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Revolutionizing International Cargo Transportation: A Data-Driven Strategy for Fleet Management Optimization and Workforce Efficiency

Master's thesis of artificial intelligence

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Abstract:

This thesis expands on the logistic needs of the Finnish transportation company that promises their client single day delivery. Route planning and Cargo distribution has been a labor-intensive task for the planners as a plan is constructed from all over Europe to Helsinki harbor and continuing on truck by road. The main objective of this thesis is to automate this process of planning by reducing manual labor and use ML/AI techniques to enhance the system to be more adaptive and resilient to the changes.

Historical data is collected from creating an ORM around the non-relational database to extract essential information we need to visualize the past interactions and devise a plan for automation. OpenStreetMaps and custom cargo distribution algorithm is formulated to work in a unified manner. Cargo allocation into the containers is coupled with a route plan to properly distribute the temperature sensitive products. Transport planners are provided with a graphical user-interface to interact with the plan and make essential changes to it, which is being stored and processed to train the machine learning and artificial intelligence algorithm. Deep Q-Network is used to handle hidden parameters in an iterative feedback loop to integrate weights back into the optimized system.

Keywords: Artificial intelligence, machine learning, Cargo distribution, route optimization, fleet management.

Suomenkielinen tiivistelmä:
Tämä opinnäytetyö laajentaa suomalaisen kuljetusyrityksen logistisia tarpeita, jotka lupaavat asiakkailleen yhden päivän toimituksen. Reitin suunnittelu ja rahdin jakelu on ollut suunnittelijoille työvaltainen tehtävä, sillä suunnitelmaa rakennetaan eri puolilta Eurooppaa Helsingin satamaan ja jatketaan rekoilla maanteitse. Tämän opinnäytetyön päätavoitteena on automatisoida tämä suunnitteluprosessi vähentämällä käsityötä ja käyttämällä ML/AI-tekniikoita järjestelmän tehostamiseksi mukautuvammaksi ja muuttuvammaksi.

Historiallisia tietoja kerätään luomalla ORM ei-relaatiotietokannan ympärille tärkeiden tietojen poimimiseksi, joita tarvitsemme aiempien vuorovaikutusten visualisoimiseksi ja automaatiosuunnitelman laatimiseksi. OpenStreetMaps ja mukautettu lastinjakoalgoritmi on muotoiltu toimimaan yhtenäisellä tavalla. Lastin jakaminen kontteihin on yhdistetty reittisuunnitelmaan, jolla lämpötilaherkät tuotteet jakautuvat oikein. Kuljetussuunnittelijat saavat graafisen käyttöliittymän vuorovaikutukseen suunnitelman kanssa ja siihen oleellisten muutosten tekemiseen. Suunnitelma tallennetaan ja käsitellään koneoppimis- ja tekoälyalgoritmin kouluttamiseksi. Deep Q-Networkiä käytetään piilotettujen parametrien käsittelemiseen iteratiivisessa takaisinkytkentäsilmukassa painojen integroimiseksi takaisin optimoituun järjestelmään.

Avainsanat: Tekoäly, koneoppiminen, rahdin jakelu, reittioptimointi, kalustonhallinta.

Preface

This master's thesis presents my research on the topic "Revolutionizing International Cargo Transportation: A Data-Driven Strategy for Fleet Management Optimization and Workforce Efficiency" conducted under the umbrella of the Department of Mathematical Information Technology at University of Jyväskylä.

I would like to express my gratitude to Professor Vagan Terziyan, my supervisor, for providing me with invaluable learning opportunities during this educational journey. Their assistance and direction have enabled me to complete this worthwhile study and make a contribution to my field.

I also want to take this opportunity to express my gratitude to my colleagues for the incredible interactions and for sharing their expertise and insight with me.

Jyväskylä, May 24, 2024
Muhammad Adeel Tahir

Glossary

VRP	Vehicle Routing Problem
CLO	Container Load Optimization
VRO	Vehicle Route Optimization
LAFF	Largest Area First Fit Algorithm
RL	Reinforcement Learning
MDVRP	Multi-Depot Vehicle Routing Problem
MADRL	Multi-Agent Deep Reinforcement learning
MARL	Multi-Agent Reinforcement learning
DS-VRP	Dynamic and Stochastic Vehicle Routing Problem
MARDAM	Multi-Agent Routing with Deep Attention Mechanisms
ORM	Object-Relational Mapping
OSM	Open Street Maps
DQN	Deep Q-Networks
LSTM	Long Short-Term Memory

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1 Introduction

Due to severe inefficiencies in route planning and the improper use of container capacity, the international cargo and logistics industry is in dire need of massive innovation and thought. The goal of this thesis is to provide improvement to the cargo distribution while optimizing the routes out of Helsinki harbor by using the latest technologies like artificial intelligence (AI) and machine learning (ML).

The Cargo Planning and distribution industry has been historically dominated by humans, where most of the work is done by hand. This takes lots of effort, time and the effect of different humans acting differently, which leads to frequent delays and lots of labor time. In order to plan a tour, the major responsibility was with the transport planner. Whose knowledge and experience is something that leads to decisions which is naturally prone to errors and can lead to unfinished jobs, underutilization of the transport capacity as well as a major impact on the resulting expenses.

Heuristic Techniques like Simulated Annealing, the genetic Algorithm or the Greedy Algo all of which are used with the purpose of finding valuable solutions for the optimization problems within tolerable time restrictions. These have been widely used in cargo distribution allocation and its routing. Despite their effectiveness and abundance of use over the past, the one thing they lack or are not fully equipped to handle is dynamically changing circumstances. There are techniques like predictive analysis of machine learning (ML) that forecasts demand and optimizes the route based on the past data. Some others are regression analysis, clustering, decision trees and more which are used to forecast delivery dates, traffic patterns and cargo volumes. Modern AI-powered systems are currently being used to improve route choices and cargo loading dynamically. Examples of these systems include deep neural networks, reinforcement learning, and multi-agent AI systems. Specifically, multi-agent systems allow numerous agents (vehicles or logistic nodes) to coordinate simultaneously, enabling complex, decentralized decision-making processes that can dynamically adjust to changes in the logistics. The best thing about these is they adapt, learn and train from their previous iterations making their next decisions more precise and accurate. This is very helpful where we have dynamically changing situations and requirements. As an example we can see, by efficiently learning from actions of past routes and roadblocks data, reinforcement learning algorithms are now capable of adapting to dynamic requests to reroute deliveries in real-time.

In this study, real-time roadblock data is used, which enables dynamic rerouting to cut down on possible delays. This part of the AI program greatly improves the efficiency and accuracy of routes. This thesis greatly emphasizes on the application of adaptive AI modes, these improve their results and forecasts in response to the variable inputs from transport planners. This adaptive learning capability is essential in maintaining the systems accuracy while handling unpredictability and complex logistic problems.

So, reiterating it briefly, the objective of this thesis is to revolutionize international cargo transportation by using the state-of-the-art ML and AI technologies. This aims to improve the fleet management, route planning and more which results in less human intervention, reduces the operational costs while also increasing the productivity and effectiveness. The practical application, effects of algorithms on planning procedures, and operational efficiency are all covered in detail in the subsequent chapters.

2 Literature Review

VRPs (Vehicle routing problems) were first proposed by Dantzig and Ramser in 1959. Later studied by Zhigou Fan and Mengkun Ma (2018) in order to lower the expenses while enhancing the efficiency of vehicle distribution routes (Fan & Ma, 2018). The Saving Algorithm, the Value-inserting Method, and the Sweep Algorithm are three heuristic algorithms that are evaluated in this study, each of which works in its own way to reduce the expenses and minimize distance in a different way. According to their research, sophisticated, data-driven algorithms that make use of real-time data and predictive analytics are replacing traditional VRP systems, improving both cost effectiveness and customer satisfaction. Despite using these the problem is still there and there is still a need for adjusting algorithms to fluctuating traffic, demand of customers. This proves to be a logical point in highlighting the need for more study in AI-enhanced, flexible VRP systems. This also stresses on the point how extremely vital these creative VRP solutions are in advancing logistics capability and effectiveness.

In his Master's thesis, Isfandyar Khan Mian builds on the fundamental concepts of Gendreau et al. (2006). It investigates integration of 3-dimensional container loading (ED-CLO) with route optimization (VRO). Based on the footprint area, the thesis strikes a balance between requirements of real time logistical cargo arrangements and computing efficiency. This is done by innovatively modifying the famous LAFF (largest area first fit algorithm). Keeping the container limits into account a mathematical operation function is used to efficiently control the vehicle capacity and the transportational cost to the optimal extent. The progressed LAFF strategy is confirmed by experimental testing, demonstrating its convenience and viability in real-world coordination's and bridging the gap between hypothetical optimization and real-world application (Mian, 2020).

By combining profound learning (DL) with reinforcement learning (RL), Ali Arishi and Krishna Krishnan's 2023 consider presents a novel multi-agent profound support learning (MADRL) approach to the multi-depot vehicle steering issue (MDVRP), progressing supply chain administration and coordinations (Arishi & Krishnan, 2023). The MADRL model keeps on improving routing choices by learning from interactions with the environment; this is done with the use of an encoder-decoder architecture and a policy gradient technique. The aim of this provided reward function is to minimize to the maximum extent the distance traveled by all possible paths. This approach outperforms more established approaches like closest neighbor techniques, OR-tools, and evolutionary algorithms in terms of efficiency and adaptability because of the faster calculations and cheaper route costs. It includes a major point about the implementation of the strategy and possible difficulties, also it talks about the importance of training deep learning models to optimize the overall process and automate with the same goal making it more reliable. One major recommendation is to use hybrid models to tackle the optimization and scalability challenges by analyzing how to apply MADRL to real world logistical problems.

Yamen Habib and Andrey Filchenkov present a unique multi-agent reinforcement learning (MARL) technique for the Vehicle Routing Problem with Dynamic and Stochastic Information (DS-VRP), a challenging logistical problem, in their 2022 paper that was published in *Procedia Computer Science*. They made dynamic decision-making with geometric Laplacian eigenmaps instead of relying on human minds and drivers for the same planning purpose. They provide a two-phase customized RL agent training approach for DS-VRP requirements. As per the outcomes, we can deduce that this technique beats the MARDAM framework as well as Google OR. Specially in terms of its efficiency of performing and flexibility to adapt. These performance comparison experiments confirm the efficacy of the MARL approach. As per this study, it can be deduced that MARL offers a viable solution to the logistical operations via DSVRP. In order to expand its applicability across complex systems, it also calls for more research (Habib & Andrey Filchenkov, 2022).

3 Framework For Methodology

With primary focus on operations happening at the Helsinki harbor, the content below provides an overview of the problems like route optimization and container management in Finland and the steps taken to address these challenges. It explains the methodologies used to recognize functioning of transport planners, help in collecting data and describes the analytical methods used to improve the logistical framework.

3.1 Information Gathering

This study is carried out on behalf of Finnish Transport company, where a detailed historical data analysis is done for almost 3 decades. This includes all logistical operations from Europe to Finland. This data also puts spotlight on the role of the transportation planners, who have over the decades drawn these routes by their bare hands.

3.1.1 Database Issues & Solutions

Initially, the data was kept in an old database that provided support to abstract associations between tables only. Sequelize, an Object-Relational Mapping (ORM) tool, was used to overcome this problem by explicitly defining relationships across data tables, resulting in better data organization and retrieval. The database consisted of different tables associated with overall journey activities. Important tables reviewed include:

- Activity Tables:
  The data set in the tables is for the daily operations. Visualization of this data explains a pattern about the regular operations as well as details of the irregularities happening over the years on route planning.

- Trucks:
  Details on the fleet, such as capacity, type, and maintenance history, are crucial for optimizing load and route planning.

- Resource Combination:

  The combination that includes information regarding logistical resources used for transportation such as labor, vehicles, loading equipment etc.

- Product:

  Information on the goods being transported, necessary to handle containers according to special requirements such as temperature sensitivity or fragility.

- Status and City:

  Geographic and operational status data, vital for understanding the dynamics of regional logistics and operational health. This explains the local and regional working of logistics, behavior and patterns in the geographic pin as well as the operational well-being

- Sales Order Leg and Delivery Status:

  As the order execution, its current state, delivery times and the route status are essential and is monitored. Doing all of this is essential for analyzing the previous routes, their efficiency, time to deliver and planning ahead for the future.

```sql

SELECT TOP 1000
    GenericDatabase.dbo.LogisticsTable.OrderNumber AS OrderNumber,
    StartActivity.ActivityNumber AS StartActivityNumber,
    StartActivity.ActivityDate AS StartDate,
    StartActivityType.ActivityCode AS StartActivityCode,
    StartActivityType.ActivityDescription AS StartActivityDescription,
    StartActivity.Latitude AS StartLatitude,
    StartActivity.Longitude AS StartLongitude,
    StartActivity.PostalCode AS StartPostalCode,
    StartActivity.City AS StartCity,
    StartActivity.CountryCode AS StartCountryCode,
    EndActivity.ActivityNumber AS EndActivityNumber,
    EndActivity.ActivityDate AS EndDate,
    EndActivityType.ActivityCode AS EndActivityCode,
    EndActivityType.ActivityDescription AS EndActivityDescription,
    EndActivity.Latitude AS EndLatitude,
    EndActivity.Longitude AS EndLongitude,
    EndActivity.PostalCode AS EndPostalCode,
    EndActivity.City AS EndCity,
    EndActivity.CountryCode AS EndCountryCode,
    ProductDetails.Description AS ProductDescription,
    CargoDetails.UnitAmount AS UnitAmount,
    CargoDetails.UnitCode AS UnitCode,
    CargoDetails.Weight AS Weight,
    CargoDetails.LoadingMeter AS LoadingMeter,
    CargoDetails.MinTemperature AS MinTemperature,
    CargoDetails.MaxTemperature AS MaxTemperature,
    CargoDetails.SetTemperature AS SetTemperature
FROM
    GenericDatabase.dbo.LogisticsTable
    INNER JOIN GenericDatabase.dbo.Activity AS StartActivity ON LogisticsTable.StartActivity = StartActivity.ActivityNumber
    INNER JOIN GenericDatabase.dbo.Activity AS EndActivity ON LogisticsTable.EndActivity = EndActivity.ActivityNumber
    INNER JOIN GenericDatabase.dbo.ActivityType AS StartActivityType ON StartActivity.ActivityType = StartActivityType.TypeNumber
    INNER JOIN GenericDatabase.dbo.ActivityType AS EndActivityType ON EndActivity.ActivityType = EndActivityType.TypeNumber
    INNER JOIN GenericDatabase.dbo.Cargo AS CargoDetails ON LogisticsTable.Cargo = CargoDetails.CargoNumber
    INNER JOIN GenericDatabase.dbo.Product AS ProductDetails ON CargoDetails.Product = ProductDetails.ProductNumber
    INNER JOIN GenericDatabase.dbo.Unit AS UnitDetails ON CargoDetails.Unit = UnitDetails.UnitNumber

```

Figure 1. SQL Query - Historical Data

Figure 1, is the working query that helps connect different models on database level generated via ORM. In order to read only the essential part of the historical data when there are no database relations existing on actual level was a complex task. So, a database model was created around the database using the ORM that define the relationships on the surface level. This helped us form the complex queries, as shown in the figure above.

3.2 Transportation Planner's Role

The research acknowledges the past contribution and importance of planners, and recognizes that their intellect and knowledge for this has led to many steps in development of the new AI based optimization models. It is a point to consider that the algorithms should be smart enough to replace and improve on the currently used manual planning techniques. This has to be implemented while keeping in mind their approach towards issues and resolution techniques in the past, and learning from these. The value they have added over the years would play a vital role in developing the future technologies.

3.3 Strategy for Container Management and Route Optimization

Specifically tailored to the local environment, the container management and route optimization plan places a focus on Finnish logistics out of Helsinki Harbor. The strategy comprises of different methodologies, which are presented below:

- Analyzing Operational and Traffic Patterns:
  This method makes use of historical data to pinpoint common inefficiencies and bottlenecks in logistics. This takes into account the working mechanism for traffic routes by using road network of heavy-duty vehicles and using historical data to map onto it.

- Machine Learning Models for Predictive Analytics:
  Creating forecasting models that take into consideration variations in cargo volume, traffic, and weather to maximize route scheduling and anticipate any delays.

- Container load optimization:
  CLO is the management of the load in an extremely efficient way keeping in mind the factors like the type of cargo transporting, the physical conditions, the pickup and drop off location for the cargo. All of this is done to maximize the load transport based on the available space with fewer damages and cheaper cost.

3.4 Data Analysis

The data analysis, extraction and examination were immensely improved by the use of Sequelize as an ORM for querying the database system. This data was later used for the deduction steps of this study in the later phase.

One of the most amazing results of this kind of data analysis and processing is that it can be later arranged as needed in the form of heat maps representing truck respondents and the operations being done like loading, unloading etc. Apart from the benefit of the visual representation, this also helps in identifying the hazards, hotspots and challenges so that they can be understood and future algorithm changes can resolve these. The information gathered from this heatmap is crucial for focusing future research efforts on the areas that will have the biggest impact on lowering costs and improving operational effectiveness.

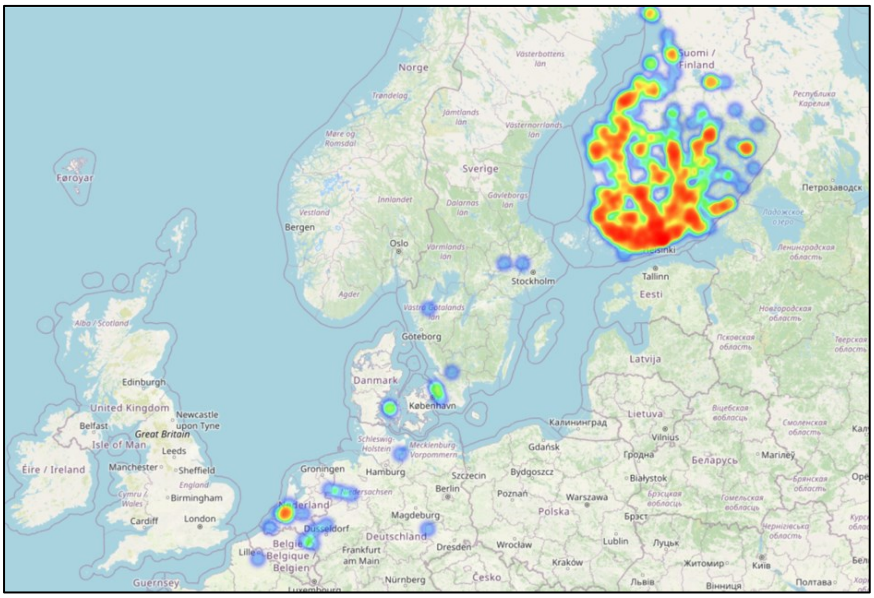


Figure 2. Heatmap - Historical Data

The SQL query formed on-top of the ORM is used to fetch the data we need to visualize the interaction of trucks throughout Finland. This helps understand the activity level at regions as shown in the Figure 2.

The methods of data management, processing, and analysis used in this chapter provide the groundwork for the creation and use of algorithms focused on route optimization and container management, which are discussed in greater detail in subsequent chapters.

4 Research Questions

This chapter delves into the application and initial evaluation of the sophisticated route planning algorithm utilized in real-world logistics settings answering the research questions. This chapter describes when testing phases start, how the algorithm fits into the workflows already used by transport planners, and what technological approaches are used to assess the system's potential to reduce operational costs and plan timeframes.

4.1 Route Optimization Implementation

This specific section talks about the practical implementation of the optimized route needed to achieve our goal of delivery with the optimal time and fuel efficiency.

4.1.1 Integration of Finland's Road Network

An in-depth knowledge of Finland's road network is necessary for effective route design. The Python-based OSMnx tool and OpenStreetMap (OSM) open-source data are used by the application to retrieve and alter comprehensive road network data. OSMnx is required for extracting current geographical data so that our navigation system is updated with the most correct road information available.

4.1.2 Managing Traffic Data in Real Time

The flexibility of the route to adapt to traffic information in real time is essential for dynamic route optimization. This integration includes data on traffic density, and unplanned closures, & ongoing construction projects, or blockages. Through APIs that are connected to real-time traffic management systems, the algorithm collects the most recent data. As a result, the algorithm may adjust routes in real-time to reduce delays and increase travel times, maintaining the effectiveness of the route over time.

4.1.3 Using Folium to Visualize Route Information

For enhanced route viewing and analysis, we use Folium, a Python script that enhances the Leaflet.js library's from javascript with interactive map-building capabilities, this is well renowned and abundantly used in the IT industry This feature allows for a visual analysis of the effectiveness of route optimization and the impact of incorporating real-time traffic data, which is particularly useful during the testing phase. This enables instantaneous performance evaluation of the algorithm.

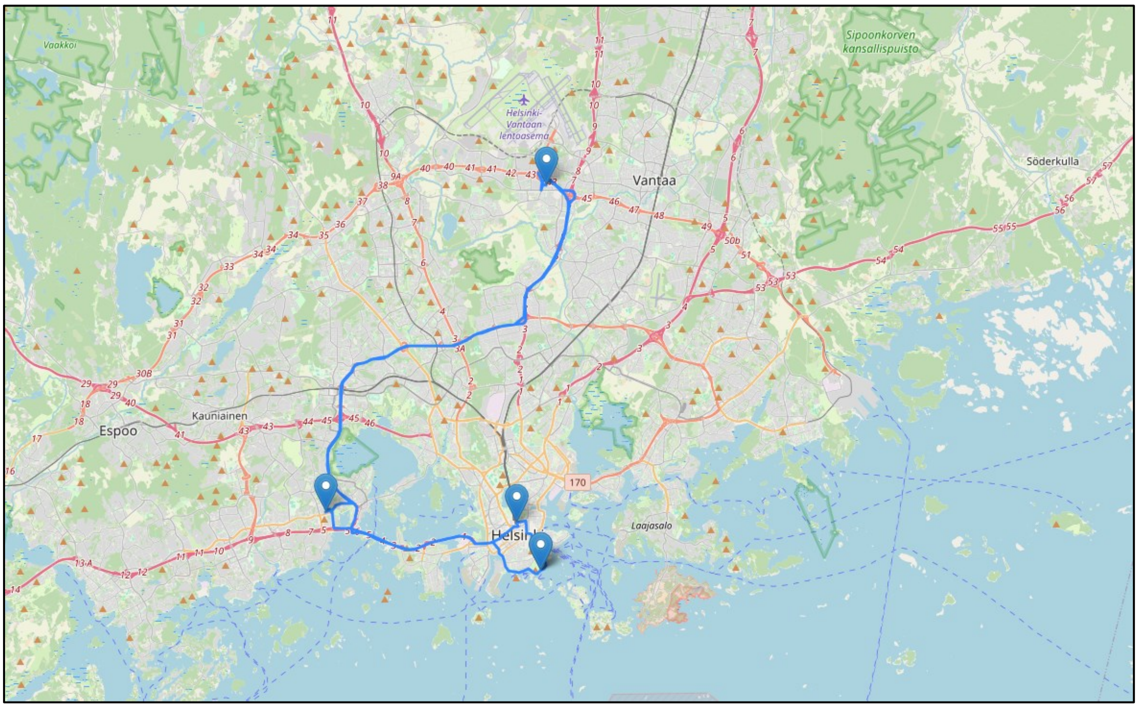


Figure 3. Folium - Custom Visualization Tool

This route generated on top of the map through road network was made possible by using folium. It helped created the interactive map and not just an image.

4.1.4 Distance Tracking and Optimization Techniques

Basically, the route optimization algorithm finds the most cost-effective routes between targets while taking into consideration many restrictions like the vehicle's maximum cargo capacity, the roads infrastructure, and the time to deliver from Stop A to B. The Haversine formula (Ary et al., 2023) is employed to compute the separations between locations. This method is crucial for analyzing and deciding traveling time, this is done by taking the shortest or fastest routes possible.

4.1.5 Additional Technical Tools Used

To improve the route optimization process, the algorithm integrates several additional technology resources:

- Matplotlib:
  This is a program used to generate basic and complex visual representations of route data for analytical research.

- Google OR-Tools:
  This all-inclusive toolkit is used to tackle more difficult and complex extensive cargo routing problems, like multi-vehicle coordination or a range of logistical requirements. It provides a wide range of modeling and problem-solving skills which leads to enhancement in the route and logistical operations.

When combined, these technologies offer the route planning algorithm a strong feature set that enables it to function well in the intricate dynamics of international logistics for freight transportation.

4.2 Cargo Distribution

Efficient freight distribution is necessary for logistics operations optimization. This covers our first research question, "How different parameters are prioritized while distributing cargo to each container?". It covers the methods and strategies used to optimize cargo distribution based on weight management, temperature control, and space management. Each component is controlled by specific algorithms to maximize the usefulness and efficiency of freight transportation.

4.2.1 Technical Implementation of Integrated Cargo Distribution

This chapter delves into the detailed practical implementation of the cargo distribution algorithms implemented to our solution. This translates the mathematical formulas into code to achieve the goal needed for our use-case

- Weight-Based Cargo Distribution:

  WB cargo distribution, which is about the weight of the cargo, is done using a linear programming (LP) model to distribute items throughout a number of cargo carriers as effectively as feasible while minimizing total distribution costs and ensuring that no vehicle is overburdened. In this approach, the decision variables indicate whether or not a cargo item is placed into a certain truck. The goal function calculates the total weight distribution cost by multiplying the cargo weights with every cargo item and the choice factor of the truck/cargo (Grakovski et al., 2020). Limits ensure that each item is loaded only once and that any vehicle's overall weight stays under its weight limit. PuLP and Google OR-Tools are two libraries that are adept at converting these models into executable code.

- Space Management:

  By using a 3D bin packing strategy to arrange cargo within each transport unit, space management maximizes the use of available space. This problem is NP-hard and essentially combinatorial due to the computational expense of exact approaches; heuristics and approximation algorithms are commonly used to solve it (Lee & Lee, 2005). The goal function seeks to maximize the volume utilization ratio by taking into account each cargo item within the constraints of the size of the transport unit.

- Temperature-Based Cargo Management

  Dynamic programming ensures that cargo stays within specified temperature limits while being transported. This approach minimizes the cumulative deviation from the target temperature set points during the voyage by dynamically adjusting the interior environment of the vehicle to maintain these settings.

4.2.2 Unified Algorithm Integration for Distribution

It demands a complex strategy that considers various elements at the same time to develop a cohesive and adherent system that incorporates multiple cargo distribution algorithms. In order to perform this, an optimization-based algorithm is created that uses a combined constraints & objective function to solve issues like distribution of weight, temperature control for the cargo, and space allocation in a unified manner.

Following work involves integrated objective function:

Weighing several logistical factors against one another, the integrated aim of the combined cargo distribution system consists of a composite function.

$$Z = \alpha \Sigma_{i=1}^{n} \Sigma_{j=1}^{m} w_{ij} x_{ij} + \beta(1 - U) + \gamma \Sigma_{t=1}^{T} |T_t - T_{set}|$$

Equation 1. Unified Cargo Distribution

The above equation 1 presents the minimize function donated with the letter Z. It consists of different substructures which are explain below -

- Weight Allocation Expense:

$\Sigma_{i=1}^{n} \Sigma_{j=1}^{m} w_{ij} x_{ij}$ denotes the total weight of cargo item j on vehicle i, multiplied by a binary decision variable xij indicating whether item j is assigned to vehicle i.

- Utilization Efficiency Penalty:

$(1 - U)$ where U represents the ratio of space utilized, incentivizing maximal use of available space.

- Temperature Discrepancy Expense:

$\Sigma_{t=1}^{T} |T_t - T_{set}|$ calculates the absolute differences between the actual temperature Tt and the set temperature Tset over the transport duration T, penalizing deviations from desired temperature conditions.

The coefficients α, β, and γ function as weights to distribute the importance of each factor based on particular logistical needs and priorities.

Consolidated constraints contribute a major weightage to the overall working of working function. The integrated algorithm operates inside a framework of unified restrictions to ensure adherence to vehicle capacities, spatial configurations, and temperature criteria.

- Limitations on Vehicle Capacity
  - This equation ensures that the entire weight of goods on any vehicle does not exceed its maximum weight capacity.

$$\Sigma_{j=1}^{m} w_{ij} x_{ij} \leq WeightCapacity_i$$

Equation 2. Weight Capacity Equivalence

  - While this equation makes sure that the vehicle's volumetric capacity is not exceeded by the total volume of freight.

$$\Sigma_{j=1}^{m} v_j x_{ij} \leq VolumeCapacity_i$$

Equation 3. Volume Capacity Equivalence

Where vj represents the volume of the cargo item denoted as j.

- Limitations on Cargo Positioning
  Making sure the cargo fits inside the transport unit's dimensions and does not overlap. Determine the proper loads by considering stability and orientation while adhering to placement specifications.

- Temperature Constraints
  Maintaining the cargo temperature within the accepted ranges during the tour. Depending on the ambient temperature, we might need to impose further restrictions on heating or air conditioning. Regular checks by outside suppliers manage the technical parts of the truck's operation.

4.2.3 Sequential Algorithm

The technique handles the complexities of logistical processes involving weight, space, and temperature optimization by applying algorithms one after the other (Guralnik & Karypis, 2001). Prioritizing logistical limitations and essential cargo attributes enables efficient and fruitful operations.

Following factors determines how priority scheduling should be catered.

- Temperature-Sensitive Cargo:
  Temperature-sensitive goods are situated in the sections of the car that can maintain the required temperatures. These areas are typically situated nearer temperature control systems or apart from the exterior walls of the vehicle.

- Weight Distribution and Space Optimization:
  Temperature-sensitive cargo is positioned appropriately, and then 3D bin-packing and weight-distribution algorithms are used to optimize the remaining space in order to maximize space utilization and distribute weight evenly throughout the fleet.

Multi-layers are defined based on the following criteria,

- Layer 1 (Critical Requirements):
  This layer prioritizes safety and regulatory compliance to guarantee that temperature-sensitive and dangerous (hazardous) materials are handled properly.

- Layer 2 (Operational Efficiency):
  This subsequent layer enhances time, space, and cost efficiency by accounting for factors such as fuel use, route optimization, and delivery dates.

4.2.4 Heuristic Algorithm

The system incorporates heuristic adaptations to accommodate unexpected operational changes that exceed the capacity of pre-established algorithms. This makes it possible to make decisions quickly and flexibly in changing circumstances.

- Real-Time Reevaluation of Traffic:
  Adjusting for Traffic and Weather It adjusts routes and loading strategies automatically based on weather forecasts and traffic data. For instance, rerouting to avoid warm roadways or altering freezer settings may be necessary during an unforeseen heat wave.

- Adjustment for Modifications in the Delivery Schedule:
  The system dynamically rearranges cargo arrangements and routes in response to changes in delivery schedules, giving priority to deliveries that need to be made on time.

- Adaptive Heuristic for Backup Strategies:
  The fallback procedures minimize cargo integrity disruptions. It is integrated into the system. They achieve the optimization by providing essential backup measures in the event of substantial delays or refrigeration breakdowns. It could be any kind of breakdown, vehicle damage among the most common ones.

- Load Adjustment:
  In situations where traditional optimization algorithms are unable to deliver rapid solutions. The utilization of heuristic techniques like nearest neighbor or first-fit allows for quick load changes (Elmongui et al., 2011). This helps in better load adjustment, it takes truck's LoadingMeter into consideration too.

- Ongoing Improvement:
  During each delivery journey, the data is collected related to cargo distribution and delivery accuracy. By using this data to compare actual performance to predict. The

algorithms are repeatedly improved and worked on through iterative feedback cycles in terms of weight distribution, spatial usage, and temperature control.

By using an integrated strategy, logistical operations may be made both efficient and standard-compliant. This allows for a dynamic response to meet demands of current cargo distribution. The plan gives transport planners the tool they need to successfully mark a compromise between strict safety and quality standards and operational efficiency.

4.3 Integrating Route Management Optimization to Cargo Distribution

As discussed in the previous chapter how cargo distribution is prioritized, this chapter talks about the strategic integration of cargo allocation with optimal fleet routing with the use of sophisticated algorithms and real-time data management (Liu et al., 2019). This chapter also covers the thesis question, “What is the effectiveness of real-time data integration of cargo distribution into dynamic rerouting in response to unexpected road blocks and traffic conditions”.

This integration system skillfully handles scenarios in which different kinds of cargo have a shared destination but need to be separated based on temperature into different trucks. So following algorithms adapt to the distribution plan based on the best routes and delivery locations.

4.3.1 Optimized Cargo Allocation Based on Routing

Sequencing algorithm determines how delivery features are handled in the system by keeping in account different parameters.

- Data Sources of Routes:
  The system uses OpenStreetMap and Google Maps APIs to produce optimal routes. OpenStreetMap and OSMnx Python module combined offers geographical information about the routes. It also includes a road network for different kinds of vehicles. And to get real-time traffic information Google Maps are included. All in all

we have two different geographical sources working together to get us the essential information.

- Sequence Logic:
  Using this information, the sequencing algorithm arranges the pre-positioning of cargo in accordance with the intended delivery order. Prioritizing items intended for earlier stops reduces unloading delays while taking temperature zones and the loading meter capacity of each truck into consideration.

- Temperature Segregation:

  The algorithm assigns goods to transport vehicles passing through the relevant locations based on their location (Alastalo, 2018). This prediction is based on temperature data gathered during loading and OSMnx route data. When the order is received transport planners have the pre-hand knowledge on the temperature requirements for each cargo.
  The distribution algorithm makes sure that temperature-sensitive goods are properly separated.

- Algorithmic Checking of Loading Meter:
  At every stop, the algorithm checks the loading meter capacity and modifies cargo placement to maintain weight balance and avoid overloading. This guarantees excess space for deliveries of fruit or flowers (Pinho et al., 2018). It keeps track of loading meter at all times as new pickup orders might come-in as the previous journey is in progress. So, it modifies the route and suggest the driver with the next pickup location.

- Weight Management Tool:
  To ensure balanced weight distribution throughout the journey, loading meter tracking is tracked through the use of PuLP and Google OR-Tools.

- 3D Bin-Packing Algorithm:
  Using the stop sequence and the loading meter's available capacity as focus points, the 3D bin-packing algorithm arranges goods spatially in order to utilize the full capacity of the truck (Hasan et al., 2019). This method reduces rearranging during unloading and maximizes space use.

4.3.2 Temperature Management in Routing:

- Climate Control Segregation:
  Cargos are loaded into the trucks by making sure it doesn't violate the temperature requirement of the cargo. Flowers intended for 5-6 Degrees are kept separated from frozen section (Basconi & Shirts, 2013). Infact If the temperature difference between different parts of container is not enough, separate truck is being used.

- Implementation:
  As we have used Pandas and NumPy before for analyzing historical data. We will be using same techniques and tools to implement logic for cargo arrangement in container zones.

4.3.3 Adapting to Real-Time Route Changes

The adaptive routing algorithm that we have implemented keeps itself abreast of any changes. It modifies based on unloading sequence to update its route in the event of traffic congesting or road blocks. By getting pre-hand knowledge of traffic and road situation, unexpected delays are avoided.

- Traffic Updates:
  Delivery windows are highly cut down by getting traffic data knowledge from Google Maps API, and OpenStreetMaps road network knowledge take these parameters to adjust the route. End goal of delivering temperature sensitive items on time is achieved with this knowledge.

- Visualization:
  Logistics managers can modify delivery plans by using interactive maps that are powered by Folium. It generates interactive graphical maps using Mapbox to track fleet movement and analyze rerouting modifications in real time. Folium plays a role of a wrapper that sits on top of Mapbox maps and pass in the essential parameters to make it interactive.

These technological improvements guarantee that freight distribution (Salais-Fierro & Martínez, 2022) maximizes efficiency and complies with safety regulations by dynamically matching with optimal routes and logistical restrictions.

4.3.4 Problem Statement & Solution

Moving temperature-sensitive cargo through Finland while managing the fleet of them is a challenging problem within the domain of logistics. For this particular problem, a logistics business based out of Helsinki wants to optimize the weight and space within each truck. With timed delivery of goods as the main focus point of their business requires them to dynamically assign routes based on delivery and pickup points. Following are the steps followed to understand how the problem statement is broken down for solution.

- Truck Initialization:
  Provided the availability of the trucks along with their temperature settings we would initialize the number of trucks required to cater this specific problem as it should correlate with the temperature requirement of the cargo.

- Distribution of Cargo:
  Determine how goods should be distributed among trucks based on temperature requirements and delivery points. Algorithms as we have established earlier would combine weight, space and temperature requirements to suggest the most efficient approach.

- Route Optimization:
  Determine the most optimal route by utilizing delivery points and OpenMapsApi to take into account possible blockades and traffic information. This would help ensure timely delivery of goods and fuel efficiency.

- Determining delivery sequence:
  Utilizing all three previous approaches to determine the most efficient route delivery plan so trucks returning won't be empty thus not costing much to the business.

{} input-data.json > {} 2


```json
[
        {
          "description": "Chilled Dairy Products",
          "weight": 2500,
          "loadingMeter": 5,
          "temperature": 4,
          "startCity": "Helsinki",
          "endCity": "Tampere",
          "startCoords": [60.1699, 24.9384],
          "endCoords": [61.4978, 23.7610]
        },
        {
            "description": "Frozen Seafood",
            "weight": 3000,
            "loadingMeter": 8,
            "temperature": -18,
            "startCity": "Helsinki",
            "endCity": "Oulu",
            "startCoords": [60.1699, 24.9384],
            "endCoords": [65.0126, 25.4715]
        },
        {
          "description": "Fresh Flowers",
          "weight": 1500,
          "loadingMeter": 3,
          "temperature": 4,
          "startCity": "Helsinki",
          "endCity": "Lahti",
          "startCoords": [60.1699, 24.9384],
          "endCoords": [60.9827, 25.6612]
        }
]
```

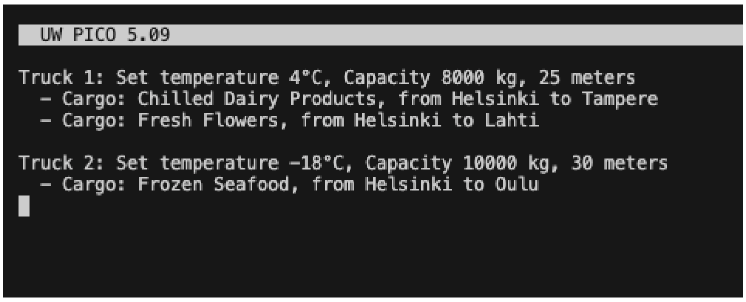

Figure 4. Input Data Parameter for Algorithm

Figure 4, shows the set of input variables in the structured JSON format works for the backend algorithm solution to receive and process as needed.

It includes the information regarding weight, loading meter, start and end coordinates and temperature requirement.

Following are the outputs of the system generated into a text file and that is read via terminal,

- Truck and Cargo Configuration:

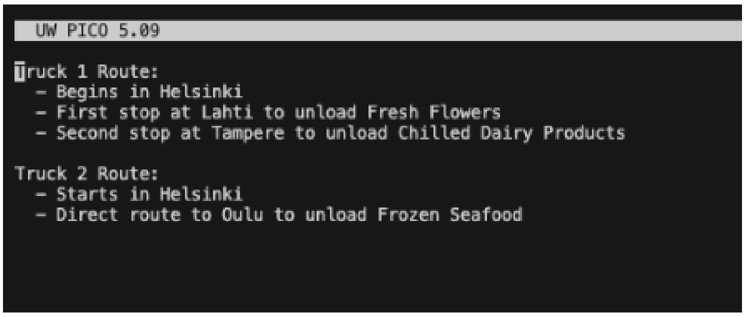


```
UW PICO 5.09

Truck 1: Set temperature 4°C, Capacity 8000 kg, 25 meters
  - Cargo: Chilled Dairy Products, from Helsinki to Tampere
  - Cargo: Fresh Flowers, from Helsinki to Lahti

Truck 2: Set temperature -18°C, Capacity 10000 kg, 30 meters
  - Cargo: Frozen Seafood, from Helsinki to Oulu
```

Figure 5. Truck and Cargo Distribution Configuration

This solution recommends what cargo belongs to which particular truck. This also determines how many trucks are required to achieve this particular goal. In this particular scenario another truck was needed based on the temperature requirement of the cargo.

- Route and Stop Sequence:



```
UW PICO 5.09

Truck 1 Route:
  - Begins in Helsinki
  - First stop at Lahti to unload Fresh Flowers
  - Second stop at Tampere to unload Chilled Dairy Products

Truck 2 Route:
  - Starts in Helsinki
  - Direct route to Oulu to unload Frozen Seafood
```

Figure 6. Route & Stop Sequence

Given the cargo distributed in trucks, this solution recommends the route it needs to take in the specific order to deliver goods. This keeps in context the best optimized way in terms of time and travel distance while achieving the goal.

If we combine both of the outputs into a single tabular form, this is how it'd be presented for users to see.

Truck	Route	Stops	Cargo	Destination	Temperature	Capacity (kg)	Length (m)
Truck 1	Starts in Helsinki	Helsinki -> Lahti -> Tampere	Fresh Flowers	Lahti	4°C	8000	25
			Chilled Dairy Products	Tampere	4°C	8000	25
Truck 2	Starts in Helsinki	Helsinki -> Oulu	Frozen Seafood	Oulu	-18°C	10000	30

Table 1. Route and Cargo Sequence

In the table 1 it's a tabular representation of the data being generated and saved in a text format. It defines each truck's route and the path it needs to follow and what cargo needs to be transported and unloaded at which destination. It is further combined with the initial data being provided for the coordinates and drawn onto the map for the transport planners to visualize.

Technical features that are considered while formulating the responses are given as following:

- Route Management Efficiency:
  Each truck's route is customized to maximize the fuel efficiency via the shortest travel time to deliver cargo goods.

- Dynamic Cargo Allocation:
  Our cargo distribution algorithm arranges cargo in trucks in the order that it ensures regulatory compliance. It does so by strategically placing cargo in trucks based on the available capacity and temperature-controlled environment.

- Delivery Timing:
  Delivery timings are highly reduced by arranging the order of cargo in a particular sequence so it doesn't go on route that costs us the time.

This problem statement and its generated solution is the working example of how strategically distributing goods integrated with route management can greatly impact the logistics business. This ensures on-time deliveries in ideal conditions across different ranges of geographical areas.

4.4 Algorithm Implementation and Initial Testing

This part covers the practical implementation of the cargo distribution and route optimization algorithms. Independently and together to generate an optimized solution. It is going through the first testing phase with the goal of improving logistical operations through Finland. This arises our third research question, "How effectively an AI-driven system manage cargo allocation of temperature sensitive items ensures the optimal delivery?".
The thorough testing of the algorithm involves verification of reduced operational expenses and planning times that it takes for generating optimized route plan, optimal truck space utilization and distributing goods. It's integrated with the planning phase tasks of the transport planners.

4.4.1 Integration

The route planning algorithm was incorporated into the work flows and processes of transport planners. Important cargo information, such as dimensions of cargo, weight, and required temperature, is entered by planners together with coordinates for the collection and delivery sites. These detailed data points are necessary to create logistical plans that are optimal for route and distribution suggestions.

- System Operations:
  After receiving the data, the system evaluates it to calculate an optimal route. It then suggests how many trucks should be considered for this trip and arrangement of the cargo within each vehicle to maximize volume and weight distribution.
  Taking into account the efficiency of the delivery system this route generated by the system covers the whole area of Finland.

- User Interface and Interaction:
  Transport planners first see the results of the algorithm through an easy-to-use interface that displays detailed cargo placement diagrams for every truck as well as optimum routes.
  Using dropdown menus labeled "road block," "suboptimal route," "reposition cargo," "adjust delivery window," and "change vehicle type," planners can alter suggested plans and instantly have the system produce updated options. Enhancements.

- Integrating Feedback into a system:
  Transport planners' feedback is incorporated into the algorithm in order to enhance it for future suggestions. All communications with planners, whether they are confirming or changing a plan, are carefully documented and saved into the system. This information on routes and distribution of cargo is stored in a vector format, offering rich data for further research and enhancements. And setting the base for implementing AI and ML based solutions later.

4.4.2 Testing Phases

A series of tests were performed to determine the working and efficiency of the system.

- Simulation Test:

  Using simulations of how transport planners would interact with the system involving edge case scenarios in operating days, such as heavy traffic, holidays, and unfavorable weather conditions, the algorithm was tested.

- Field Test:

  After a simulation test, transport planners were presented with the working solution to provide their actual input and how they interact with the system. And what kind of parameters they required to devise a system plan. This helped us collect real-time data.

- Planning Time:

  To verify the efficiency improvements from applying the algorithm, the amount of time saved on manual planning was measured. Previously it was taking a manual effort of 2-3 days to plan the whole operation for a particular delivery cycle.

- Accuracy and adaptability:

  A detailed assessment was conducted to determine the system's capacity to adapt to modifications on routes while preserving accuracy in cargo distribution.

4.4.3 Result Verification

The tests and their results showed significant improvements in their operations efficiency.

- Cost Reduction:

  The algorithm's capability to efficiently generate optimized routes was demonstrated by the significant decrease in fuel consumption and associated planning. Main contribution was to space management to reduce the number of trucks used in the particular delivery journey. And utilizing route management it ensured that trucks do not return empty and have the space fully utilized throughout.

- Time efficiency:

  Numerous previously manual procedures were automated, as seen by the greater than 40% reduction in planning hours. With that planner only need to collect order information and feed it to the system and have a visualized plan of the journey.

- Adaptability:

  The system showed its adaptability to a variety of logistical requirements by modifying routes in response to planner inputs. It adheres to the live traffic information and road blockades.

In one such example, a truck transporting temperature-sensitive items was first suggested by Route One to a transport planner. The planner chose to use the system's interface to change the route after receiving a notification of a road blockade. This particular blockade information is a notification which is not yet reflected on the live feed of the map. The system suggested Route Two as an alternative, successfully avoiding the dead-end and avoiding delivery delays.

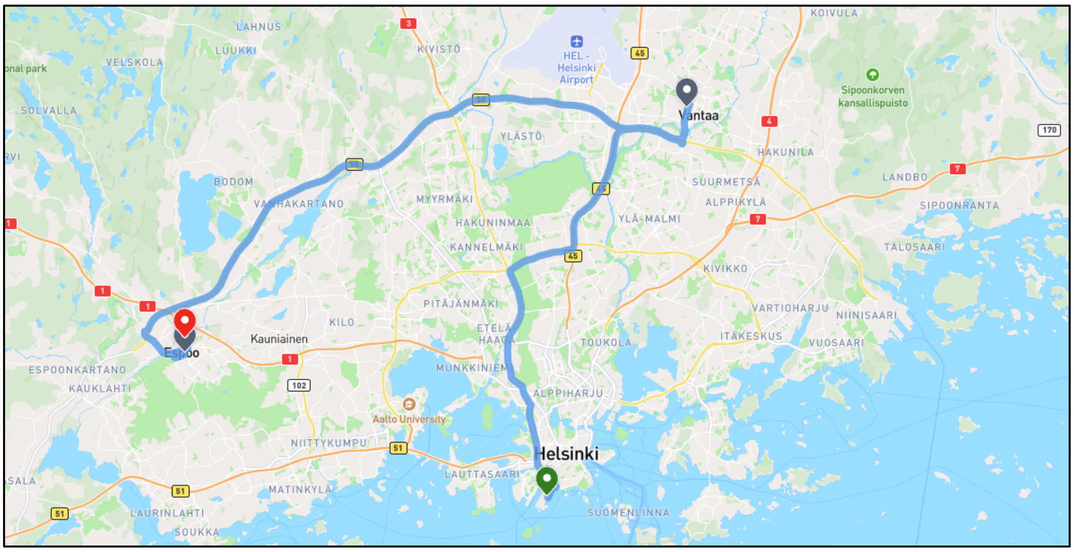


Figure 7. Route Plan A - Before Planner's Feedback

The interface offered visual comparisons of the original route and the modified route after transport planner’s input, this also includes any cargo placement alterations that were required.

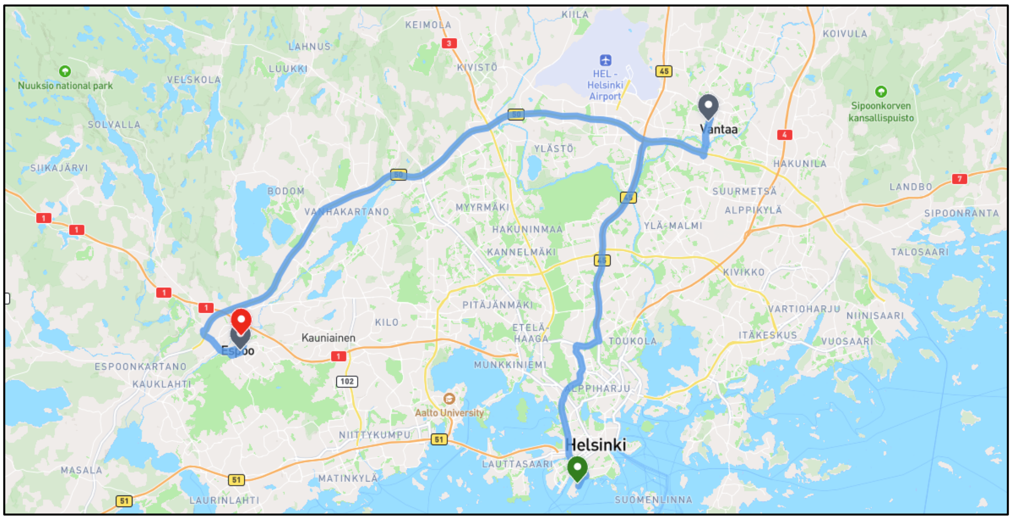


Figure 8. Route Plan B - After Planner's Feedback

Logistics management has been greatly enhanced by the route planning algorithm's successful implementation and testing. In addition to improving cargo distribution and fleet management, this system offers transport planners a flexible, dynamic tool that can be adjusted to fit their changing demands. Like just exploring the suggestive route in advance of any delivery and cross-verifying it with road-blockade information. Furthermore, a strict methodology was used to collect and arrange data and input in the vector format, laying the basis for upcoming developments in AI and ML.

4.4.4 Data Management & Storage

All of the data that has been processed and calculated through the iterative feedback sessions are stored in database to be used for later.

- Format:

  A structured vector format is used to carefully store a vast amount of data in a database that is gathered throughout input from the transport planners. This includes original cargo details, routes suggested, and any revisions that were made. This format supports machine learning applications and is perfect for complex numerical analyses.

- Vector Storage:
  Data vectors hold the multidimensional characteristics of every logistics activity, including temperature settings, planner alterations, initial and updated routing coordinates, and cargo data. This structure ensures that every use-case of logistics operation may be measured and easily accessed for algorithmic evaluation.

- Collection and Processing:
  For this particular task a python library named Pandas was used. It's very well known for managing and processing data. NumPy is another library famous for numerical tasks used to process large sets of data efficiently. Python as a language and framework is known for its strong data manipulation abilities and quite fast when it comes to data processing.

- Storage and serialization:
  Python's Pickle module was used to serialize and de-serialize Python object structures into a small binary format. This makes sure of the data integrity and facilitates speedy retrieval of data.

- Feedback Loop:
  Transport planner information is integrated with the optimized route solutions via an adaptive feedback loop. Planner’s edits are recorded together with the original plan's contents along with the justifications for the modifications.

- Feedback Integration:
  This feedback loop improves the dataset for upcoming AI/ML applications. In addition to altering the operational parameters it also provides a thorough log of operational decisions by the transport planners and their results by combining algorithmic decision-making with manual planner interventions.

4.4.5 Preparation for AI and ML Implementations

The structured and extensive stored data is ready to be utilized in the creation of machine learning models to enhance and decision-making procedures:

- Machine Learning Models:
  Predictive models were developed using the stored structured vector data to determine the best routing and cargo distribution plans. It is based on past data and recurring patterns. This also speeds up the optimization part to produce results with greater efficiency.

- AI-Driven Predictions:
  To increase the system's ability to adapt dynamically and autonomously to the challenging logistical problems, we are going to investigate advanced AI techniques such as neural networks and deep learning. Through thorough literature review and testing we will determine which technique fits perfectly with our use-case.

In conclusion, the application and testing stages of the route planning algorithm have established a strong basis for utilizing Artificial Intelligence methodologies.

4.5 AI and machine learning Integration

Following the successful implementation and initial evaluation of the route planning algorithm described in the previous section. This section focuses on the more advanced integration of Artificial Intelligence, to be more specific it utilizes a Reinforcement Learning (RL) approach. This advanced AI method improves cargo distribution and route planning by dynamically adapting through gathered experience of the planners in the real-time integration of logistical constraints. This finally arises our final research question, “What is the impact of adaptive learning from transport planner’s feedback on the accuracy and efficiency of AI models used in cargo routing”.

The large-scale, structured vector dataset of the optimized solutions and transport planner feedback is essential training data for the development and improvement of the RL model (Ernst & Louette, 2024). The application of this RL model to continuously optimize logistical operations will be explained in this section.

4.5.1 Reinforcement Learning Model Development

Model for training is designed based on following key factors:

- Acceptance Criteria:
  The principal objective of the RL model is to reduce overall operating costs, including fuel consumption, and improve delivery efficiency by reducing transit times while ensuring cargo safety and compliance with laws (Hing et al., 2006).

- Space State:
  Consists of several components such as truck locations, cargo statuses, traffic reports, road conditions, meteorological conditions, and delivery dates.

- Action State:
  It is estimated by possible routes, trucks loading configuration and adjustment in schedule

- Mechanism for reward:
  Designed to provide a reward for activities that reduce delivery times, save costs, and maintain cargo integrity (Dayan & Balleine, 2002). Delivery delays, breaking rules, and inefficient route use can result in sanctions.

Next step after model creation is the data processing and collection steps.

- Data Collection:
  The system gets detailed information from transport planners, such as dimensions of the cargo, the temperature at which it must be kept, and the coordinates of the pickup and delivery locations. Additionally, it records all adjustments made by planners in reaction to logistical unexpected events such as obstacles.

- Feature:
  Large-scale cargo space (size and truck capacity), temporal factors (planned vs. actual delivery times), thermal requirements (necessary conditions for temperature-

sensitive goods), and path optimization (effectiveness of selected routes based on length and cost) are some of the key features processed for the RL model. The operational complexity of logistic activities is reflected in the detailed planning of these features.

- Data Compilation:
  As discussed in previous methodologies about data collection it consists of logistical operations that capture a range of problematic and successful routes. Along with planner comments incorporated it represents real-world obstacles and situations.

- Verification:
  This set, which is assembled from more recent operations, assesses the model's generalization skills by putting its learned methods to use in new and untested scenarios.

4.5.2 Training and Validation Process of the Model

- Algorithm:
  It is a model-free reinforcement learning algorithm. The Q-Learning algorithm uses a Deep Q-Network (DQN) technique to approximate Q-values, which portrays various dynamical states in the network design (Hester et al., 2018).

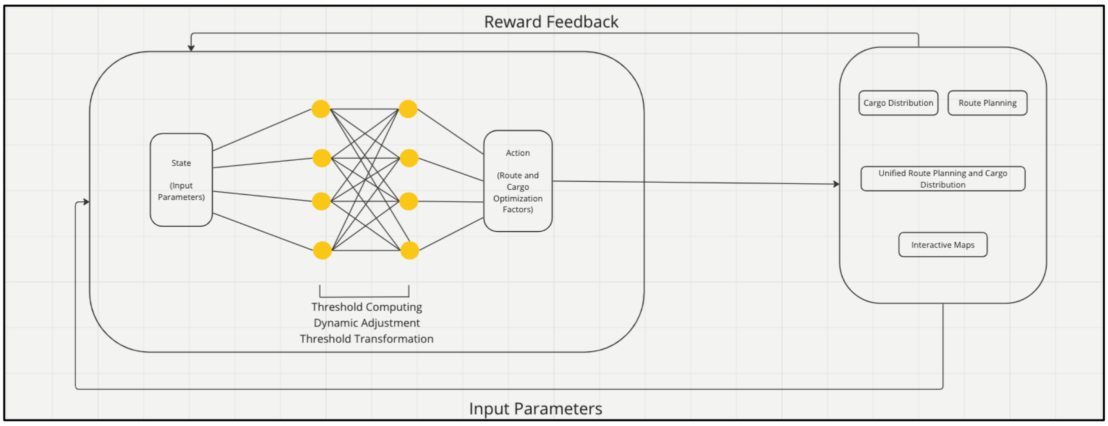


Figure 9. Architecture of the System

The Figure 9, explains the working mechanism for Algorithm integrated with system. Input Layer consist of initial input parameters that comprises of essential information to derive the algorithm. Hidden Layer takes into account all the factors which influence the output decision. Factors like live traffic updates, weather condition, road conditions and roadblocks contribute to this hidden layer. And output layer is what it produces at the end. An output in a human readable form that can be utilized.

- Iterativity:
  During training, the RL agent selects actions based on pre-existing policies, assesses rewards, updates its state, and fine-tunes the policy. It does that in an effort to get the best possible future rewards. This cycle is repeated episode by episode. This loop helps the agent to strike a balance between trying out new strategies and using already existing methods.

- Tuning of Hyperparameters;
  It is the crucial part of the process as key hyper-parameters such as the exploration rate, discount factor, and learning rate are carefully altered. With constant feedback and iterative state updates, algorithm state is in constant state of tuning. This helps in the optimization part of the solution to maximize learning and improve the model's ability to make decisions on its own.

- Model Validation:
  It’s the process of carefully comparing the predictions of the model to actual results. It is first carried out in simulated setups and then in real world situations.

- Evaluation Metrics:
  The model's accuracy in predicting routes, following temperature regulations, efficient use of available space, and delivery punctuality are evaluated.

5 Integrating AI Model into Cargo Distribution & Route Optimization System

Reinforcement learning (RL) model's learned weights generated in the previous chapters are incorporated into the current suggestive logistic solution. It greatly increases the efficiency of the route planning and cargo distribution procedures. A description of the technical integration's implementation is provided below.

5.1 Integrating AI Model Weights

The AI model's weights that were calculated from extensive iterative training for our AI-based logistical solution, are used to improve the heuristic algorithms that are currently a part of our system. As a result, the algorithms can adjust dynamically in response to new data. It considers and take into account various factors like cargo quantity, urgency, traffic circumstances, and temperature requirements.

5.1.1 Improved Routes

This enhanced algorithm generates the best possible routes, which are shown using OpenStreetMap to the transport planners. OpenStreetMaps offers a user-friendly mapping interface that a user can interact with. This helps in decision making by allowing planners to see AI-recommended routes with optimized time, weight and space.

5.1.2 Integration Layer of Model Weights

Model weight layer is seamlessly integrated into previously generated optimized solutions. The model weights allow the solution to make supervised decisions to generate the best possible solution.

5.1.3 Real-Time Data Handling

This model and integrated system is capable of dynamically modifying parameters based on transport planner's feedback. It allows traffic api updates, route blockades, and human intervention to be seamlessly integrated into the system that allows the RL model to adaptively adjust its weight and make appropriate recommendations accordingly.

5.1.4 Manual Adjustments

Transport planners are equipped and trained to make manual modifications to the system. Based on previously implemented iterative loop of feedback. It goes into storage as feedback that helps AI to improve itself.

5.2 Ongoing Learning and System Refinement

Our RL model is equipped to continuously cater changes and evolve with every iteration. Following description contributes to the continuous learning and adaptivity of the solution.

5.2.1 Continuous Model Training

The AI model adjusts its weight to improve the algorithm's performance. Every time new data is generated based on transport planners' feedback or through live updates of the OpenStreetMaps it adjusts its weights.

5.2.2 Adaptive Feedback Mechanism

The model's weights are adjusted by transport planners' inputs and through a feedback loop built into the system's design it keeps the model up to date and extremely responsive to the logistical environment.

We have created an extremely dynamic and effective framework for our logistics operations by integrating AI model weights into heuristic-based cargo distribution and route planning technologies. OpenStreetMap real-time mapping and advanced AI algorithms enhanced our logistics operations. In addition to improving the present logistical needs, this solution scales to meet upcoming obstacles. The RL model keeps getting better over time, thanks to an adaptive feedback system and an iterative learning model. As a result, our logistics operations are kept at the highest priority to changes. It helps to keep it ready to take on challenging logistical challenges surrounding route and cargo distribution.

Threshold Parameters	Tolerance	**Action**
Temperature Stability	± 1 °C	This triggers the action such as recalibrating refrigeration units or re-routing.
Route Deviation	± 15%	Recalculate and suggest another better route
Traffic Congestion	Level rated 3/5	Higher the rate, higher is the priority
Fuel Consumption	± 5%	Take fuel efficiency into consideration while planning the route.
Vehicle Loading Weight	± 15%	Ensure the loading capacity to reroute to add another cargo on the way
Delivery Priority	Level rated 4/5	Prioritizing this parameter to adjust routes to complete delivery promises.

Table 2. Threshold Parameters

In Table 2, explains the priority threshold parameters that would influence the decision of the outcome based on the values that we have set. For our specific use-case temperature sensitivity is of highest priority, as it ensures that goods stay the same and meet the minimum temperature requirement. Next main parameter is delivery priority, it ensures that relevant cargo is loaded into the trucks to deliver the promise company has with the clients. Loading weight is tied with the business need for trucks, as it ensures that trucks are not returned empty and thus costing the company.

Following Table 3 shows the priority thresholds based on our set parameters in the Table 2.

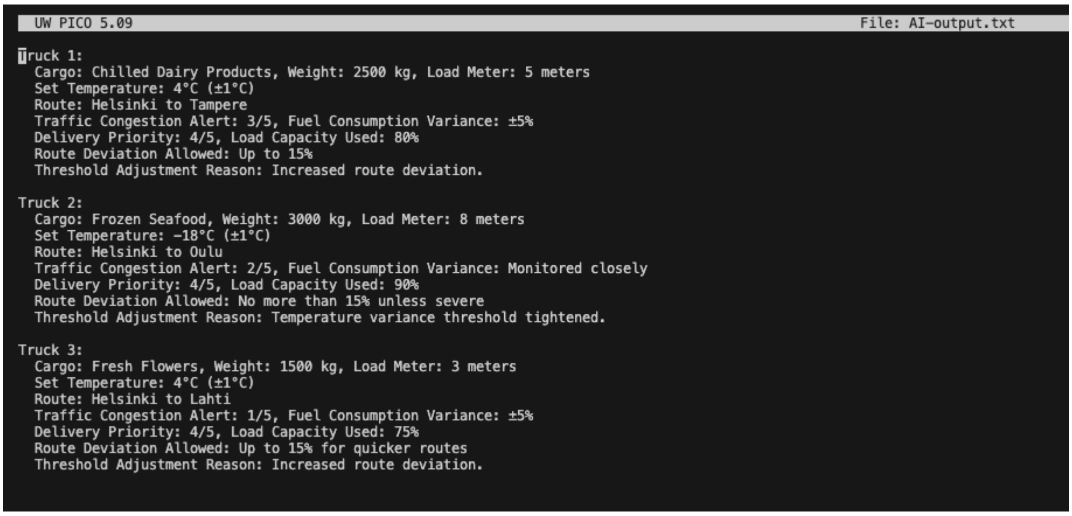
Input Parameters	Priority
Temperature	1. Thermal Equilibrium 2. Delivery Priority

	3. Congestion Sensitivity 4. Route Deviations 5. Vehicle Loading Balance 6. Fuel Consumption
Weight	1. Vehicle Loading Balance 2. Fuel Consumption 3. Congestion Sensitivity 4. Thermal Equilibrium 5. Route Deviations 6. Delivery Priority
Distance	1. Route Deviation 2. Congestion Sensitivity 3. Delivery Priority 4. Fuel Consumption 5. Vehicle Loading Balance 6. Thermal Equilibrium

These parameters and weights adjusted are integrated back into the system that produced us the improved output. Provided the reason for prioritizing which threshold should make the decision.

If we study previous optimization solution and current solution based on AI, it produced slightly different results that shows the adaptability and decision-making capability of the system. This helps us understand how AI model responds to real-time changes ensuring optimal solution.

Figure 10 below shows the output generated by our system after dynamically adjusting the threshold parameters to change the decision of the previously generated outcomes. Moreover, it also gives the explanation for why the threshold was prioritized in that specific scenario.



```
UW PICO 5.09                                                          File: AI-output.txt

Truck 1:
  Cargo: Chilled Dairy Products, Weight: 2500 kg, Load Meter: 5 meters
  Set Temperature: 4°C (±1°C)
  Route: Helsinki to Tampere
  Traffic Congestion Alert: 3/5, Fuel Consumption Variance: ±5%
  Delivery Priority: 4/5, Load Capacity Used: 80%
  Route Deviation Allowed: Up to 15%
  Threshold Adjustment Reason: Increased route deviation.

Truck 2:
  Cargo: Frozen Seafood, Weight: 3000 kg, Load Meter: 8 meters
  Set Temperature: -18°C (±1°C)
  Route: Helsinki to Oulu
  Traffic Congestion Alert: 2/5, Fuel Consumption Variance: Monitored closely
  Delivery Priority: 4/5, Load Capacity Used: 90%
  Route Deviation Allowed: No more than 15% unless severe
  Threshold Adjustment Reason: Temperature variance threshold tightened.

Truck 3:
  Cargo: Fresh Flowers, Weight: 1500 kg, Load Meter: 3 meters
  Set Temperature: 4°C (±1°C)
  Route: Helsinki to Lahti
  Traffic Congestion Alert: 1/5, Fuel Consumption Variance: ±5%
  Delivery Priority: 4/5, Load Capacity Used: 75%
  Route Deviation Allowed: Up to 15% for quicker routes
  Threshold Adjustment Reason: Increased route deviation.
```

Figure 10. Output After Integration

6 Future Work

So far, we have addressed the present practical hurdles and inefficiencies in the logistics sector. This whole research and implementation revolve around helping transport planners in the logistics company. With several promising areas that are still untapped could be explored and we can take this research to further ends.

The use of Long Short-Term Memory (LSTM) networks is one important field. LSTM is exceptionally great at processing sequential data (Tomasz Grzejszczak et al., 2023). This particular feature of it makes it a perfect tool for forecasting future logistical requirements and route optimization based on past trends.
Cargo distribution, delivery schedules and traffic factors could be integrated with high efficiency using LSTM to further improve the existing solution.

Another scope of this particular project involves a vessel management system (Sarkodie et al., 2018) which is not covered in the scope of this thesis. With its integration, the logistic chain will be improved so efficiently. This would help connect Finland with the rest of Europe from where the cargo is imported. It'd ensure the smooth transition of goods between different modes of transport across continents. Maritime transportation will be highly improved ensuring great success.

By integrating both systems in unified form into a single system would make the whole operation highly seamless. It'd provide a detailed automated delivery system from Europe's land transportation to maritime transit, and ultimately to Finland.

To sum it up, the amalgamation of AI methodologies including LSTM and vessel management system would cover the ever-changing demand of current logistics business. It would reduce the dependability of the transport planner and margin of error would be so low, as it's constantly improving itself.

7 Conclusion

In order to optimize the inefficiencies and obstacles that current logistics company is facing while operating a business that transport goods from Europe to Finland, route planning and container management system was integrated with Machine Learning and Artificial Intelligence approaches. It helped the transport planners to save 2-3 days of manual work.

The strategy includes understanding historical data of truck drivers and their activity points through-out the journey. This gave us the strategy to blend predictive analytics with heuristic techniques. Traditional heuristic approaches don't adhere to the everchanging demand and is not adaptable to dynamic settings. Throughout AI methodologies our system was able to learn from previous events and adjust in real-time. Providing an output in a graphical format so its easily understandable by the truck drivers and transport planners.

The utilization of dynamic rerouting based on cargo delivery points and real-time obstacle data integration is the crucial part of this research. By using this data, system was able to learn and improve with every decision it has made with or without the interference of human factor. Overall, it greatly cut down on the planning time delays and delivery timing delays. Maintaining effective operations in case of significant foreign factors like weather and traffic patterns make this system highly efficient and adaptable.

The system forecast probable delays, cargo volumes, and traffic patterns through the use of Machine learning models. By using these factors, plan is estimated efficiently and management is dispersed effectively. By combining cargo distribution with route management results in lower transportation costs and enhancing overall system.

Transport planners were able to seamlessly use the system and be part of the process in enhancing the system capabilities. Their feedback helped improved the system and set the crucial base for training of ML and AI models. Human interference not only ensure automated logistical processes but also continually improves the system's adaptive learning curve.

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