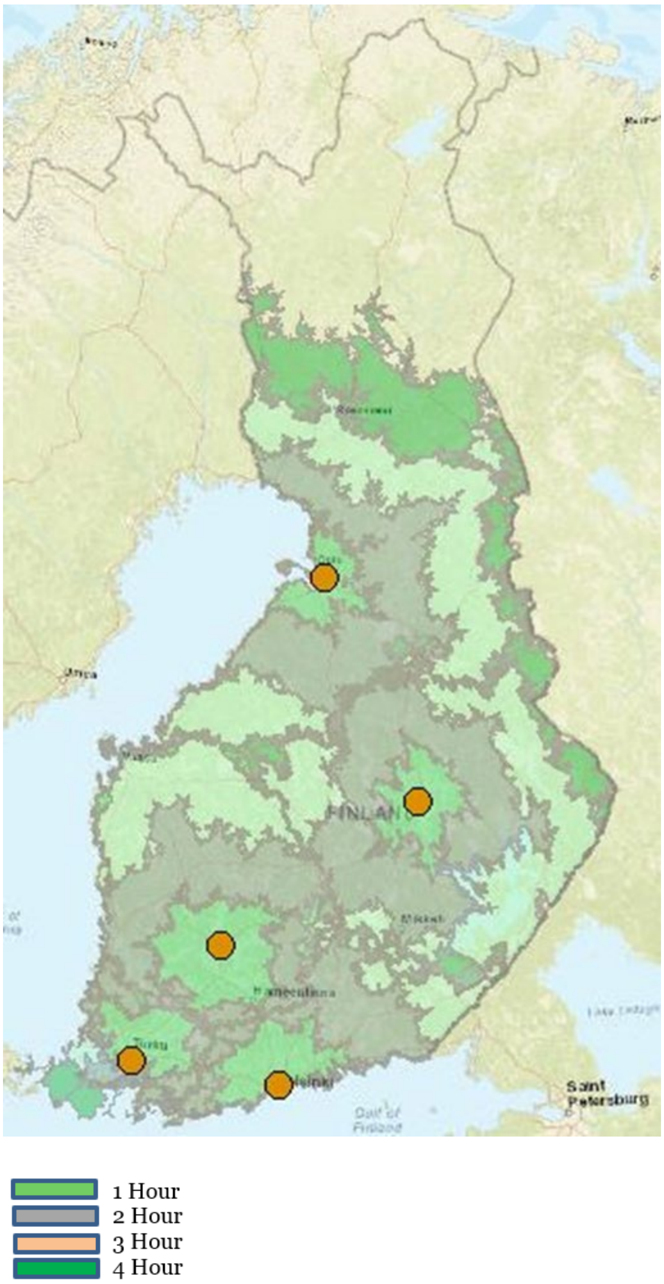

Figure 19. Finland 5 DC service areas

Table 6. Sweden 5 DC Information

Location	Allocated Demand
Umeå	882,926
Örebro	2,010,478
Göteborg	2,062,856
Stockholm	3,089,431
Eslöv	1,949,462

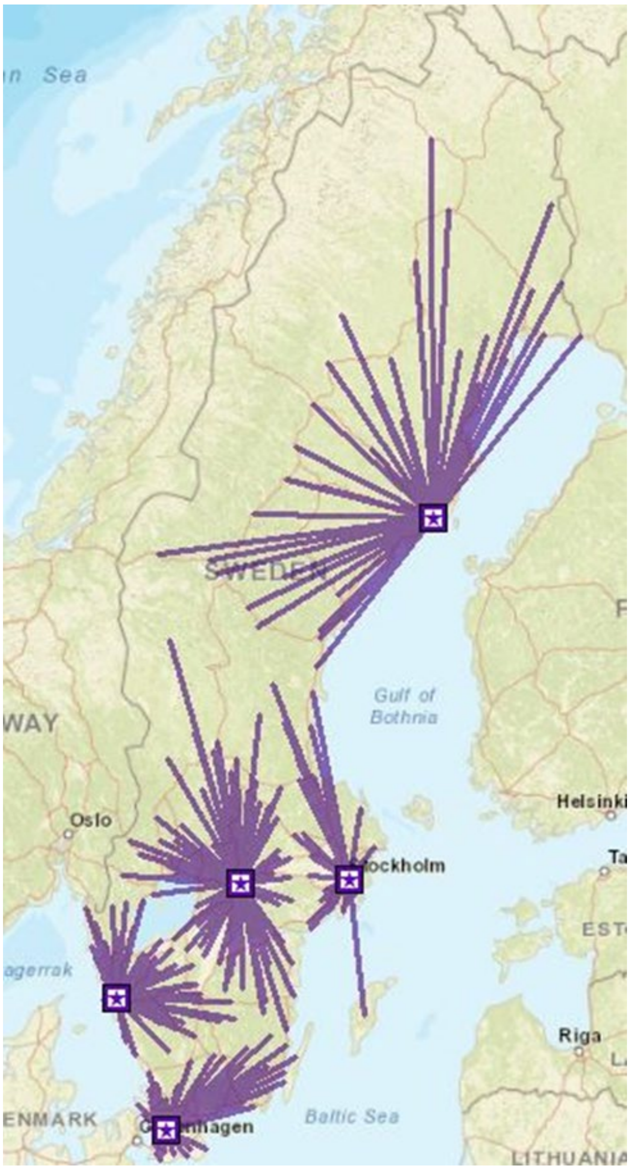

Figure 20. Sweden 5 DC locations

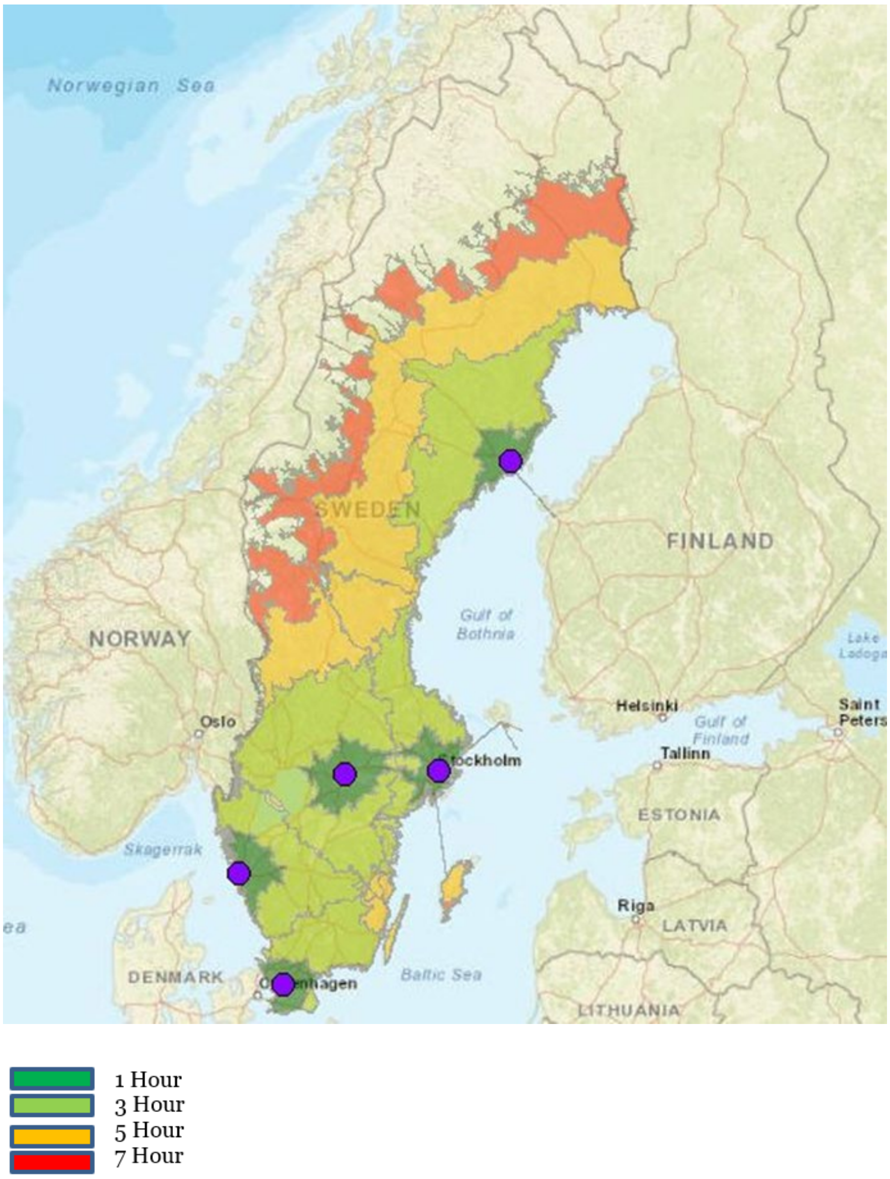

Figure 21. Sweden 5 DC service areas

Table 7. Norway 5 DC Information

Location	Allocated Demand
Sørreisa	397,035
Trondheim	805,722
Bergen	624,795
Sandnes	710,135
Oslo municipality	2,713,060

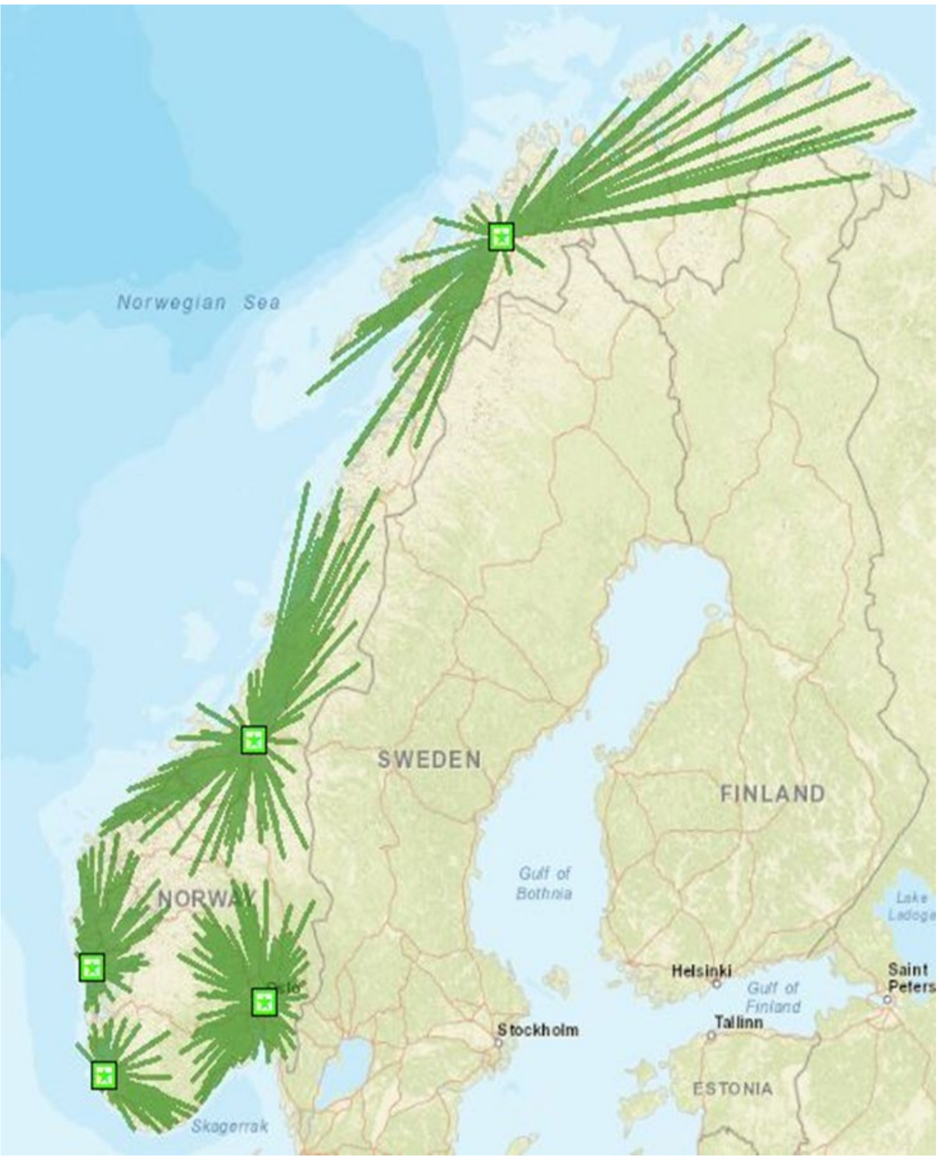

Figure 22. Norway 5 DC locations

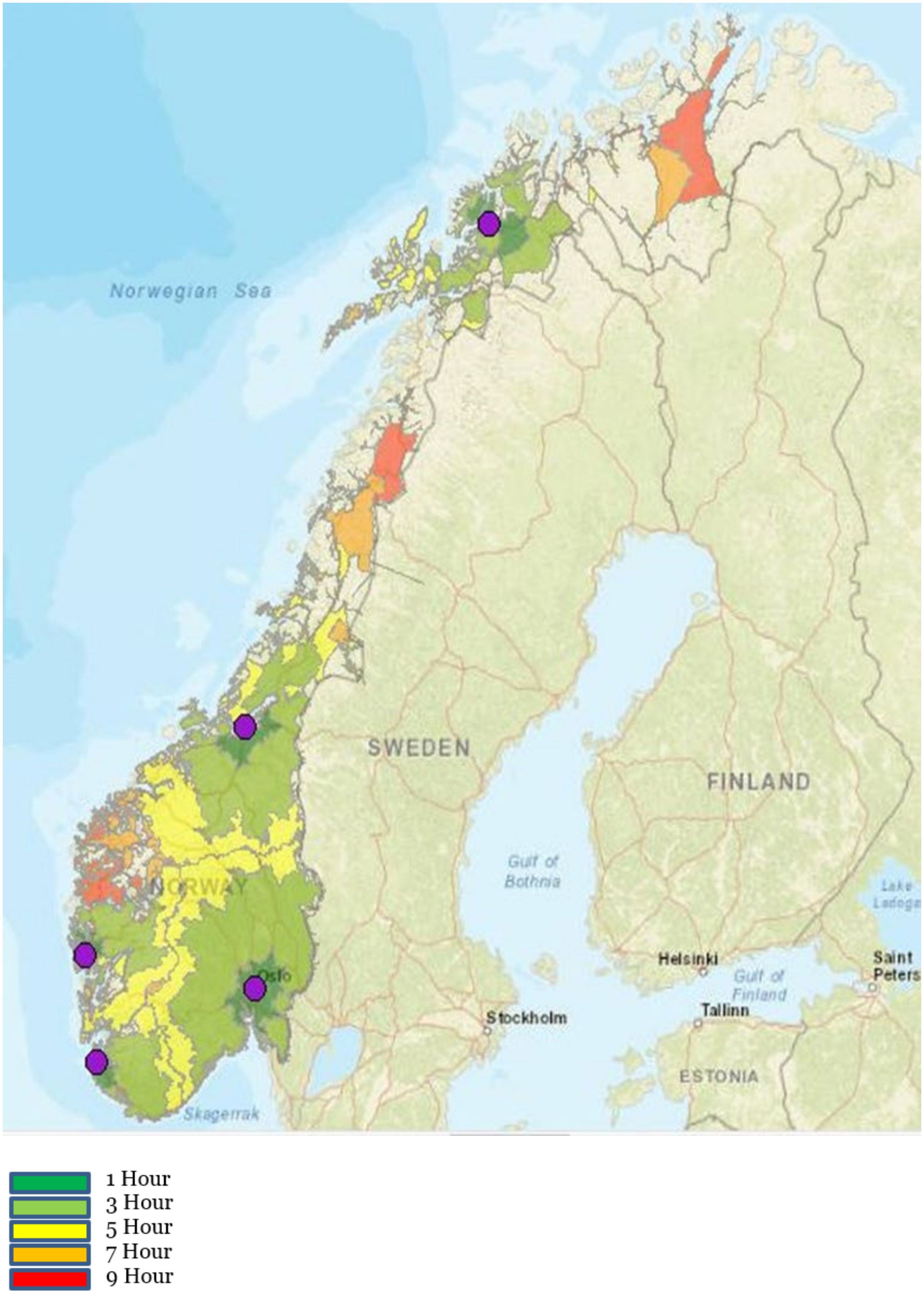

Figure 23. Norway 5 DC service areas

Table 8. Nordic level 5 DC Information

Location	Allocated Demand
Stockholm, SE	4,747,991
Hämeenlinna,FI	5,858,537
Oslo, NO	4,456,798
Halmstad, SE	4,128,914
Steinkjer, NO	1,556,458

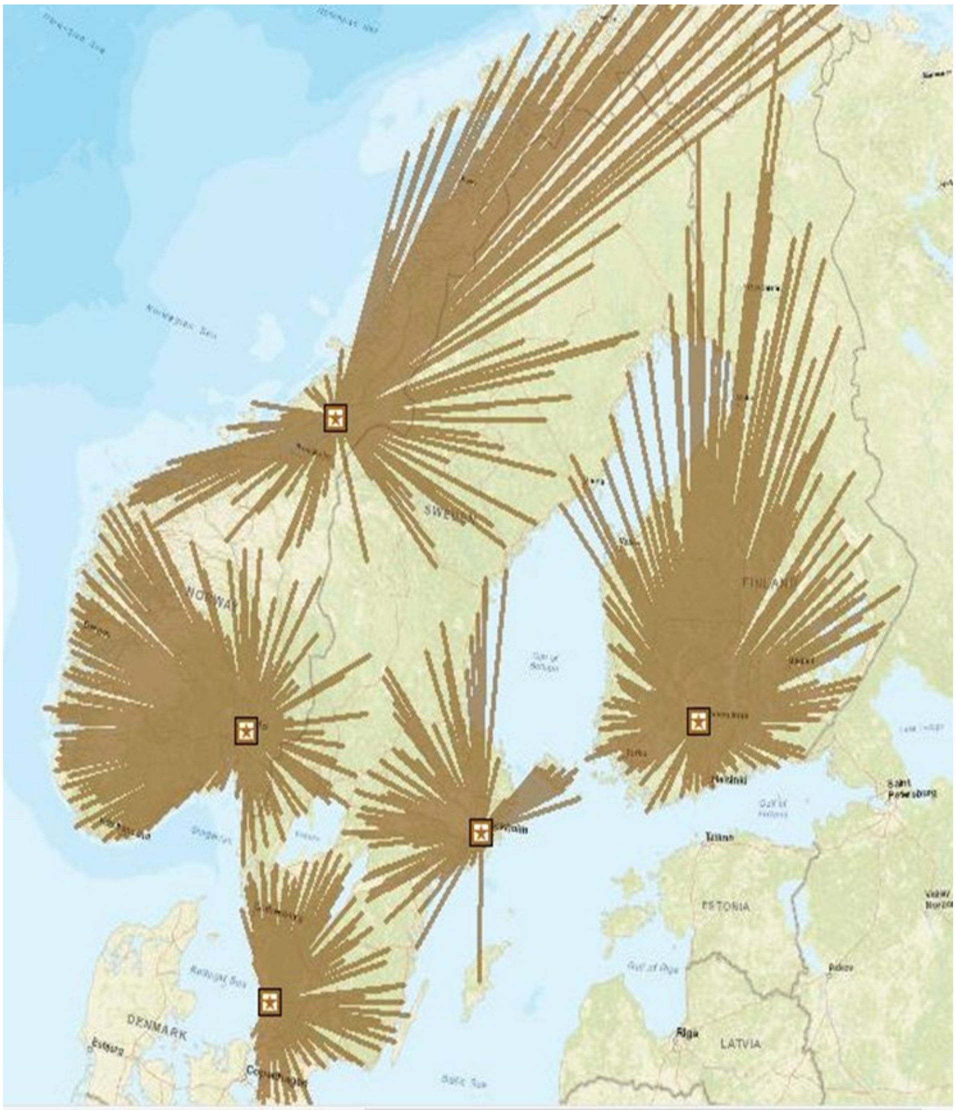

Figure 24. Nordic level 5 DC location

Figure 25. Nordic level 5 DC service areas

4.2 Wood collection

In this case, a set of critical performance indicators have been introduced to evaluate the process productivity. The truck number transporting tree logs from a facility is provided in figure 25. In addition, the number of trucks is illustrated based on weekdays and separated by each facility. This detailed information supports the management team to plan comprehensively for the company's logistics operation. The charts below represent only scenario one execution, but the same indicators exist for scenario two.

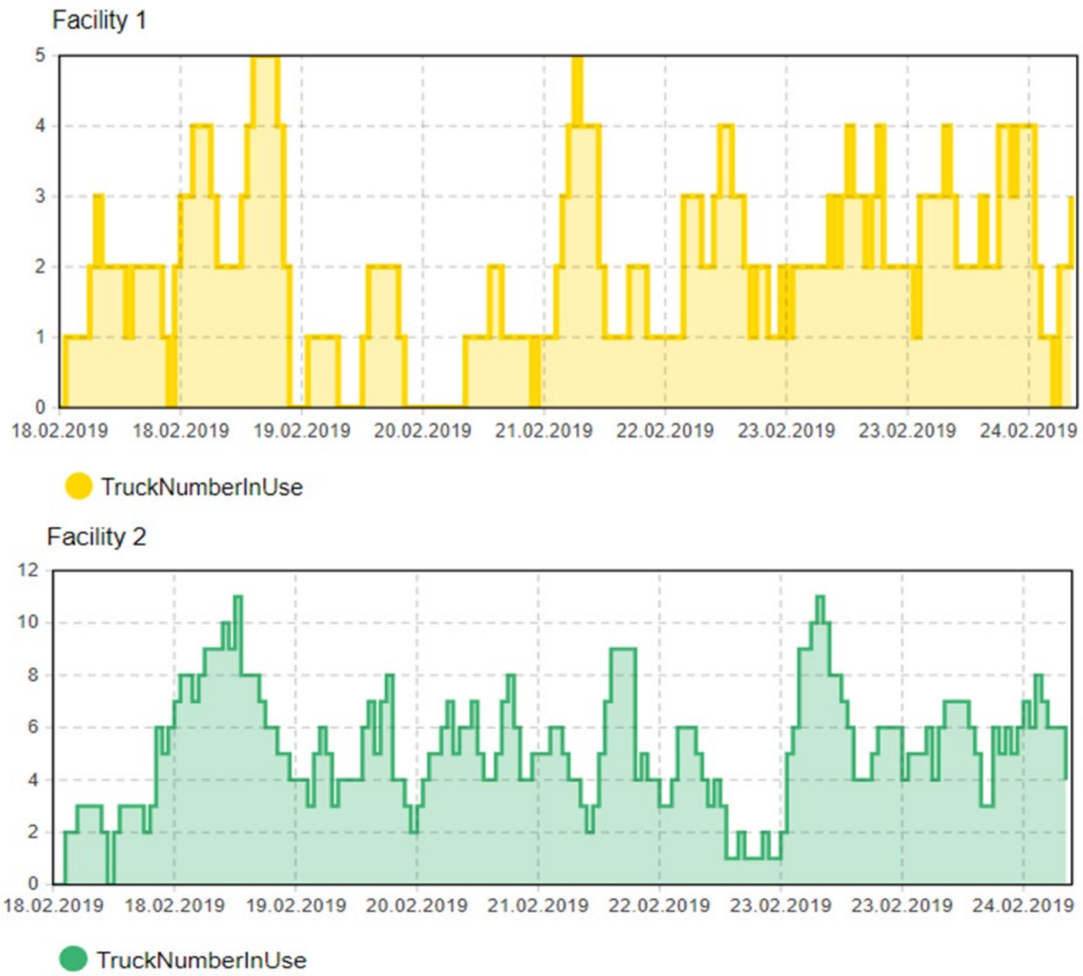

Figure 26. Truck number in use

Inventory level is another key performance indicator to assess the process efficiency, inventory expenses, or storage restrictions. When the pickup and delivery procedures to a facility are completed, the inventory level is refreshed immediately as displayed in Figure 26. In addition, when the train carries logs from facilities and delivers them to the factory, the inventory levels at facilities are subtracted.

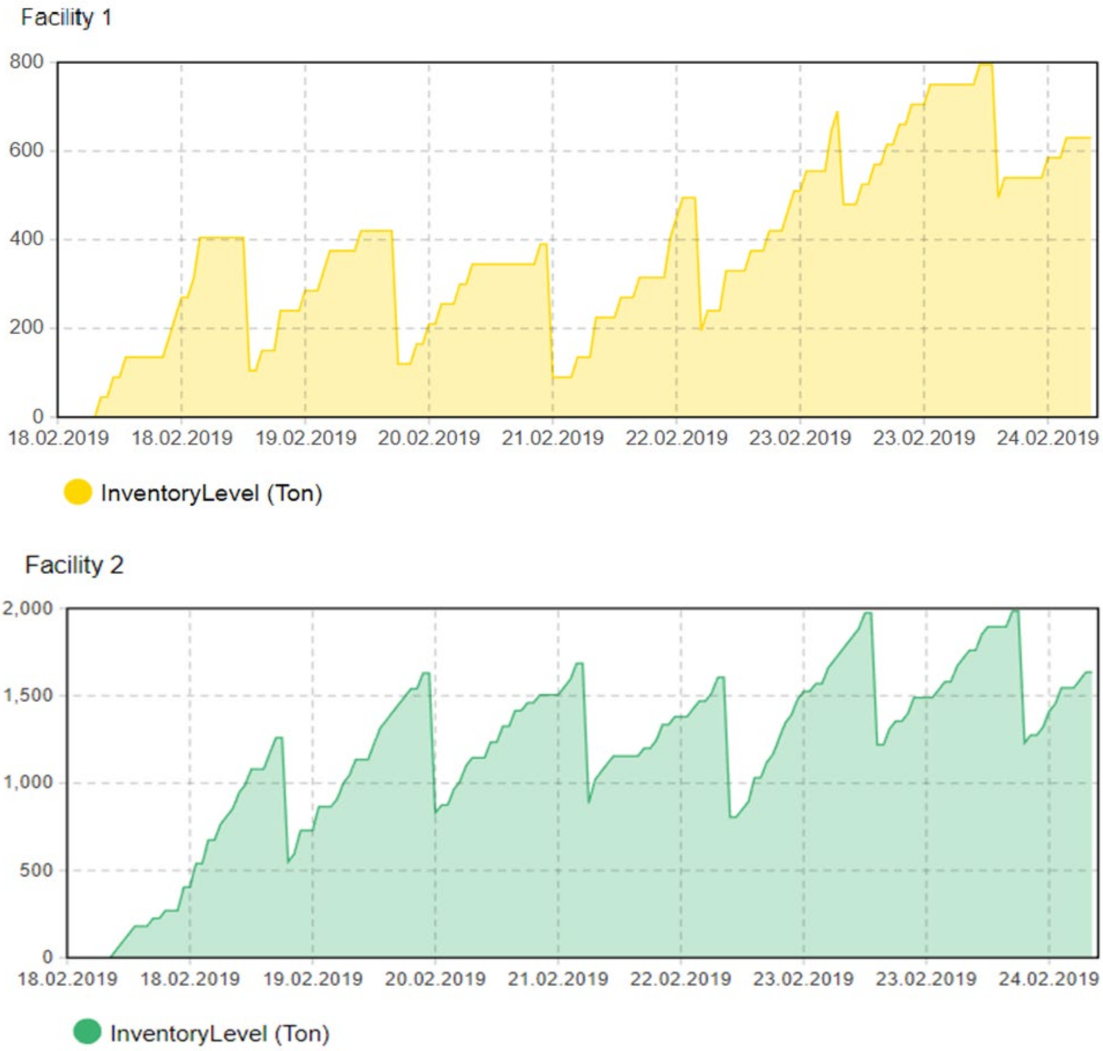

Figure 27. Inventory Level (Ton)

Total travel distance can be another considerable factor in logistics cost. Therefore, the total kilometer driven for each facility based on real-world routes is calculated and provided by a chart, Figure 27.

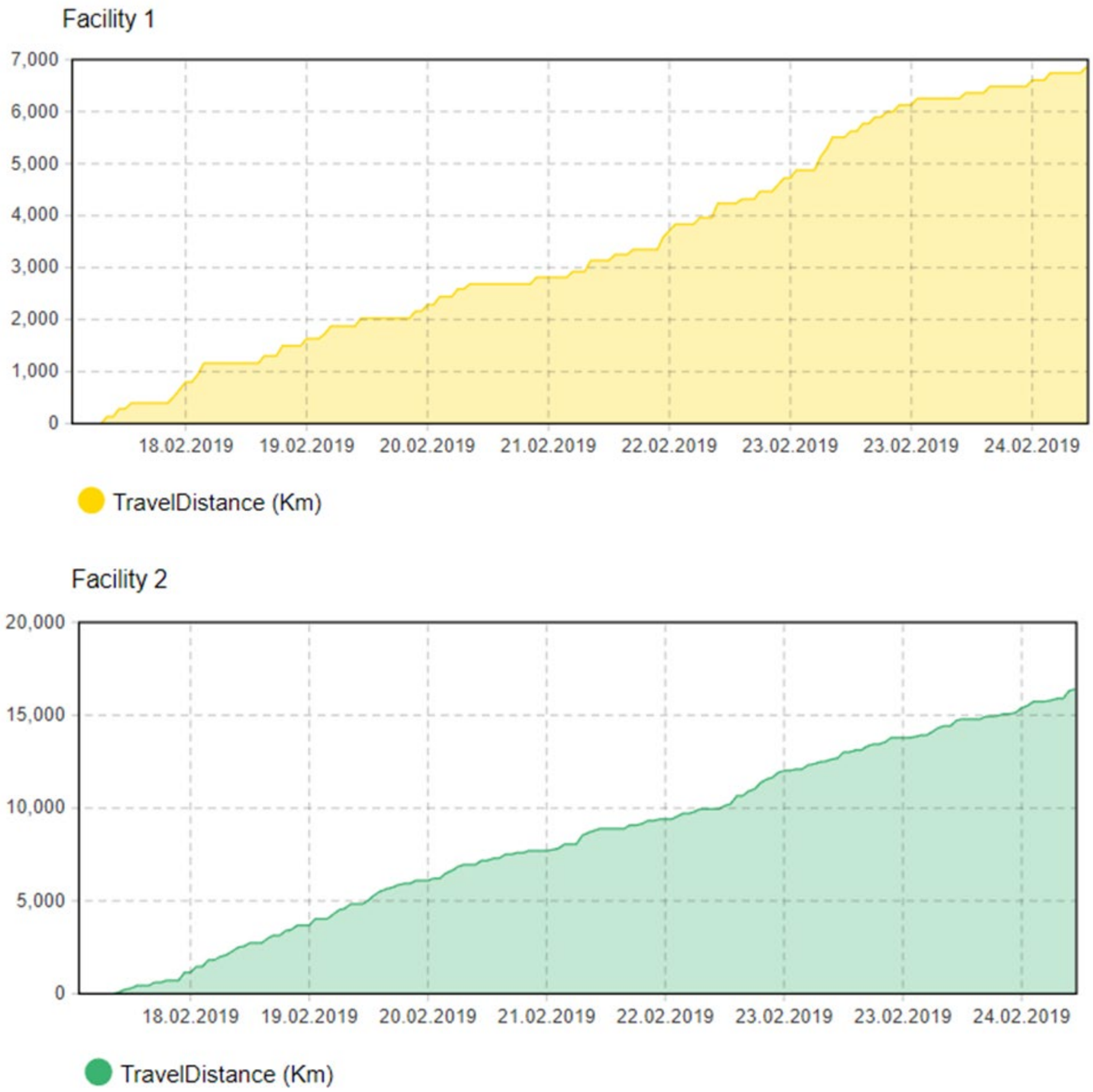

Figure 28. Travel Distance (Km)

The logistics expenses are heavily influenced by the placement of facilities and the size of fleets assigned to each facility. The number of facilities and their locations differs between Scenario 1 and scenario 2 and GIS maps for both scenarios are demonstrated in Figures 28 and 29.

As the logistic costs were modeled in section 3.2, the optimization seeks to determine the minimum transportation cost by altering the fleet size assigned to each facility and by comparing the total logistics cost of each simulation run. Simulation modelling is executed exclusively for both scenarios 1 and 2. Finally, the minimum transportation cost for scenarios 1 and 2 are compared to identify the best facility locations set up for the case company.

Each simulation version within a scenario runs for the time frame of two weeks with a different combination of truck numbers for every facility and each version is iterated within a defined number of times. The minimum and the maximum number of trucks for each facility are set as 0 and 10 respectively and transportation costs with all generated scenarios are evaluated.

The *Current* column in Figures 29 and 30 presents the last run fleet assignment and transportation cost for each scenario and column *Best* represents the most optimal outcome of all simulation runs.

The optimization outcome of scenario one, Figure 30, suggests that six trucks should be assigned to facility one and zero trucks to facility two with a transportation cost of 920,859 euros. Scenario two in which the potential facility locations are different from scenario one proposes that the company should assign five trucks to facility two and no truck to other locations. The transportation cost presented in Figure 31 is 755,345 euros. It can be noticed that the prospective facility locations and the number of trucks in scenario two yield significant transportation cost savings within two weeks of operation. Additionally, the optimization parameters and input are presented in table 9.

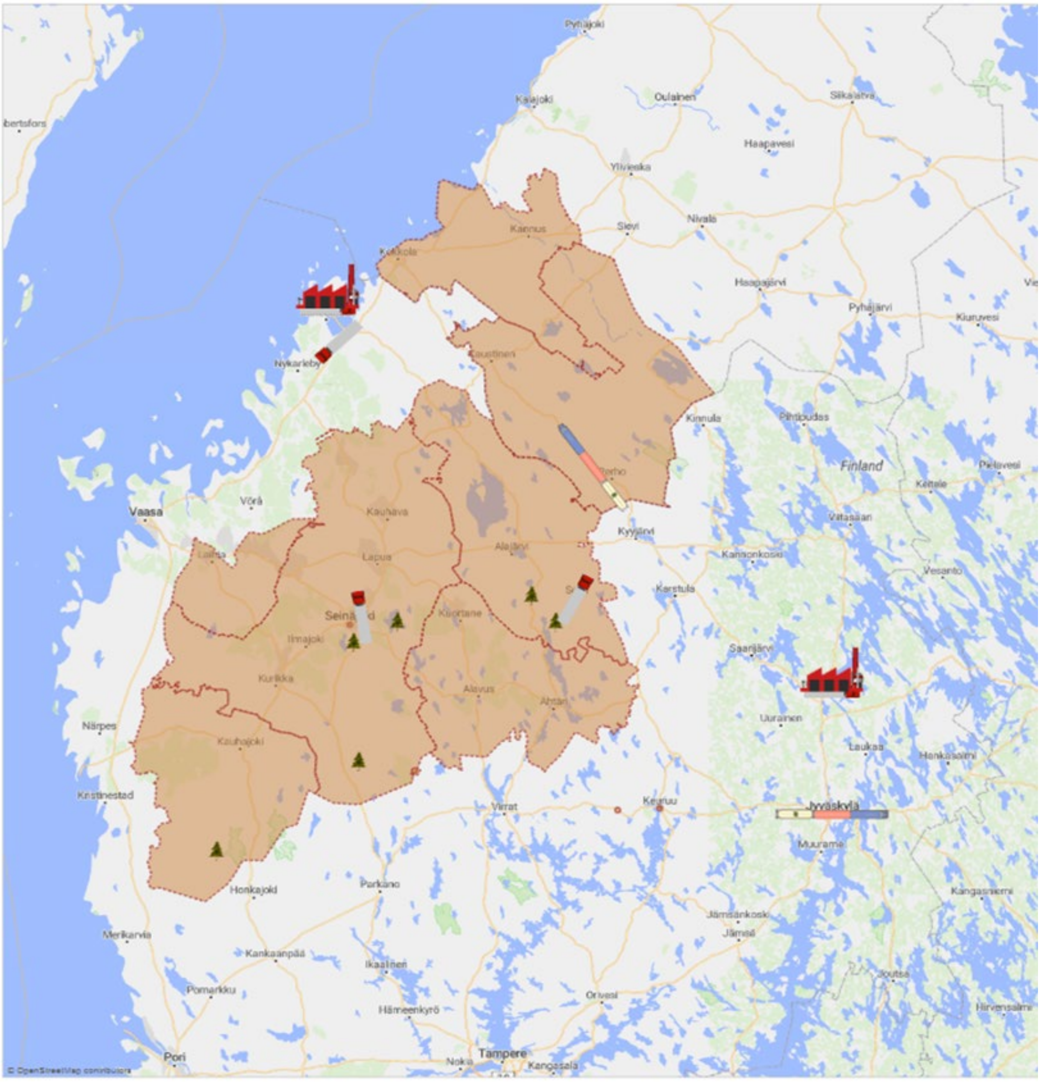

Figure 29. Scenario 1 – GIS map and facilities location

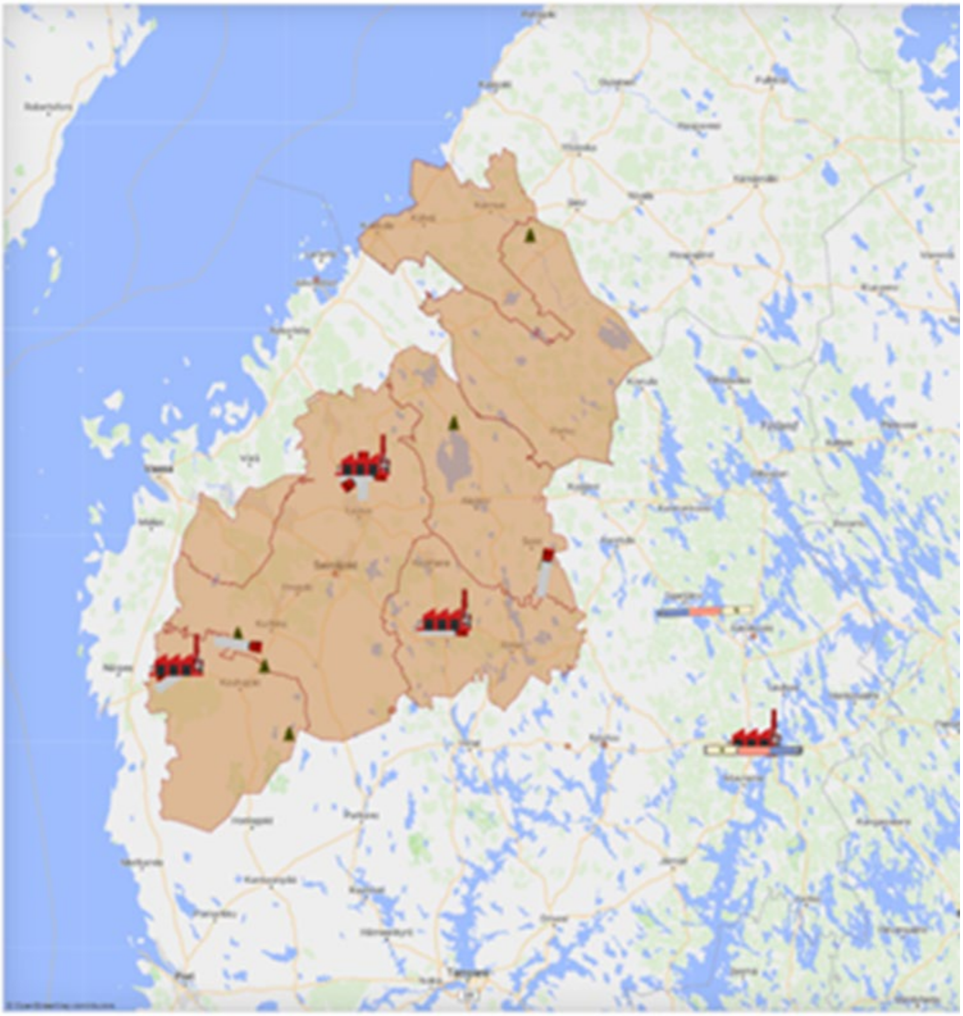

Figure 30. Scenario 2 – GIS map and facilities location

Table 9. Optimization model parameters

Optimization Parameter	Scenario 1	Scenario 2
Facility 1_Truck_Number	*Number of trucks assigned to collection point 1*	*Number of trucks assigned to train station 1*
Facility 2_Truck_Number	*Number of trucks assigned to collection point 2*	*Number of trucks assigned to train station 2*
Facility 3_Truck_Number	–	*Number of trucks assigned to train station 3*
Factory	–	*Number of trucks assigned to factory*
Truck fixed cost (Fc)	150000 Euro	150000 Euro
Truck driving cost per kilometer (Dc)	1.56 Euro	1.56 Euro

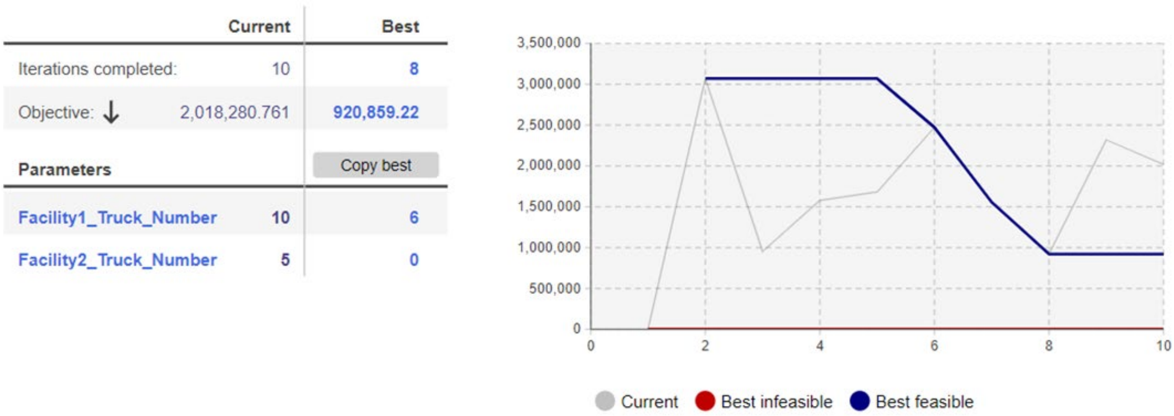

Figure 31. Scenario 1 – transportation cost optimization

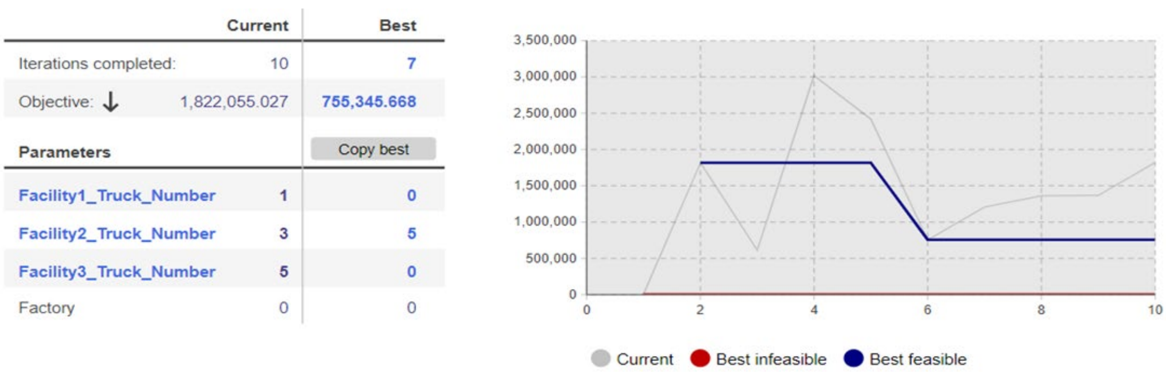

Figure 32. Scenario 2 – transportation cost optimization

4.3 Transportation design

The simulation outcome is presented using a variety of core performance indicators and scenarios. The total quantity of collected materials at the factory is demonstrated in a figure with a time axis as displayed in Figure 32. (Rouzafzoon & Helo, 2018)

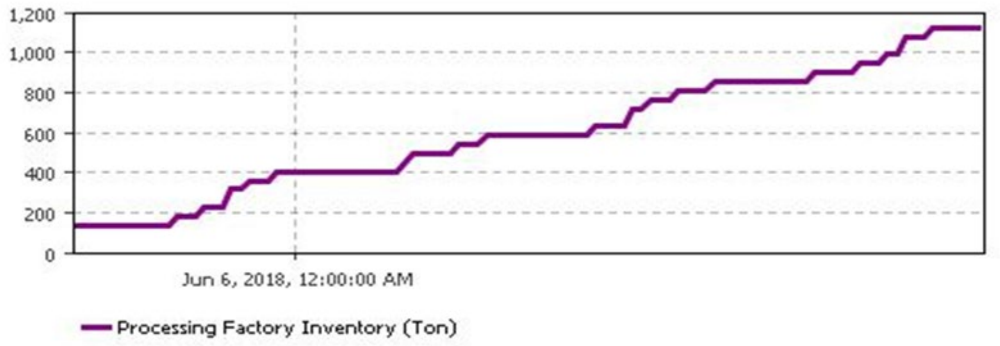

Figure 33. Factory Inventory (Ton)

A plot with inventory quantities in tons and time dimensions is also generated to illustrate storage levels at every manufacturing unit. Each unit of manufacturing is represented by a single color. The inventory quantity is refreshed once a vehicle loading process is finished. The chart in Figure 33 allows managers to keep track of stockpile levels on various weekdays. (Rouzafzoon & Helo, 2018)

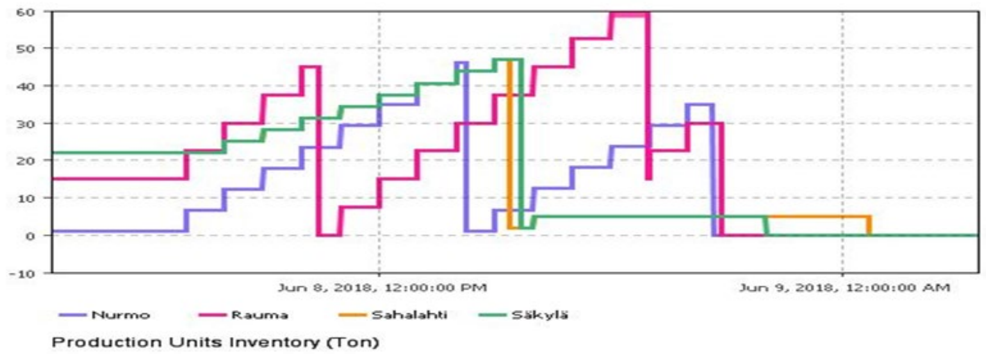

Figure 34. Production Units Storage (Ton)

Because truck efficiency is an important cost element for businesses, the number of vehicles in use is measured and presented on the chart in Figure 34 using the time axis. Company executives can specify the vehicle resource pool first, and then track how many vehicles are deployed in shipments according to the manufacturing rate and delivery timetable. (Rouzafzoon & Helo, 2018)

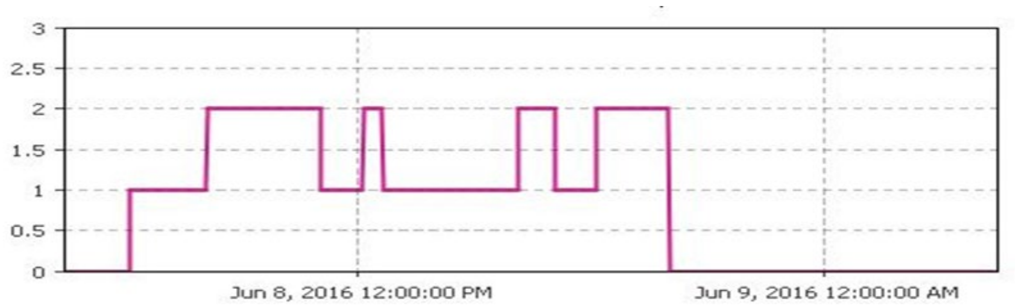

Figure 35. Number of Trucks in Use

Modeling allows you to explore different situations without needing to put them into practice in reality. Sliders for specifying the vehicle number and modifying the rate of production are built throughout the modeling process. Managers may quickly change the inputs and monitor the resulting consequences. The simulation modeling is carried out using the specified production rates provided by the case company personnel. Different scenarios with two, four, and six trucks are generated for determining the optimal size of vehicles. (Rouzafzoon & Helo, 2018)

4.3.1 Scenario 1: Two trucks

Figure 35 indicates that the stockpile of the Nurmo and Rauma manufacturing sites is not entirely carried for the weekend with two vehicles. Figure 35 shows how levels of inventory in manufacturing facilities rise to 70 tonnages in 3 days of the week. (Rouzafzoon & Helo, 2018)

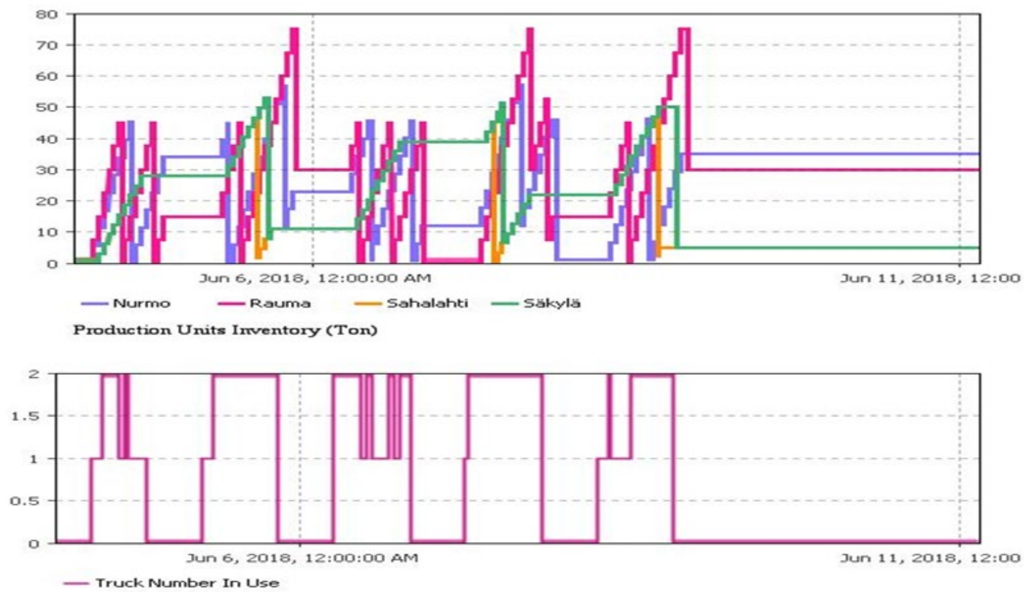

Figure 36. Key performance indicators with two trucks

4.3.2 Scenario 2: Four trucks

Every day of the week, the manufacturing unit inventory maintains at 45 tonnages, and all product is entirely loaded at the end of the week. In addition, as shown in Figure 36, four vehicles are only employed three days a week at maximum.

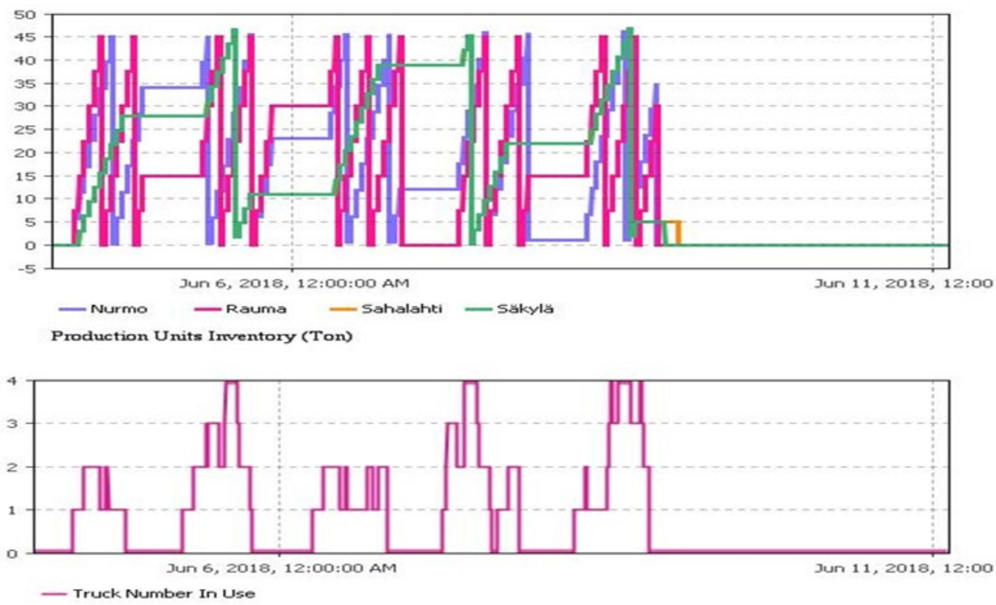

Figure 37. Key performance indicators with four trucks

4.3.3 Scenario 3: Six trucks

The stockpile of manufacturing facilities stays at 45 tons, as shown in Figure 37, and products are entirely loaded prior to the weekend. Furthermore, in this case, we have six vehicles accessible, but only the fifth vehicle is operated on the final day of the week. Throughout the week, the sixth vehicle is never used.

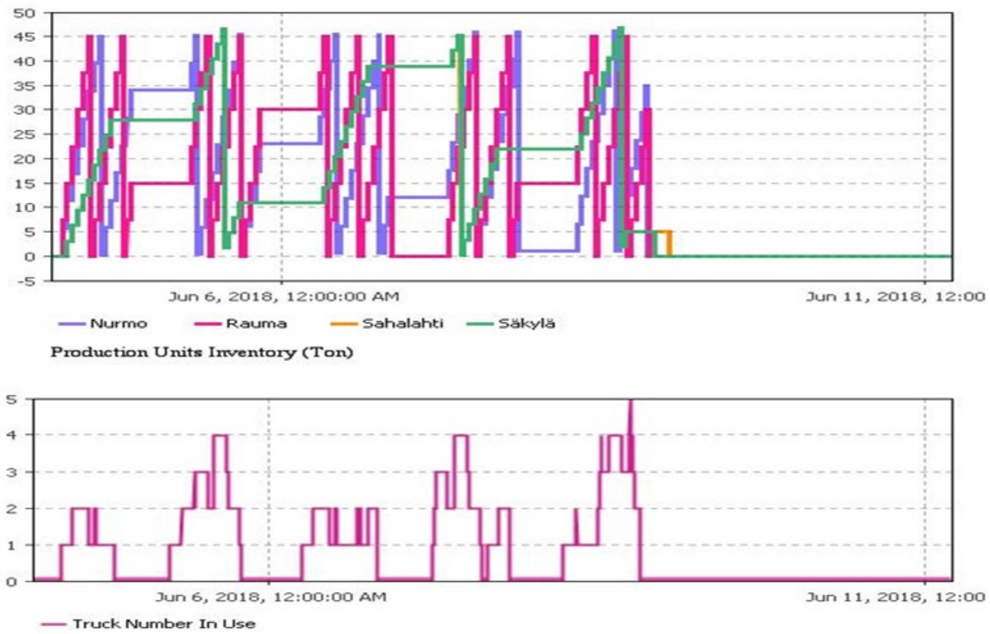

Figure 38. Key performance indicators with six trucks

When the number of trucks is changed and the results are compared to the preceding figures, it can be seen that the inventory of the manufacturing units is completely loaded with a minimum of four trucks a week. Furthermore, when analyzing levels of inventory between cases with four and six vehicles, there is no change in inventory levels; nevertheless, the fifth vehicle was only deployed in the third case on the last day of the week. (Rouzafzoon & Helo, 2018)

5 DISCUSSION

5.1 Contribution to theory

The conceptual contribution of this research, on a broad level, is in integrating key components of supply chain and logistics, utilizing open-source road and population datasets, adding spatial analysis and GIS features, providing operational key performance indicators for any time period, and creating optimization methods for different scenarios.

Since a variety of factors can influence the operational performance of complex supply chains, the broader factors should be considered when determining the best solution for supply problems.

In the recent research for supply chain networks design and optimization, (Abd El Karim & Awawdeh, 2020; Aranguren et al., 2021; Guo, 2020; Huang et al., 2022; Li et al., 2020; Wang et al., 2022) employed quantitative and qualitative methods such as bi-level programming model, K-means clustering algorithm, simulated annealing metaheuristic approach, particle swarm optimization (PSO), GIS-based multicriteria decision analysis (GIS-MCDA), and cuckoo search algorithms (CS); however, the proposed ABM and optimization methods in this paper allow for the modeling of a variety of components. In the Wood collection and Transportation design cases, facility locations and their processes, transportation, inventories, and routing factors are included in the modelling, and logistics cost minimization is sought under these parameters' integration.

The ABM approach, unlike other modeling approaches, is adaptable and can be adjusted to include a range of key parameters; for example, in Wood collection and Transportation design cases, ABM modeling can help to coordinate logistics operations by providing fleet sizing information on a regular basis (hourly, daily, weekly, or monthly) and by integrating several forms of transportation, for example, trains and trucks, to transfer cargo between facilities and pickup locations. Furthermore, the presented ABM technique can integrate transportation to facility operations by merging discrete event and agent-based simulations.

As logistics cost optimization may lead to numerous economic prosperities, facility location selection and fleet management enable management to make strategic decisions. The wood collection case aims at both facility locations and truck number delegation to minimize the transportation cost.

The proposed ABM method forms a transportation model based on potential facility locations and truck numbers and computes the total logistics costs. In the optimization procedure, the simulation is implemented for the combination of fleet allocation to each facility and geographical location of facilities, and then, transportation costs of different scenarios are compared. The minimum transportation cost for scenario 1 is 920,859 euros with allocating six trucks to facility one and for scenario 2 is 755,345 euros with assigning five trucks to facility two; the case company can reduce the logistics cost by selecting the scenario 2 setting.

The GIS feature employed in ABM modelling is a valuable tool in logistics management. This functionality analyses existing roads, calculates traveled distances and locates the facility nearest to the demand or pickup point. The traveled distance, in particular, is a significant factor in determining transportation costs and can be measured using GIS.

In the case study of DC locations in Nordic, another method of distribution center location-allocation was presented. In Nordic level countries, the GIS framework and tools were used to define the most cost-effective facility locations. The scenarios are hypothetical, but since this premise is also true for many consumer-related goods, we assume that the optimized resolutions will provide some vision in how distribution centers are attracted as the degree of requests increases.

Population data and road datasets from each country are used to locate potential facility locations and demand points. The length between the plant and the location of demand is computed by using the roads dataset. The spatial point of population location was integrated as both demand nodes and potential facility sites to identify the most optimized facility sites. To identify optimized DC locations and service areas within different travel times, heuristic methods were used. Cases for identifying 5 optimal facilities nearby customers from candidate locations were used for Finland, Norway, Sweden, and the Nordic level. Top 5 facility locations and their service areas on an hourly basis are identified and other information such as the allocated population to each selected facility is provided.

The proposed AB approach in the Transportation design case presents various benefits for manufacturing and logistics companies. It merges factory process stages, routing and traffic information, production ordering system, vehicle scheduling, and fleet optimization. Inventories quantity and fleet number in use can be tracked precisely on the scale of time and day.

The implemented agent-based approach provides significant flexibility for planning companies' operations. Key values such as order point, vehicle schedules, trip time, production rate, loading and unloading time, truck numbers, and truck average speed can be modified and the derived outcome is presented by various key performance indicators. In addition, fleet number optimization based on different scenarios, and fleet operation and arrival/departure schedule are implemented in the Transportation design case.

Tables 10, 11 and 12 provide a summary of each case study investigated in this dissertation. The scenarios column presents scenarios description under each research question and the analysis column provides solution methods applied for each case. The Results column summarizes the final outcome of each case study.

Table 10. DC location in the Nordic case summary

Case Number	Research Questions	Scenarios	Analysis	Results
1. DC locations in Nordics	1) How DC locations can be allocated by using geographical population data and optimization in Sweden, Norway, and Finland and at the Nordic level?	1) Determine the Nordic level's most optimal locations for 5 distribution centers nearby customers.	Network Optimization methods/ GIS	The spatial points of population location were incorporated as both demand nodes and potential facility locations to identify the most optimized facility sites with heuristic methods. Five distribution centers and assigned populations at Stockholm SE (4,747,991), Hämeenlinna FI (5,858,537), Oslo NO (4,456,798), Halmstad SE (4,128,914), Steinkjer NO (1,556,458) are chosen.
1. DC locations in Nordics	2) How several service zones can be defined depending on the selected facility locations at each country and Nordic level?	2) Create distinct service regions depending on facility locations at the Nordic level.	Network Optimization methods/ GIS	After defining the five potential locations, the conventional Dijkstra's technique is applied to identify the shortest link between a facility location and the population geographical location. One, two, and three hours service areas generated for those top five distribution centers are presented in Figure 24.

Table 11. Wood collection case summary

Case Number	Research Questions	Scenarios	Analysis	Results
2. Wood collection	1) How ABM can be used to model the transportation structure of collection operations and evaluate the number of fleets required for each facility location?	1) Facility location and fleet optimization in collecting trees from seven regions, delivering to two potential collection points, and transporting trees by train to the main factory	ABM/DES/GIS	The proposed ABM approach, incorporating discrete event and agent-based simulation, connects the transportation to facility operations. Key performance indicators such as truck number in use, inventory levels, and travel distance present the most updated status of logistics operation. The transportation cost optimization model is generated according to the number of trucks in use and travel distance. The least logistics cost for scenario 1 is 920,859 euros with assigning six trucks to facility one.
2. Wood collection	2) How ABM can analyze the impact of selecting a certain facility location setting on the transportation cost?	2) Facility location and fleet optimization in collecting trees from seven regions, delivering to three train stations, and transporting trees by train or trucks to the main factory	ABM/DES/GIS	Utilizing the ABM approach to model transportation operations, Key performance indicators such as truck number in use, inventory levels, and travel distance provides the current status of transportation operation. By allocating five trucks to facility two, the minimum cost of transportation is achieved in scenario 2 with 755,345 euros.

Table 12. Transportation design case summary

Case Number and Title	Research Questions	Scenarios	Analysis	Results
3. Transportation design	1) How ABM can solve fleet size and scheduling of periodic cargo transportation?	1) Fleet number and vehicle schedule optimization in perishable products pickup and delivery process with two trucks	ABM/DES/GIS	ABM provided an approach to merge factory process stages, routing and traffic information, production ordering system, vehicle scheduling, and fleet optimization. Inventories quantity and fleet number in use can be tracked precisely on the scale of time and day. In Scenario 1, inventories of Nurmo and Rauma manufacturing facilities were not transported fully before the weekend and it increased to 70 tons, over the allowed limit, in three days of the week.
3. Transportation design	2) How departing and arriving periods of vehicles impact on truck resource pool numbers?	2) Fleet number and vehicle schedule optimization in perishable products pickup and delivery process with four trucks	ABM/DES/GIS	The production unit stocks remain at 45 tons each day of the week, and all products are entirely transported at the end of the week. In addition, only four vehicles are used three days a week at maximum.
3. Transportation design		3) Fleet number and vehicle schedule optimization in perishable products pickup and delivery process with six trucks	ABM/DES/GIS	The stockpile of manufacturing units is still at 45 tonnages, and all materials have been delivered by the weekend. Furthermore, in this case, there are six vehicles accessible, although only the fifth vehicle is deployed on the final day of the week. Throughout the week, the sixth vehicle is never operated.

5.2 Managerial implications

The ABM simulation can be also utilized for modelling and optimization purposes. Logistics simulations can be implemented for any time frame with various values for targeted parameters and the most optimized values for those parameters can be identified based on the objective function.

Unlike other modeling approaches, managers can employ ABM to conveniently evaluate different scenarios by adjusting a range of key parameters. In addition, ABM can be used to monitor or improve operational performance.

ABM modelling applied in the Wood collection and Transportation design cases can contribute to planning logistics operations by supplying fleet sizing information on a regular basis (hourly, daily, weekly, or monthly), and by combining various transportation types such as trains and trucks carrying the cargo between facilities and pickup locations. Company managers can utilize that data to oversee the performance of the supply chain.

Furthermore, the proposed ABM approach, incorporating discrete event and agent-based simulation, can link transportation to facility operations; for instance, companies can observe inventory level fluctuation because of deliveries for every facility during operating hours.

The ABM model proposed in the Wood collection case can be used as a practical method for managers to set key organizational variables and observe potential outcomes by adjusting its value in the modeling; for instance, major operational components such as facility locations, fleet number, trucks driving speed, routing methods, trip time, the order assigning policy, number of pickups per region and loading and unloading amount can be tailored by managers and the generated outcome is promptly illustrated through different key performance indicators.

Additionally, the proposed modelling provides an effective method to plan for companies' prospective developments. If a company intends to build a new facility or halt one, the possible scenarios and their influence on the company's operational performance can be measured with the ABM system.

Furthermore, the ABM approach offers a comprehensive tool for companies operating under similar conditions to what was modeled in the wood collection case on how to model random pick-up points within an area and evaluate the performance.

The DC locations in the Nordics case are also typical of many larger companies, where an integrated transportation network allows for relatively easy and delivery of commodities at a low cost from a single place. Businesses can profit from decreased demand instability and lower inventories due to the risk-sharing impact on safety stocks by consolidating delivery hubs; however, direct shipping expenses will rise to some amount.

The implemented agent-based approach in the Transportation design case provides significant flexibility for planning companies' operations. Key values such as order point, vehicle schedules, trip time, production rate, loading and unloading time, truck numbers and truck average speed can be modified and the derived outcome is presented by various key performance indicators.

Moreover, managers can execute the simulation based on their daily setting, and extract the vehicle schedule for the working day. In addition, if a company intends to add, close, or relocate any facility, the change can be simply implemented in the modelling and the new result can be used for planning the company's operation.

Vehicle scheduling and fleet sizing problems arise frequently in real-world applications and companies require instant solutions for these problems. For instance, a morning schedule of vehicles and deliveries can be required for a company. The input data may be available only a few moments before the start of operations and a quick response is vital for supporting company operations. In addition, rescheduling may be required if unexpected conditions such as cancellation or change in a production unit schedule, and vehicle failures in the fleet.

5.3 Limitations of the ABM models

This chapter provides the research limitation and next steps for further research. The type of research implemented in this paper requires an intermediate level of Java programming skills to be able to integrate different factors together; therefore a considerable amount of time is dedicated to developing logic and coding, testing the code and improving the modeling process. An advanced level of coding is required if the research is going to be expanded to include more parameters or develop improved optimization techniques.

The population data for the DC locations in Nordic was collected mainly from official population and statistics websites of each country. Population data could also be accessed from different sources which can include higher accuracy or improved scale regarding the spatial information of the population.

The road datasets also included primarily the main roads while applying the analysis to a road dataset that contains several levels of road data could potentially improve the research outcome.

In the Wood collection case, fleet optimization was performed under two scenarios, while truck number optimization can be expanded to include various scenarios. Moreover, the only objective function constraint was considered as the time between requesting order and assigning order to a truck should be less than 60 minutes, while other constraints including the trip number per truck within a day, the truck traveled range and truck trip time could be added to the optimization formulation.

Further research can be also performed by integrating more components to the modeling such as connecting the live order rate database to create an integrated system to schedule the deliveries and monitor the process.

In the Transportation design case, vehicle schedules were limited to certain values, while further research can be performed by including a dataset of values or creating an objective function for optimization that includes detailed vehicle schedules arrival/departure factors. In addition, the next steps in the research could be creating an objective function with constraints on inventory levels.

6 CONCLUSION

The problem of facility location and vehicle number optimization has long been a subject of research. Transportation systems in supply chain management rely heavily on decision-making on facility location and fleet number. The performance of supply chains is heavily influenced by tactical decisions made in response to these challenges.

The key concept of ABM modelling is established based on agents that can act autonomously, interact with other entities and the environment, and make choices based on a set of objectives. This feature of the ABM method is used to model the transportation cost simulation and to integrate broader supply chain components, including the geographical location of potential facilities, inventory levels, real-world vehicle and train routes, task assigning policies, and fleet sizing to achieve a highly accurate resolution.

The solution approach in the Wood collection case is described by using forestry company data in Finland. The case company plans to gather tree logs from various regions and send them to potential facility locations in two scenarios; in scenario one, the logs are transported from regions to two fixed collection points, while in scenario two, they are transported to three train stations and a factory. The proposed modeling method is created with agents interacting with each other such as facility, factory, truck, train, order, and region.

The order agent represents the tree log pickup site, and a truck from the nearest facility is deployed to load and deliver the logs to the facility. The tree log pickup point is random within each region and the facility for delivering logs is selected according to the shortest route between the pickup point and facilities. The GIS embedded in modeling provides the existing route and trip time information between pickup points and facilities for trucks and trains.

Various key performance indicators illustrate the ABM modeling outcome of transportation and facility operations. This case study uses indicators such as truck number in use, inventory levels, and traveled distances for each facility.

Furthermore, parameters such as truck fixed cost and driving cost per kilometer are used to construct transportation cost modeling. The logistics cost optimization is generated through scenarios that change the geographical position of potential facilities as well as the number of trucks assigned to each one. The transportation cost is minimized under scenario two with a total cost of 755,345 euros and five trucks allocated to facility two and no trucks to others.

The Transportation design case presents a new versatile and efficient approach for the inventory pickup problem under restrictions such as facilities inventory levels and perishable products. In these problem types, several visits to a facility may be required in a day to avoid the facility shut down due to these restrictions.

In this research project, vehicle scheduling and sizing problems are particularly considered since they have a significant effect on the transportation system's overall cost. These problems are considered complex supply chain problems since various dynamic variables such as routing, trip time, vehicle schedules, and inventory levels are involved.

The objective of this case is to optimize the fleet number and transfer products to the central factory within the allowed time period. The central plant, four manufacturing units, vehicles, and orders are all modeled as agents, with problem constraints such as facility operating hours, warehouse capacity, and storage duration factored in.

The processing plant receives a shipment request from the manufacturing units, and a vehicle is dispatched to the relevant manufacturing unit to load supplies. Shipment demands are created accurately based on a fixed order level or a scheduled timetable.

Furthermore, using the GIS component of the simulation program, the factory and manufacturing units are situated on a map, and vehicles perform distributions according to the most up-to-date real-world traffic data. The number of trucks employed for fleet size optimization is tracked using a vehicle resource pool.

To track the progress of the operations, several key performance indicators are developed such as the aggregate quantity of goods collected at the factory, stock levels in each manufacturing unit, and the number of vehicles in use. Finally, manufacturing rates, truck timetables, and vehicle numbers are presented so that company managers can change the parameters to assess the influence.

The problem of vehicle scheduling and sizing optimization occurs regularly for companies and it requires instant and practical solutions. The proposed agent-based modeling approach connects the vital elements in supply chain performance such as facility location information, production ordering system, vehicle schedules, fleet number, and routing information, and it presents the whole supply chain outcome derived from these elements' interaction.

Using a geographic information system to incorporate spatial information into facility location decision-making can be considered a realistic solution.

Furthermore, the increased computing capacity of computers and the availability of commercially available GIS tools aid in the evaluation of logistical location decisions based on geographic data.

The population of Nordic countries is used to identify the geographical point of distribution centers in DC locations in Nordic case. The spatial data of the population is considered both as potential facility location and demand point. The study aims to investigate a hypothetical situation in which the customer's location is a key factor in the final delivery. The scenarios of 5 DC locations are analyzed at the Nordic countries' level. Prospective distribution center sites are assessed employing the heuristic optimization approach, and service areas based on different travel times are created. Table 13 presents case information, research questions, and the summary of results in this paper.

Table 13. Research questions and case summaries

Case Number and Title	Research Questions	Results
1. DC locations in Nordics	1) How DC locations can be allocated by using geographical population data and optimization in Sweden, Norway, and Finland and at the Nordic level? 2) How several service zones can be defined depending on the selected facility locations at each country and Nordic level?	Heuristic approaches were used to determine the most optimal facility sites by using the geographical points of population location as demand nodes and as possible facility locations. Five distribution centers and allocated populations at Stockholm SE (4,747,991), Hämeenlinna FI (5,858,537), Oslo NO (4,456,798), Halmstad SE (4,128,914), Steinkjer NO (1,556,458) are selected. The five potential locations are first identified, and then the traditional Dijkstra's technique is used to determine the geographic location of the population and the location of the facility that forms the shortest link. One, two, and three hours service areas are created for those top five distribution centers.
2. Wood collection	1) How ABM can be used to model the transportation structure of collection operations and evaluate the number of fleets required for each facility location? 2) How ABM can analyze the impact of selecting a certain facility location setting on the transportation cost?	The suggested ABM approach links transportation to facility operations by using discrete events, agent-based simulation, and GIS. The number of vehicles in use and the distance traveled determine how to optimize transportation costs. The minimum logistics cost plan for scenario 1 involves allocating six trucks to facility one, totaling 920,859 euros. In scenario 2, the minimal transportation cost of 755,345 euros is attained by designating five trucks to facility 2.

Case Number and Title	Research Questions	Results
3. Transportation design	1) How ABM can solve fleet size and scheduling of periodic cargo transportation? 2) How departing and arriving periods of vehicles impact on truck resource pool numbers?	ABM provides a method for integrating the phases of a factory's production order system, routing and traffic data, vehicle scheduling, and fleet optimization. On a scale of time and day, the size of inventories and the number of operating fleets can be properly tracked. In Scenario 1, Nurmo and Rauma's inventories rose to 70 tons in three days, exceeding the permitted maximum. In Scenario 2, the production unit's weekly stock levels stay at 45 tons, and at the end of the week, every product has been transferred. In addition, only four trucks are operated, at most, three days a week. The stockpile of production plants in Scenario 3 is still 45 tons, and all of the materials were delivered by the weekend. In this instance, six trucks are available, but only the fifth vehicle is used on the last day of the workweek. The sixth truck is never used across the duration of the week.

Unlike other modeling approaches, the ABM approach is versatile and can be tailored to provide a variety of necessary details. Including autonomous agents, ABM can incorporate various elements existing in the complex supply chain and generate a similar system to evaluate the supply chain performance. For instance, factors such as candidate locations, factories production process, transportation; various routings such as roads, railroads and sea lanes; ordering policy, demand points, fleet management and sizing, trip time, cargo quantity, and inventories are modeled as independent agents within the case studies.

The proposed ABM and GIS approaches are comprehensive and practical tools for managers to assess the performance of a system; key performance indicators based on various time scales such as hourly, regular, weekly, or monthly can be applied to evaluate a company's operational effectiveness; for instance, inventory levels, truck utilization and traveled distance indicators on the daily scale can be generated.

As employed in the case studies in this paper, managers can also investigate how a system responds to various system attribute values, including the number of facilities and their locations, the number of pickups, loading and unloading time, vehicle driving speed, and routing methods parameters, and analyze the outcomes before implementing those scenarios.

The ABM simulation can be also utilized to model and implement the optimization process. Operation procedures can be formulated with an objective function and set of variables. For instance, in the Wood collection case, logistics costs were formulated and the minimum cost of transportation was determined based on parameters such as trip distance, number of fleets, and facility locations. In the optimization process, scenarios can be executed for any time period with different values for targeted parameters and the most optimized values for those parameters can be determined based on the objective function. The ABM simulation and optimization can provide an opportunity for executives to improve supply chain efficiency by identifying the best values for target parameters.

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