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MASTER THESIS

Systematic comparison and evaluation of different transport demand forecast methods

Submitted in Partial Fulfillment of the Requirements of the Academic Degree

Master of Science in Engineering, Msc

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Statutory Declaration

I hereby declare that

- I have independently written the presented Master thesis by myself;
- I have prepared this Master thesis without outside help and without using any sources or aids other than those cited by me; any thoughts from others or literal quotations are clearly marked.
- The enclosed Master Thesis is the same version as the version evaluated by the supervisors.
- I have not used any other unauthorized aids and have consistently worked independently and when using generative AI models (e.g. ChatGPT), I realize that I am responsible how the content will be used and to what extent.

Zaragoza, September 2024 Luis Miguel Rodrigo Ruiz de Arriaga

Abstract

Freight transport demand forecasting plays a critical role in the planning and policy-making processes of the European Union (EU) since the offer a critical scenario analysis for they assessment of potential strategies or policies. As the region faces increasing pressure to meet decarbonisation goals and address the evolving dynamics of global logistics, any valuable tool as freight transport demand forecasting will be required. This thesis presents a systematic comparison of various forecasting techniques based on a multi-criteria evaluation. This framework applied in this work assesses each method across ten categories, with the aim of identifying the most suitable approaches for long-term freight transport forecasting in the EU context.

In addition, this thesis explores the integration of these techniques between each other for enhancing the forecasting capabilities and to better achieve the final goal. It is also highlighted the growing importance of digitalisation, decarbonisation and new logistics concepts, emphasising the need for forecasting models that can adapt to structural changes and EU policy shifts.

After carrying out the evaluation of techniques, the discussion's aim is to present the current state of the freight transport demand forecasting framework, making it clear what are the current possibilities for the different techniques in terms of applicability. Finally, by reviewing current models used at practice level, additional insights are found to reaffirm the degree of implementation of the forecasting techniques.

Key words: Freight Transport Demand Forecasting, Econometric Models, Time Series, Machine Learning, Simulation Models, Long-term Forecasting. Logistic System, EU scale.

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Chapter 1

Introduction

1.1 Motivation

Today's continuing globalisation leads to a steady increase in demand for transport. This transport can be for different reasons (leisure, work, moving, etc.), of different nature (passengers or goods), using different means (road, train, ship, plane, etc.) and of different scope (local, regional, national or international). In any case, this is a challenge for the reliability of the transport system due to the increased number of vehicles and the consequent congestion, as well as having a direct impact on the environment through greenhouse gases (GHG), noise pollution, alteration of the natural environment, etc.

Therefore, accurate forecasting becomes crucial to be able to manage the increasing demand and to be able to act to mitigate or diminish its negative effects [1].Historically, most efforts have focused on passenger movement as it represents the largest proportion of transport, with a significant focus on the urban environment due to the major issue affecting day-to-day life in large cities, traffic congestion. This is why in transport demand prediction modelling research, as many authors point out, freight models lag behind passenger models [2].

However, the importance of freight transport should not be underestimated, as it still accounts for a significant portion of today's transportation and remains a major actor. Freight transport serves as the backbone of modern economies, enabling the movement of goods from production sites to markets, both domestically and internationally. Moreover, as industries continue to expand and global trade intensifies, the demand for freight transportation is expected to increase significantly in the coming decades, requiring improvements in both the infrastructure and efficiency of the transportation system to avoid bottlenecks affecting the entire supply chain [3].

Considering that this type of transport has such an important effect on the overall transport network, the environment as well as on the economy, as the world economy is deeply intertwined with the efficiency and reliability of freight transport systems, this work lies in this field. Despite having been lower research relevance in the past, this does not imply that it is any simpler than passenger transport. In fact, the dynamic nature of global supply lines, fluctuations in economic activity and the increasing complexity of logistics networks present substantial challenges in forecasting freight demand. It is therefore necessary to increase research efforts in improving current freight demand forecasting models.

Some of the reason why having a precise freight forecasting is crucial are:

- **Infrastructure Planning:** Governments and private entities must make substantial investments in transport infrastructure. Without accurate demand forecasts, these investments risk being either insufficient or excessive, leading to underutilisation or congestion, respectively.

- **Operational Efficiency:** Transport companies rely on demand forecasts to optimise fleet management, route planning, and inventory control. Accurate predictions allow for more efficient resource use, reducing costs and improving service levels.

- **Environmental Impact:** The transportation sector is a significant contributor to greenhouse gas emissions. Precise forecasting can aid in better planning of logistics operations, leading to reduced fuel consumption and, consequently, a lower environmental footprint.

- **Economic Stability:** Fluctuations in freight transport demand can have cascading effects on the broader economy, impacting everything from consumer prices to employment rates. Reliable forecasting methods help mitigate these risks by providing a foundation for informed decision-making.

As seen, accurate freight demand forecasting is not merely a theoretical exercise; it is a critical component in optimising resource allocation, reducing operational costs, and minimising environmental impacts associated with freight transport, becoming a key decision-making tool for both for public policy and private companies.

1.2 Objectives

The final objective of this thesis is to contribute to the development of freight transport demand forecasting models to overcome the challenges associated to the complexity of the logistics network itself and the uncertainty of the environment, in order to support action planners to manage freight transport more efficiently, reducing the demand and/or its negative effects on the transportation system itself and the environment, as explained above.

By developing an accurate transport forecast, it will serve as a support tool for policy makers and stakeholders to develop and implement mitigation strategies in line with decarbonisation objectives. Through predicting the future transport demand and trends, it allows to calculate the evolution of emissions from this sector in the coming years.

Furthermore, it can support the economic aspects of decarbonisation by guiding investments in sustainable infrastructure and technologies, ensuring that they are made where they can have the most significant impact, thus balancing the economical aspect with long-term climate objectives. Therefore, transport demand forecasting is an essential support tool for achieving the ambitious targets set for global carbon reduction, particularly in the transportation sector, which remains a significant contributor to GHG emissions.

Since this thesis is developed in collaboration with the Institute of Logistics Engineering of the TU Graz, the framework will focus on the long-term forecasting of freight transport in the European framework. In doing so, the aim is to support the decarbonisation of transport in line with the emission targets set by the European Union for 2050, aiming at an economy with net-zero GHG emissions [4].

In order to contribute to the development of these tools, a comparison of forecasting methods is carried out in this paper, outlining the strengths and limitations of the different methods, systematically evaluating them according to 10 different factors. The aim is to establish the current state-of-the-art and to identify potential tools to improve the current freight forecasting in the European context.

On the other hand, another objective of this thesis is to assess the existing models used by different institutions or nations to forecast the freight transport demand, in order to determine the real degree of implementation of the methods, described in the systematic review of the research, in some of the most recent models currently in use. With this comparison of the state-of-the-art with the actual state-of-the-practice, it is intended to be able to establish what the current possibilities are for improving forecasting in the following years.

The ultimate freight demand forecasting model not only has to be accurate in the long term, it must incorporate more features that make it useful and reliable. It must be able to process large amounts of data in order to have a complete model, especially these days when there are so many sources producing real-time data, and it must also be adaptable to changes in data availability and quality as well as to unexpected events such as economic crises or natural disasters. It should be resilient enough to provide reliable predictions even under uncertain conditions.

They should also include the possibility to create various scenarios (e.g., economic downturns, fluctuating petrol prices, regulatory changes) and assess their impact on transport demand. This helps to understand the range of possible outcomes. In addition, the model should take into account economic and social dynamics. And, as already mentioned, it should also incorporate carbon footprint estimation to evaluate emission mitigation strategies, being also user-friendly so that it can be used by stakeholders who are not necessarily experts in modelling.

As a goal at the conclusion of this work, it is expected to answer which methods are currently the most suitable for long-term freight demand forecasting in the context of the European framework, as well as to point out what is the potential for improvement in the coming years and what are the limitations. In this way, this work can provide guidance for future developments in this field and to orientate in which direction further work should be done.

1.3 Content

This Master Thesis is divided into six chapters. The initial chapter is the introduction, providing a summary of the study's motivation and the objectives of this research in the field of freight transport forecasting. Chapter 2 provides a review of the background literature search, explaining the current transport framework in the context of the European Union, with all its implications and future trends, which complements the motivation of this work. The principles and characteristics of freight transport forecasting are also discussed, ending with an explanation of the multi-criteria that will be used for the systematic comparison of methods in this work.

In Chapter 3, the different current forecasting methods for freight transport are described, covering from the most traditional to the most state-of-the-art methods. The intention is to highlight the strengths and weaknesses of each one, evaluating them according to the multi-criteria methodology described in the previous chapter in order to be able to systematically compare them.

Once the techniques and models of freight transport forecasting have been reviewed, Chapter 4 carries out a discussion of results, comparing the state of research with the extent of its implementation in practice, addressing what the general trends are and their implications for practitioners. At the final stage, Chapter 5, main outcomes as well as a conclusion of the work is presented.

Chapter 2

Background Literature

Within this chapter, valuable background information is provided for those who are not so familiar with the field. First, the European situation that gives context to the value of transport forecasting is presented. The principles and characteristics of freight transport are also explained, essential to understand the methods that are the subject of review in this thesis, ending with the explanation of the systematic multi-criteria comparison methodology.

2.1 EU Context

Global warming is one of the biggest problems facing the world, and it concerns all of us because of its potentially fatal consequences. United Nations (UN) warns in its Emissions Gap Report 20023 of rising global temperatures while reaching a new record of total GHG emissions again [5], as shown in the Figure 2.1.

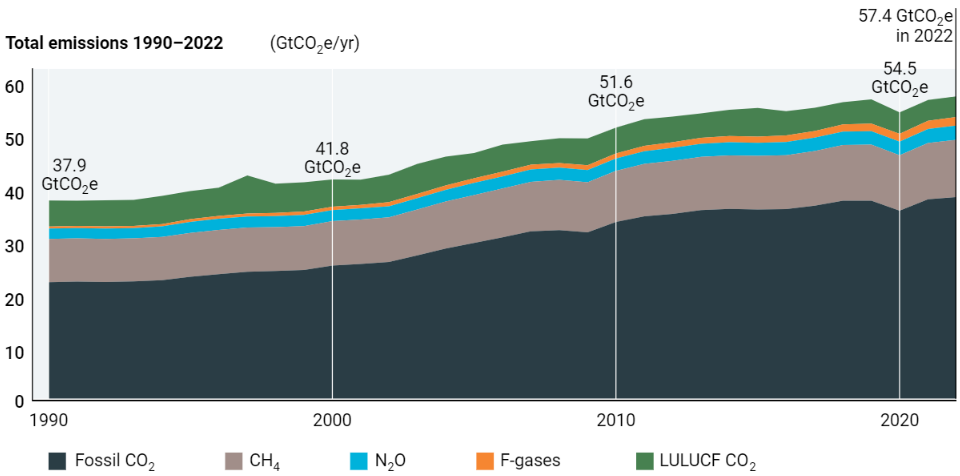

Figure 2.1: Global total GHG emissions [5]

This is evidence of the urgent need to step up efforts on climate transition before a point of no return is reached. In response to this call for action, the European Commission, in line with the Paris Agreement to keep global warming to no more than 1.5ºC, has set ambitious targets for the coming decades, with the clear aim of being neutral-climate by 2050 [4].

However, the Transport and Environment Report 2022 [6] by the European Environment Agency shows that although the current measures are effective and emissions are steadily decreasing, the targets are unlikely to be met unless further strong measures are adopted (Figure 2.2).

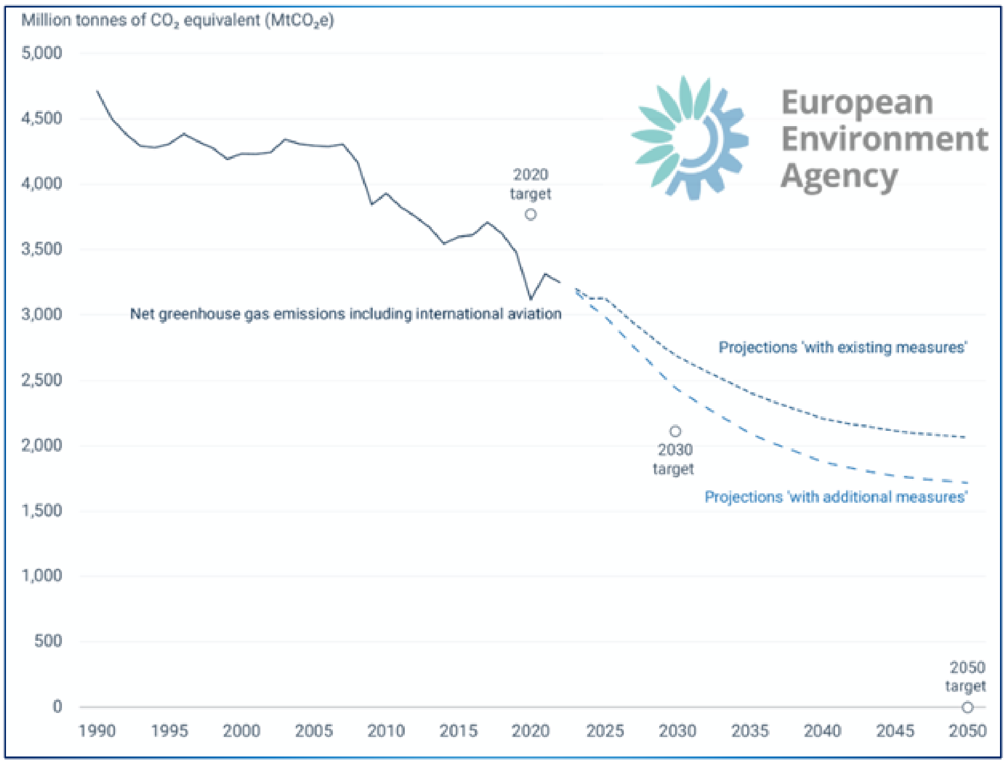

Figure 2.2: Total GHG emissions EU-27 [6]

Back to the main theme of this thesis. This European Environment Agency's report also shows that while total emissions across all sectors are decreasing, the transport sector continues to increase its emissions, reaching a quarter of total emissions (Figure 2.3). Therefore, decarbonising this sector is one of the key challenges that must be addressed in order to achieve carbon neutrality, becoming a priority for 2050 targets.

In addition, it becomes even more convenient to address this issue in the transport sector as both passenger and freight transport are projected to grow significantly over the next 30 years, following the current trend as shown in the figure 2.4, which would lead to more emissions.

The growth in transport demand is historically associated with some factors such as economic growth (GDP), increased purchasing power of the people, increased technology

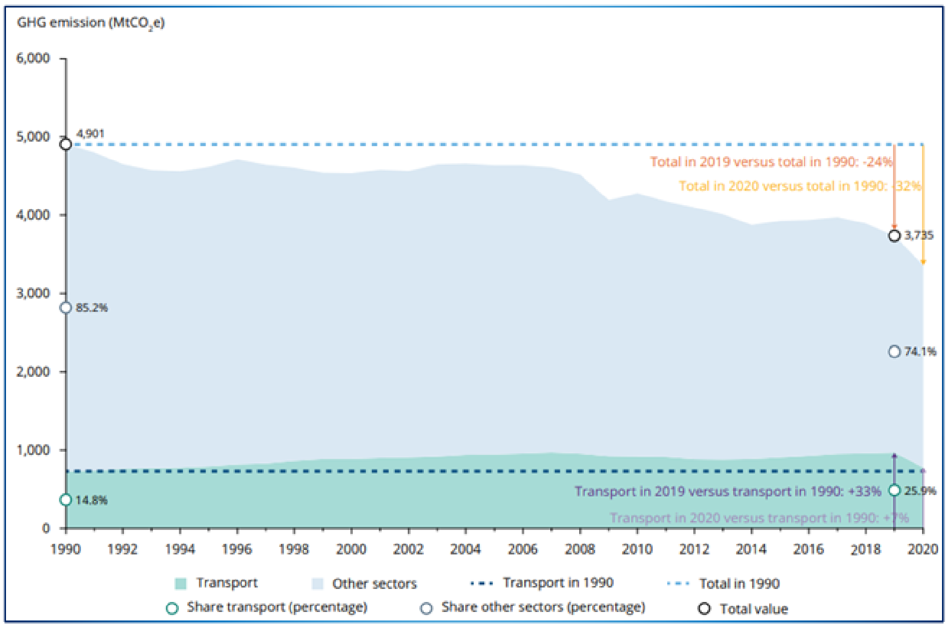

Figure 2.3: Total transport GHG emissions EU-27 [6]

and reduced travel costs or even the current lifestyle. Therefore, to preserve the climate without sacrificing the economy, it is crucial to design a major action plan to decouple the growth of transport demand from socio-economic development. Other measures, such as efficiency-enhancing technological improvements, would also help to ensure that this increase in transport demand does not lead to higher emissions.

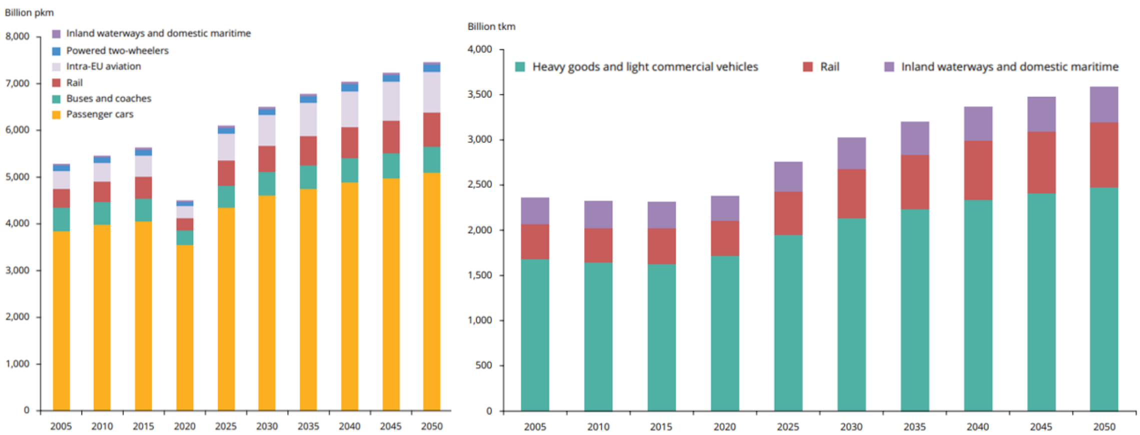

Figure 2.4: Passenger and Freight transport projection EU-27 [6]

Considering that it is not simply a matter of keeping emissions in the transport sector stable, but to reduce them, a large package of measures must be proposed. Many of the measures that can be implemented can be distinguished in 3 different groups:

- **Avoidance measures:** By adopting urban planning following the green urban model, mobility by bike, public transport or walking is promoted. Moreover, facilitating teleworking also reduces the number of commuting trips.Basically, the aim is to reduce the demand for transport while affecting lifestyles as least as possible.

- **Shift measures:** They consist of switching from energy-intensive to energy-efficient means of transport. Instead of using air transport or private cars, much more efficient means such as rail, this also leads to a reduction of travel costs and traffic.

- **Improvement measures:** This set of measures is based on upgrading vehicle efficiency such as developing low-carbon fuels, improving operational efficiency (routing) as well as new vehicle technologies that thereby reduce fuel use and promote a shift to electric vehicles.

In the case of the European Commission, some of the main actions they have taken are as follows. Firstly, the Emissions Trading Scheme (ETS) which is a key tool for reducing GHG emissions, since it's a carbon market where there is a limit set on the total amount of emissions, being reduced over time to ensure that total emissions fall [7]. Within the cap, companies receive emissions allowances and can also buy them. Currently, this system is only use in certain industries.

Another important one is the FIT FOR 55, a package of measures targeting a 55% reduction in GHG emissions by 2030 [8]. It includes the extension of the ETS to more industries, regulation towards more sustainable fuels, promotion of infrastructures for more efficient means, etc.

When implementing these important packages, policy makers need to have projections of the possible outcomes in order to know optimally which actions to implement and to what extent to implement them. This is why models such as ASTRA [9], developed as a project of the European Commission, are currently used.

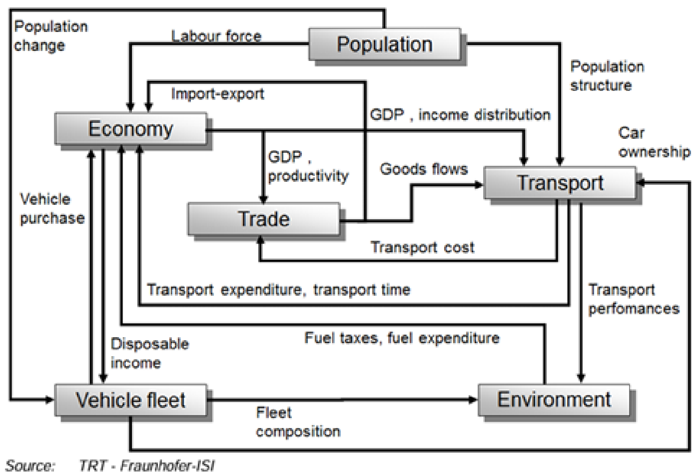

Figure 2.5: Overview of the linkages between the modules in ASTRA [9]

The ASTRA (Assessment of Transport Strategies) model is a dynamic system model designed to analyse and forecast the long-term impacts of various transport and environmental policies in Europe. The model which represents a simulation of the socio-economic structure of Europe, was developed to support decision-making by assessing the potential effects of different policy measures on the transport system, economy, environment, and society as a whole. As illustrated in the Figure 2.5, this is a complex model in which different modules are interconnected, taking into account the side effects of implementing measures in one of them.

Another model that can be quite helpful as a support tool is the LEAP (Long-range Energy Alternatives Planning) model [10]. It is an integrated planning tool to help governments jointly assess GHG, short-lived climate pollutants (SLCPs) and other air pollutants emissions; build mitigation scenarios; and understand how emissions reductions benefit climate, health and crops. Using as input data the activity of the different sectors (transport, industry, forestry, agriculture, etc.) hypothetical scenarios can be built to assess mitigation strategies, resulting in the calculation of reduced emissions as shown in the results of the Figure 2.6.

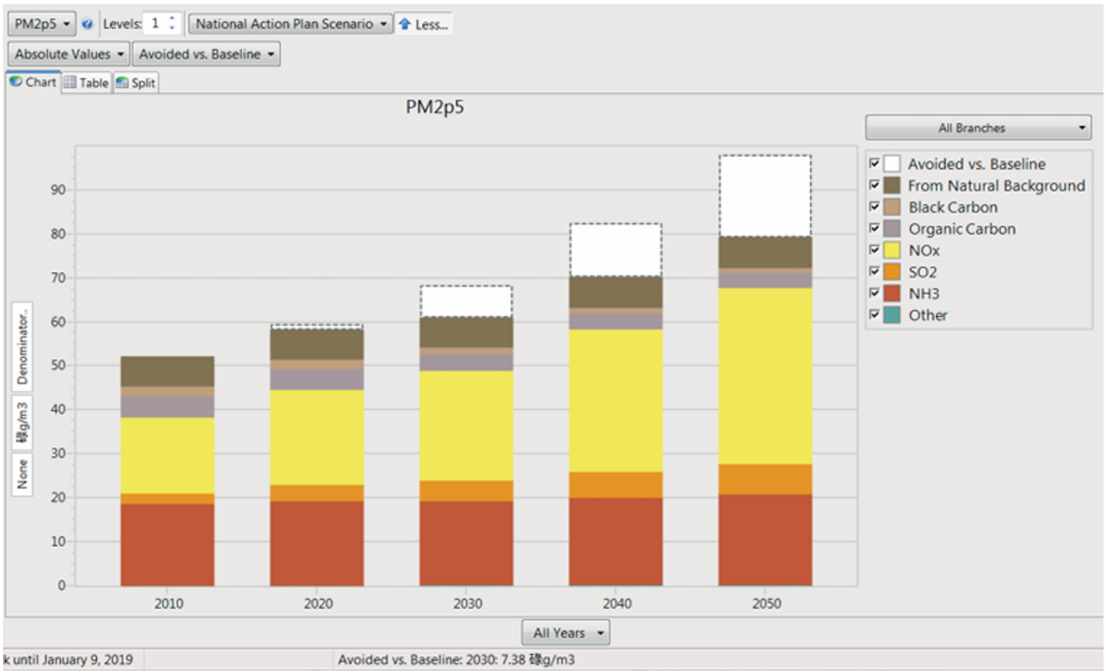

Figure 2.6: Projection of emissions in LEAP [10]

As reviewed in the literature, these models can directly help the current struggle to decarbonise our economy. However, for these models to be as truthful as possible in assessing strategies, especially for the transport sector, the transport demand forecasts used as input data in these models need to be accurate in the long-term.

2.2 Transport Demand Forecasting

Having explained the context in which forecasting models are developed, this section explains the principles that shape the forecasting models.

2.2.1 Drivers of Transport Demand

A brief introduction to transport demand itself should be made in first place, as a good forecasting model involves good prior understanding of the nature of demand. In the book *Modeling of Transport Demand: Analyzing, Calculating, and Forecasting Transport Demand* (Profillidis & Botzoris, 2018)[11] the drivers and factors that influence the demand for both passenger and freight transport are described. A summary of these causes is the following:

1. **Economic growth and activity:**
    - GDP and income levels: Economic growth directly affects transport demand as increased economic activity leads to higher production and consumption, which in turn, increases the need for the movement of goods and people. As income levels rise, personal travel demand also tends to increase.
    - Trade volumes: International and domestic trade drive the demand for freight transport. As trade increases, so does the need for freight transportation capacity to move goods.
2. **Population growth and land use:**
    - Demographics: The size and structure of the population, including age distribution, influence transport demand. Younger and working-age populations typically have higher mobility needs.
    - Land use: The growth of urbanisation increases the demand for public transport and other mobility services. Urban areas also leads to the concentration of economic activities, which affects freight demand patterns.
3. **Technological Advances:**
    - Transport technology: Innovations in transport technology, such as electric vehicles, autonomous vehicles, and high-speed trains, can alter transport demand by making travel faster, cheaper, and more efficient, modifying the current travel behaviour.

- Digitalisation: The rise of e-commerce and digital platforms has significantly increased the demand for logistics and last-mile delivery services, transforming the freight transport system.

4. **Policy and regulation:**
    - Transport policies: Government policies, including fuel taxes, subsides for public transport and regulations on emissions, influence transport demand by making certain modes of transport more or less attractive, as mentioned in the previous section.
    - Infrastructure investment: Investments in infrastructure, such as roads, railways, and ports, facilitate transport activity by reducing costs and travel times.
5. **Energy prices:**
    - Fuel prices: The cost of energy, particularly fuel prices, is a significant driver of transport demand. High fuel prices can reduce the demand for private vehicle travel and increase the use of public transport.
6. **Social and culture factors:**
    - Lifestyle changes: Society's trends such as increased remote working or the rise of the sharing economy (e.g., ride-sharing services), can alter travel patterns and reduce or increase transport demand.
    - Consumer preferences: Preferences for faster, more convenient, or environmentally friendly transport options can drive demand for certain types of transport services over others.
7. **Global events and disruptions:**
    - Geopolitical events: Wars, trade disputes, and other geopolitical events can disrupt global supply chains, leading to changes in transport demand.
    - Unexpected crises: Economic recessions, natural disasters, pandemics, etc. All these unexpected events influence transport as well as the overall economy.

Every modeller has to consider all these factors that influence transport in general when building a predictive model, the better the understanding and integration of these factors, the better the model will perform even in unplanned situations.

2.2.2 Principles of Transport Forecasting

In order to make a valid forecast, some principles have to be taken into account in the development of a model. *Modeling of Transport Demand* (Profillidis & Botzoris, 2018)[11] also explains what is the standard way to build a model from scratch, this does not mean that it is the only way, but it does appear in most of them. To do so, it presents the successive steps to be undertaken and it will serve as a guideline for explaining the principles to follow, Figure 2.7.

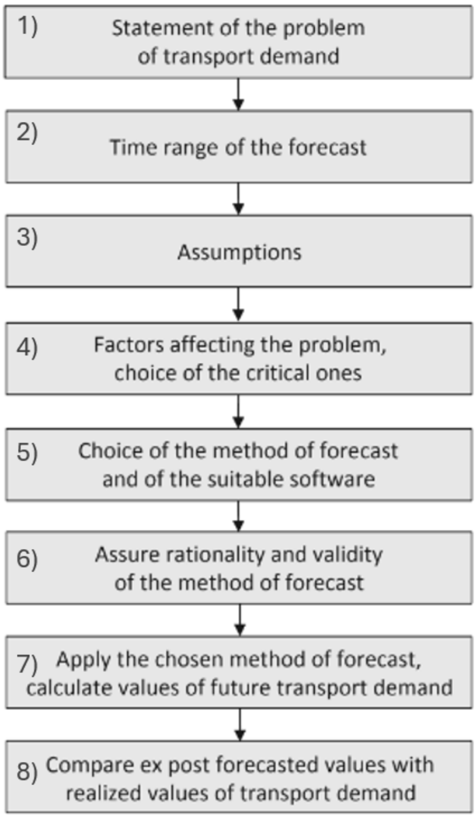

Figure 2.7: Steps for the forecast of future transport demand [11]

1. **Statement of the problem:** First of all, the problem has to be defined correctly, defining the boundaries, what is to be studied with what scope. It will not be the same process for a local authority to calculate the demand on its bus services as it is for the construction of a national transport model to evaluate investments in state infrastructure. It is important to define well the limits of studies as it is possible to simplify the model by isolating the problem. Trying to cover more than necessary can be a mistake that could be costly in terms of the model's accuracy.

2. **Time range:** The temporal scope is one of the most determinant issues in a model. Again, it is again related to the boundaries of our system and must be limited to

what our described problem needs to be solved. In the case of an investment in infrastructure, a long-term prediction covering the following decades is needed. On the other hand, a transport company looking for a model for operational optimisation will use a short- to medium-term model that is updated frequently.

3. **Assumptions:** When building a model that tries to replicate reality, it is necessary to make certain assumptions as it is unrealistic to try to reproduce the problem exactly. There is debate in the literature on the appropriate degree of complexity that a model should have. Although a complex model may initially appear to be a sample of a complete model that gives better results, it must be taken into account that very specific assumptions can lead to systematic errors that can accumulate, and a more complex model will always be more difficult to understand and interpret when validating and using it.

   As point out by Willumsen and Liu (2010)[12] the total error of any model is the sum of at least two sources: Specification error and Data error (Figure 2.8).

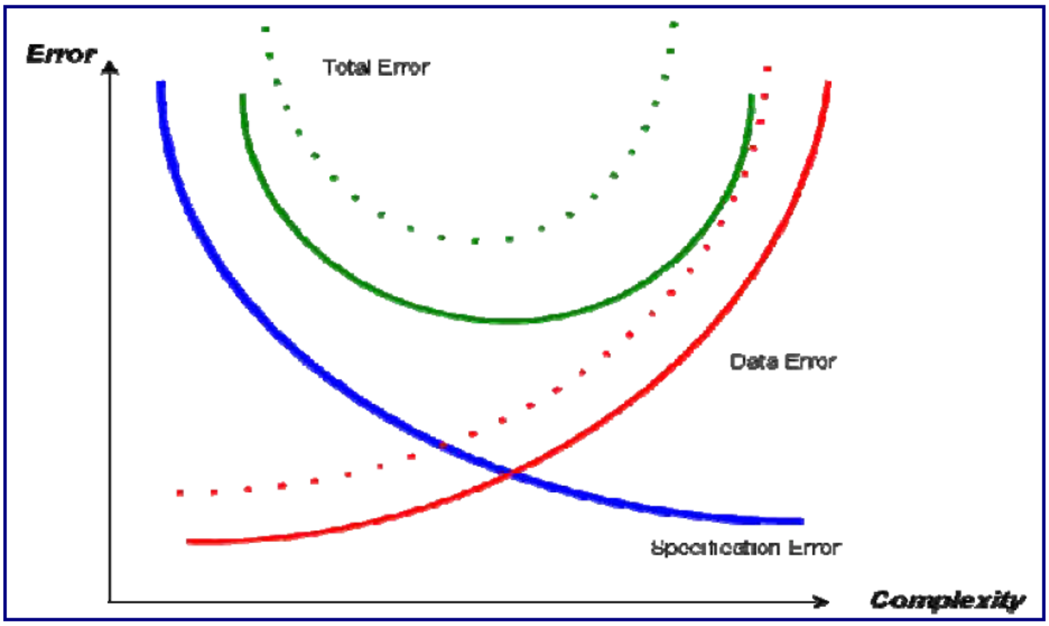

Figure 2.8: The trade-off between complexity and error [12]

The specification error stems from the simplified nature of the model: aggregation in zones, use of single parameters for large sections of the population and so on. Data error stems from the errors in the inputs to the model and how these may be amplified through the many mathematical operations and iterations. In this way a balance must be found to use sufficient complexity to obtain a minimum total error. After the assumptions have been stated, this should be consistent in the following steps.

4. **Selection of variables:** In a model there are various variables, we can differentiate between dependent and independent variables. Dependent variables in transport forecasting models are usually number of trips, number of passengers, volume of goods, etc. These are the variables that are the object of study and will be the outcome of the model. On the other hand, the independent variables represent the causes that influence the outcome variables. When choosing, one has to be meticulous in the causal relationship.

   When choosing, it is necessary to carefully analyse rationally the relationship between the independent variable and the output variables and ensure that it is a causal relationship (reminder that correlation is not necessarily a demonstration of causality and therefore there must always be a proper rationing of the independent variables). At the same time, it is necessary to select the causes that best represent the functioning of the demand (related to the demand drivers), limiting to the most critical ones. Also not to make the mistake of choosing two variables that represent the same or similar causes. For instance, instead of using GDP and GDP per capita, one could use the disposable income to represent the individual's income.

   The data collection process must always be taken into account in this step in order to understand what data is accessible and how disaggregated this available data is. Having the economic data disaggregated at municipal level or the same data aggregated at national level, will condition whether which variable should be used or not. Often, the ideal variables cannot be used because they are either not available or too costly to obtain (in terms of effort and/or money).

5. **Choice of the method:** Again, this step is highly dependent on the type of problem you have and based on that, one or the other will be selected. The aim is to use the method that best suits the problem and whose strengths can be exploited. The main topic of this thesis is based on the comparison of methods, so this step and the factors influencing the choice will be explained in depth throughout the work.

6. **Validation of the forecast:** Validation of the above steps must be carried out on a continuous loop. Model building is not a linear process and often involves iterations to redo or correct previous steps. Therefore, a critical attitude must be maintained throughout the whole process.

7. **Calibration:** In this step, the model is set up using historical data of the system to be forecast. Calibration can be done in several ways depending on the availability of data or the type of model. With error metrics such as the mean square error (MSE), the mean absolute error (MAE) or the coefficient of determination (R^2) it

is common to calculate the coefficients of models based on mathematical formulas minimising this error [11].

These error metrics are given by:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2.1}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2.2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{2.3}$$

where:

- y_i: The actual or observed value of the dependent variable for the i-th data point.
- $\hat{y}_i$: The predicted value from the model for the i-th data point.
- $\bar{y}$: The mean of all actual values y_i in the dataset.
- n: Number of total observations in the dataset.

The MSE and MAE errors provide a measure of the error. The closer these metrics are to zero, the more accurate it is. On the other hand, the coefficient of determination is a range from 0 to 1. It measures the proportion of the variance in the dependent variable that is predictable from the independent variables. An R^2 value close to 1 indicates a good fit.

However, it is important to note that a high R^2 does not necessarily mean that the model is the best; it just means that it fits the data well. An overfitting can lead to a high R^2 but poor model generalization, only obtaining that accuracy with the calibration dataset and being sensitive to unexpected ones.

Other calibration techniques are using test scenarios to adjust and ensure that the model is consistent in different situations. There are also fits using many data sets to train the model, typical of more current techniques based on artificial intelligence. However, it should be kept in mind that this step is not performed exclusively in the construction of the model, it may be necessary to recalibrate it periodically to adapt it to changes in market conditions or transport trends. This is why it is important to carry out a good documentation of the calibration, so that the model is interpretable and transparent and can be updated without the need to rely on the original modeller.

8. **Validation of results:** In validation, it is important to note that different data sets than those used in the calibration must be used in order for them to be independent and to be a true validation. If a greater difference than 15% observed

during successive predictions is detected between the values obtained and the real ones, it is a sign that the chosen method might not be the appropriate one.

Validation should not only be based on error metrics, but also on statistical validity. How to carry out a complete model check is explained in depth in the reviewed book [11], setting out the formulas used for each of the tests. Among these checks is the correlation test that seeks to demonstrate the absence of multicollineratiy, i.e. correlation between two or more independent variables affecting accuracy.

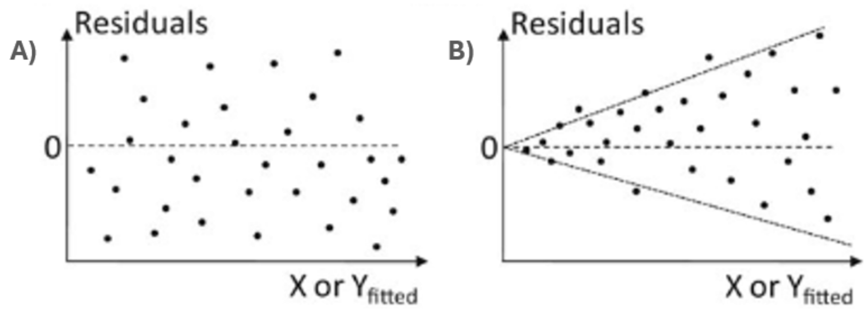

Figure 2.9: (A) Homoscedasticity and (B) heteroscedasticity representation [11]

The presence of unusual residual values (outliers) is also checked, as well as whether they follow the homoscedasticity principle,in others words, to ensure that the variance of the residual errors is constant. In the Figure 2.9, it can be visually observed the differences between homoscedasticity and heteroscedasticity. However, in the case of forecasting models for transportation demand, some heteroscedasticity may be common since many individuals do not maintain their behavior or preferences over time without apparent reason. Once these last checks have been carried out, the validation will be concluded and the model will be completed.

Forecasting methods can be distinguished into two broad categories, either qualitative or quantitative. Quantitative forecasting methods use historical numerical data and mathematical models to predict future outcomes. These methods assume that patterns and relationships observed in the past will continue into the future and it requires a sufficient amount of historical data to identify patterns and trends. They are not really easy to develop and interpret but they provide objective and consistent results, being able to be highly accurate if the model is well-specified and the data is realiable.

On the other hand, the qualitative ones are based more on intuition, experience and expert knowledge. They are subjective methods that are useful when information is scarce or not directly applicable or to identify trends outside the data. These techniques are based on surveys of transport users, surveys of experts in the field, rounds of discussions with experts to reach common conclusions, writing of potential scenarios, etc.

These qualitative methods are suitable for short- to medium-term forecasting (up to 2-5 years). Thus, they cannot be used in the context of this work, which focuses on long-term methods, and therefore will not appear in the systematic comparison of this work. However, these methods are still very useful and can support other quantitative models through stated preferences (SP) surveys that help to identify and mathematically model transport user behavior variables.

Within the group of quantitative methods, there is the 4-stage travel demand model [13]. This method will be analysed individually in the review, but since it is the method that has traditionally been the most widely used in the history of transport demand forecasting, it is necessary to introduce it at this point to give context about the development of forecasting models. This method was originally developed for passenger transport and it involves four sequential stages, as shown in Figure 2.10. This model itself is not a single method, each of these steps is usually solved with different techniques, which will also be analysed and discussed.

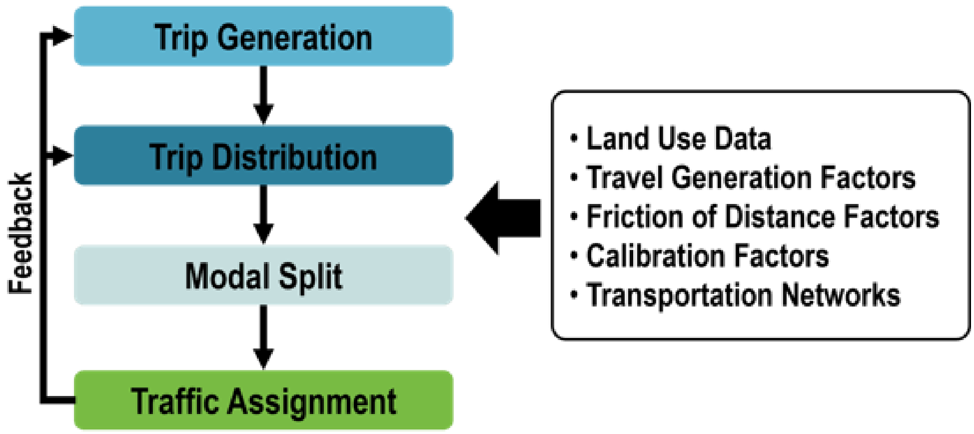

Figure 2.10: 4-stage method sequential structure [13]

- **Trip generation.** This stage calculates the number of trips that will be generated in each zone of the study area. Zones could be geographic units such as neighbourhoods, districts or regions, depending of the size and scope of the model. The function of this stage is to calculate the trip attraction and trip production of each zone. During the trip production is calculated the number of trips originating from a zone, often based on residential population, employment levels, and land use. On the other side, the trip attraction process estimates the number of trips destined for a zone, influenced by factors like job opportunities, commercial activities, and recreational facilities.

- **Trip distribution.** This stage predicts where the trips generated in the first stage will go, i.e., how trips are distributed between origins and destinations. The result is the so called (O-D) matrix which shows the number of trips between each origin-destination pair. This linkage is based primarily in factor such as distance, time and cost between pairs.

- **Mode choice.** In this step it is determined the mean of transport (e.g., car, bus, train, walking) that users will choose for their trips. Travelers' choices are modeled based on the perceived utility or satisfaction derived from each mode, considering factors like cost, travel time, convenience, and socio-economic characteristics. Previously described SP surveys can potentially be used to quantify subjective variables. The result is a mode split, which indicates the proportion of trips using each transport mode for each origin-destination pair.
- **Trip assignment.** This final stage assigns the trips (now disaggregated by mode) to specific routes in the actual current transportation network. It involves modeling the transport network to determine the routes that travelers are likely to take. Most methods employed in this stage are based on allocating users in a way that minimises the amount of travel time or based on the capacity of the network. The result is a detailed traffic flow or load on each link in the transport network, showing how the transportation system will operate under the predicted demand. The actual travel cost of each trip is another outcome of this stage, and it is used for the trip generation and trip distribution stages in a feedback loop.

This method was developed in the mid-20th century and it became widely adopted and standardised in transportation planning due its structured approach to analysing and forecasting travel demand [14]. Over time, it has been refined and adapted to accommodate advancements in data collection, computational capabilities, and changes in transportation systems. Despite being originally developed for passenger demand, it has historically also been used for freight transport modelling with some minor changes in the methods and factors used. Nevertheless, it still has some limitations and weaknesses that will be discussed along this review.

2.2.3 Freight Transport

After explaining the standard procedure for building a transport demand forecasting model, this section now looks specifically at freight transport. Despite the fact that both freight and passengers share the same types of means of transport and even the same network, freight transport is of a different nature. While passenger transport is mainly guided by human behaviour, freight transport is heterogeneous as it is conditioned by the type of commodity, the volume and the loading unit, depending on this it will be more adequate to use one means of transport or another.

It must also be taken into account that they are part of a complex supply chain that includes production, distribution and the consumption patterns, being closely linked to the functioning of the entire chain. The capacity and condition of the transport infrastructure are critical factors as bottlenecks or expansions in the infrastructure can greatly modify the initial demand by changing modes or routes. Infrastructure does not simply refer to roads, rail, sea and air routes, but also to the investment in intermodal hubs, as many goods involve multiple modes of transport and the location and efficiency of these hubs are decisive factors [15].

After explaining all these factors specific to this type of transport, it can be observed that it is much more constrained than passenger transport, to which must also be added the fact that the geographical distribution of the logistics centres as well as the seasonal nature of the goods due to agricultural cycles, the holiday season and manufacturing habits that have also a significant impact.

As mentioned above, the development of forecasting modelling has traditionally focused on passenger transport and has not been developed specifically for freight transport in the past. Despite all the factors that characterise it, freight transport forecasting has historically been done by adapting the 4-stage passenger method.

For being able to correctly use the 4-stage model for this kind of transport, it has to be taken into account that while passenger transport demand drivers are very much linked to individual decisions and therefore have an important behavioural factor, freight demand drivers have less of a subjective component and economic factors gain importance as they are so closely linked to the evolution of the economy and trade.

Furthermore, instead of having a personal decision-making, it becomes a complex process involving numerous actors with the whole supply chain, which makes it harder to determine the actual participation of each actor, and therefore to model the decision-making process in the forecasting.

Moreover, the first step of the 4-stage model (trip generation step) has to be modified. Due to the heterogeneous nature of the freight, the number of trips is no longer calculated directly as these have more dimensions in this case (type of goods and volume of goods). Thus, in this first step, instead of first calculating the O-D matrix, the volume of each type of goods produced and consumed in each zone is calculated and a production-consumption matrix (P-C) is assembled, which is strongly based on economic criteria. Once this matrix is obtained, it is commonly used historic statistic to know the probability of what size of load each type of goods usually uses, converting volume of goods between zones in number of trips for each commodity. In this way, the P-C matrix is transformed into the usual O-D matrix to be able to perform the rest of the 4-stage model.

In addition, trends in the sector must not be disregarded as recent recent innovations in the supply chain have significant implications for freight transport forecasting [16]. These changes are transforming how goods are produced, distributed and delivered, and are following trends:

- **Impact of Supply Chain Innovations:** The integration of real-time tracking and data analytics in supply chains enhances the visibility of goods in transit, allowing for more precise demand forecasting. However, it also requires forecasting models to be more dynamic and capable of processing large volumes of data in real time. Also, the adoption of JIT and lean logistics practices reduces inventory levels and increases the frequency of smaller shipments, potentially increasing the complexity of route optimization and mode selection.

- **Growth of E-Commerce:** The trend of online consumption has been increasing in recent years, especially after the Covid-19 pandemic. This explosion of e-commerce has significantly increased the demand for last-mile delivery services, which are often more complex and less predictable than traditional freight transport since it involves factors such as consumer behavior, delivery time windows and the variability of urban traffic conditions.

  The nature of e-commerce, with its emphasis on quick delivery times, has led to an increase in the number of smaller shipments and also leading to the process of decentralisation of distribution networks, with a greater emphasis on regional distribution centers and local fulfillment hubs.

- **Rising complexity in global supply chains:** It is based mainly on these 3 factors:

  - **Intermodal transport.** As global supply chains become more complex, the use of multi-modal and intermodal transport has increased.
  - **Globalization and trade volatility.** Trade policies, tariffs and geopolitical risks, introduces greater uncertainty, increasing the complexity of global supply chains since they should be flexible enough to incorporate these variables and anticipate potential disruptions.
  - **Sustainability and regulatory pressures.** The decarbonisation process of the transportation sector put pressure on the logistic system by regulating on transport cost, forcing companies to innovate for the shift towards greener transport modes.

- **Current consumer expectations and service levels:** Consumer expectations for faster delivery times combined with customized and flexible delivery options adds another layer of complexity to freight transportation.

Having characterised this type of transport, the challenges facing transport demand forecasting as a result of the above-mentioned factors described above are going to be summarised.

2.2.4 Challenges of Freight Transport Demand Forecasting

Identifying the challenges that forecasting faces, due to the nature of freight logistics, is a key step in finding solutions to these issues throughout this systematic comparison. Therefore, a summary of them is given below:

1. **Data complexity:** Unlike passenger transport, where data may be in the public domain, freight transport involves numerous stakeholders, including shippers, carriers and logistics providers, each with their own data and potential different data formats and standards.

   Additionally, this data is in domain of the private sector which might not want to easily to share to not compromise its position in the market. Data granularity increases also the complexity because of the lack of specific information on cargo types, shipment sizes or exact routes used.

2. **Complexity of supply chains:** As previously mentioned, the increasing complexity of the supply system makes accurate modeling more difficult due to the numerous variables and interactions involved. Also, the highly dynamic environment, with frequent changes in suppliers, distribution centers and transport routes, means that forecasting models must be adaptable to these changes, which can be challenging to implement.

3. **Variability and uncertainty:** Freight demand can be highly variable, influenced by factors such as economic cycles, seasonal trends, global trade dynamics (subjected to uncertainties like trade wars, tariff changes or geopolitical tensions) and unexpected disruptions (e.g., pandemics, natural disasters). Capturing this uncertainty in a forecasting model requires sophisticated approaches that can account for these potential scenarios and variability.

4. **Integration with broader economic models:** Considering that freight transport depends so much on the economy and a long term prediction is required, a macroeconomic module is needed to predict the general economic evolution and that of each sector. Also, it must be taking into account that the relationship between variables can also evolve (for instance, not always the increase in GDP will mean the same increase in freight demand, the influence between both can change over time). For this purpose, it will be necessary to be able to integrate the prediction

into existing broader economic models or to have a consistent economic module of its own.

5. **Behavioral and decision-making aspects:** The behavior and decision-making processes of the multiple stakeholders in the freight industry can be difficult to model, particularly when these decisions are influenced by a wide range of factors, including cost, time, reliability, and personal preferences. Additionally, modelling the adaptive behaviour and the resulting shifts in demand when unexpected disruptions happens is complex and requires scenario-based approaches.

6. **Environmental and regulatory factors:** It is clear that in the current paradigm, if the environmental objectives set want to be met, a profound transformation of the sector will be required. Therefore, the prediction must include the effect of the measures of this transition or have the possibility of carrying out a scenario analysis in which the desired measures can be incorporated and their effects can be predicted.

These are the main challenges that characterise freight transport. Therefore, the aim of the thesis is to be able to detect which prediction techniques are the most suitable to overcome them in order to have a long-term freight forecasting model at European level.

2.3 Systematic Review

Since the main part of this work is based on a systematic review, this methodology is going to be generally defined, and then explained how it will be applied in this specific case in the following chapter.

A systematic review is a methodical and comprehensive approach to review the existing literature on a specific research question or topic [17]. It is applied in various fields such as healthcare, medicine, social sciences, engineering, environmental studies, etc.

This methodology involves a rigorous process of identifying, evaluating and synthesising all relevant studies to provide a clear and concise summary of the evidence available, minimising the risk of bias or subjectivity by using a structured and transparent process. Therefore, it provides a valuable summary that can be used as a resource for researchers and practitioners.

To begin with the review, it is necessary to clearly defined research questions, making a statement of the intention of the work and guiding the whole process in that direction. Then, it is required a plan for searching in literature, which involves identifying relevant databases, selecting appropriate searching keywords and establishing a criteria.

By searching for articles, it is not based just on a compilation of the literature, but rather on a critical attitude to select the most relevant articles, asking oneself whether the article is addressing the problem set, whether it is transparent and factual and whether it adds value to the question of the review. Throughout the review, one must understand the connections and relationships between the sources consulted, finding trends in the literature; debates, conflicts and contradictions; or even gaps, detecting areas that need to be addressed.

Once this has been done, a discussion will be carried out on the basis of all the results of the sources in order to make it the least subjective as possible, ending with the conclusion of the review in which the main findings will be underline.

Chapter 3

Methodology

This chapter will explain the methodology followed to apply a systematic comparison specifically for the case of freight transport prediction models in the framework indicated. In addition, the use of a software for the creation of bibliographic maps to support the search will be explained.

3.1 Systematic Multi-criteria Comparison

As mentioned in the previous chapters, the aim of this thesis is to collaborate with the development of freight transport demand forecasting models. To this regard, a systematic multi-criteria comparison is carried out in order to find the answer to which is the most suitable method for long-term forecasting at European level or potential tools to support this.

It covers from the forecasting methods that have been traditionally used related to the 4-stage model to the most innovative ones, with the intention of establishing the state-of-the-art of forecasting demand for freight transport. As discussed in the previous chapter, the prediction of this type of transport has certain characteristics and challenges, which is the reason why the comparison is based on 10 different categories, evaluating how these methods overcome such issues. In this way, they are given a score from 1 to 5 in each of the following categories:

1. **Accuracy.** How well the model predicts freight transport demand values. The most accurate long-term prediction method is required.

    - *Mean error*: Difference between actual values and forecast ones.

2. **Data requirements.** What type and amount of data does the model require? Data collection must be feasible and affordable.

    - *Data availability*: The accessibility of the data. Are the required data available from existing sources or does it need to be collected? Are these data easy to access, considering any legal, regulatory or ownership restrictions? Data may come from government databases, private companies, industry reports or other sources.
    - *Data quality*: Is the data accurate and does it add value? Is it consistent and trustworthy?
    - *Data granularity*: Required level of detail of information. Spatial granularity (local, regional, national level...); temporal granularity (daily, monthly, annually). Disaggregate or aggregate data.

3. **Scalability.** Can the model be applied in different scales? The scope of this work is a long-term European-wide model.

    - *Geographic*: Is it scalable spatially (local, regional, national or international)? Is it possible to adapt the model to a region other than the original one?
    - *Temporal*: Possibility to scale up to long-term forecasting.
    - *Operational*: Volume of data, complexity of networks, different type of commodities.

4. **Complexity.** How complex is the model to implement and maintain? The more complex it is, the more difficult it is to deal with.

    - *Implementation*: Effort required to develop/upgrade the model. Effort to collect, clean and prepare data for the model requirements. Complexity of structure and algorithms.
    - *Transparency*: Are the internal dynamics of the model understandable for the user? Does the model provide clear explanation for its outputs? Transparency is key for stakeholders to trust on the forecast.

5. **Cost-effective.** How expensive it is to develop, implement and maintain the model.

    - *Cost*: Computation, development, operation and data acquisition costs. Model must be economically feasible.

6. **Timeliness.** How quickly does the model provide results?

    - *Computation time*: Set up time, simulation time, update time, etc.

- *Update frequency*: How often are the model outcomes updated? How often should the model be recalibrated? Forecasting dealing with real-time data without having to recalibrate the model would be the ultimate level.

7. **Robustness.** How well does the model work in different situations? Considering the challenges of freight transport, it is very important to have a robust model. The possibility of carrying out scenario analyses makes it possible to assess in a climate of variability.

   - *Sensitivity analysis*: Does the model give reliable outcomes despite fluctuations of independent variables? The forecasting model should be able to handle different scenarios due to the possibility of potential economic crises, sudden spikes in demand, geopolitical tensions, etc.
   - *Data handling*: Can the model still give sufficiently accurate results despite incomplete information?
   - *Outliers detection*: Is the model sensitive to extreme values (outliers)? It is important that the model is not too sensitive to unusually rare values that may alter the overall results.
   - *Adaptability*: Model's ability to adapt to structural changes in logistic system due to dynamics, innovation and regulatory changes. Through scenario analysis it is possible to study the effects of potential changes in the system.
   - *Uncertainty assessment*: Does the model provides confidence intervals or other measures of uncertainty? Risk analysis is crucial to quantify the potential impact of uncertain factors.

8. **Interpretability.** The ultimate goal of a transport demand forecasting model is to be used as a tool for decision-makers, so its ease of use by non-expert users is important. It is recommended to have a user-friendly and intuitive interface for non-technical stakeholders.

   - *User friendly*: Facility to enter input data, run simulations and observe results. It is recommended to have a user-friendly and intuitive interface for non-technical stakeholders and a learning curve as small as possible.
   - *Communication of uncertainty*: Provide the user tools to understand the uncertainty of results.
   - *Result interpretation*: Are the results easy to interpret? Visual aids to show results help in the interpretation of results.

9. **Integration.** The possibility to integrate with other models always helps to potentially improve the model by combining the strengths of different methods. A modular structure facilitates integration.

- *Compatibility with other methods*: Ease of combination with different models, methods or tools.

10. **Functionality.**Level of detail of forecasting results.

- *Degree of details*: Not only quantify the demand, but also give additional valuable information related to the shipments such as type of container, type of goods, route, etc.
- *Granularity*: Degree of granularity of results (individual shipments or aggregated flows).
- *Scope*: More dimensions of the demand results apart from volume such as frequency of shipment, time of day when travel occurs, traffic congestion, environmental impact, etc. Additional features can add significant value for policy-makers.

These 10 categories will be filled in for each of the methods to be studied in a systematic way and rated on a scale of 5 according to the above criteria. Once all methods have been compared and their degree of implementation in existing models has been discussed, valuable conclusions for future research can be reached.

3.2 VOSviewer

VOSviewer is a software tool used for the creation and visualisation of bibliometric maps [18]. Specifically, VOSviewer is used in the analysis of bibliographic data networks and can handle large amounts of data to show relationships between different publications, authors, or terms. This software is used in this work to give an initial orientation of the systematic review, and can detect early evidence of trends.

Thus, there were gathered over 1000 publications extracted from the SCOPUS [19] scientific database, under the keywords Freight/Commodity, Forecast/Forecasting, Method/Model and Transport/Transportation, to be analysed with this bibliographic software. A bibliographic map is created with these publications showing the most recurrent terms and the relationship between them as shown in the Figure 3.1.

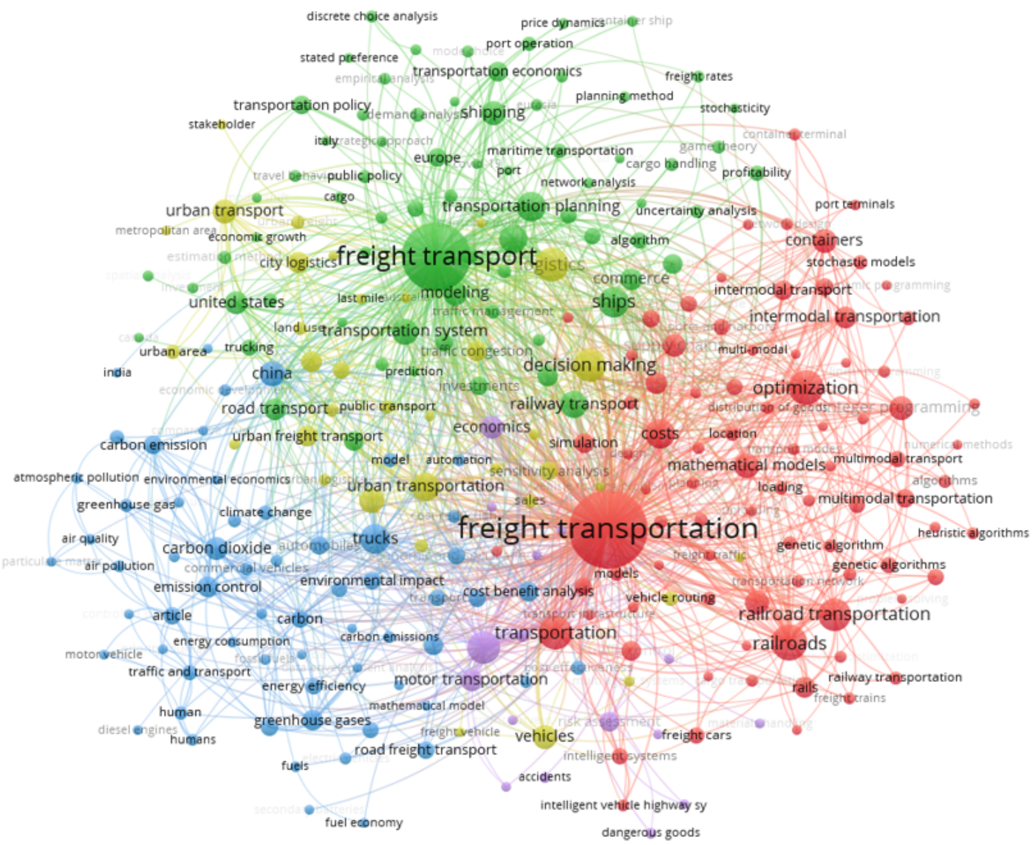

Figure 3.1: Initial bibliographic map

However, this first version of the map needs to be further processed as VOSviewer shows exactly the terms that appear in the publications, so it does not differentiate them semantically. In this way, terms that mean exactly the same, appear as independent as they are written differently, e.g. Freight Transport and Freight Transportation.

Therefore, by modifying the extracted dataset, terms referring to the same thing can be grouped together to obtain a cleaner and more visible version of the bibliographic map, making it easier to draw conclusions from it, Figure 3.2. After reducing the number of bubbles on the map to less than half with this new version, you can see that the terms are grouped into 5 families represented by different colours.

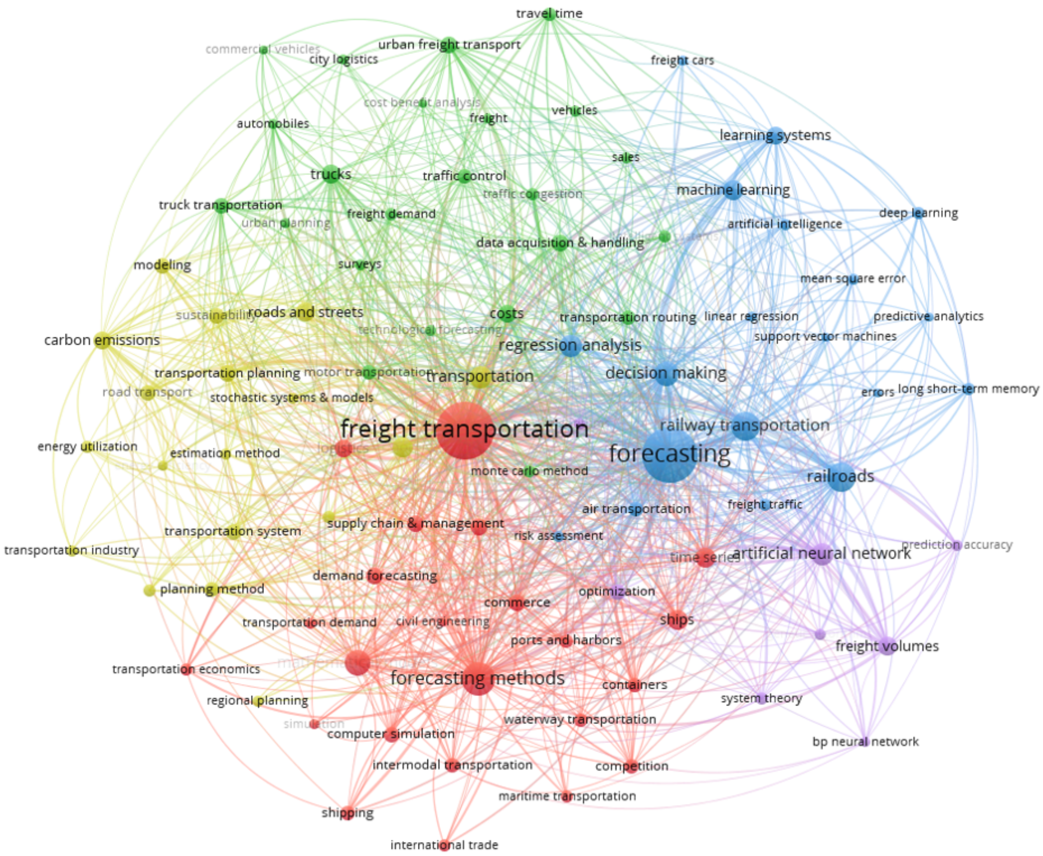

Figure 3.2: Filtered bibliographic map

Analysing these families can help us to identify topics which are relevant to research in the field of freight demand forecasting. So, they are briefly described below, mentioning some of their terms.

- **Green - Urban:** This group is related to the urban focus in the research of transport forecasting.
  - *Urban planning*
  - *City logistics*
  - *Traffic control*
  - *Commercial vehicles*

- **Yellow - Environmental concern:** This group shows the recurrence of terms referring to sustainability, which is aligned with the target of decarbonising the transport sector.
  - *Energy utilization*
  - *Carbon emissions*
  - *Sustainability*
  - *Transportation industry*
- **Red - Logistic system:** The transport network is an indispensable part of the forecasting process and therefore also plays an important role in the research.
  - *Supply chain*
  - *Logistics*
  - *Shipping*
  - *Intermodal transportation*
- **Blue - Forecasting methods:** Naturally, there are many terms referring to prediction methods.
  - *Regression analysis*
  - *Forecasting*
  - *Risk assessment*
  - *Decision making*
- **Purple - Advanced techniques:** The latter group reflects the growing importance of innovative computational techniques.
  - *Artificial neural network*
  - *Optimization*
  - *System theory*
  - *Prediction accuracy*

In addition, it can be displayed as a representation with the time dimension of these keywords. In this way, the newest terms to appear in the publications will have tones close to yellow and the oldest ones to blue. As can be seen in the Figure 3.3, most of the new terms refer to AI techniques (machine learning, learning systems, deep learning

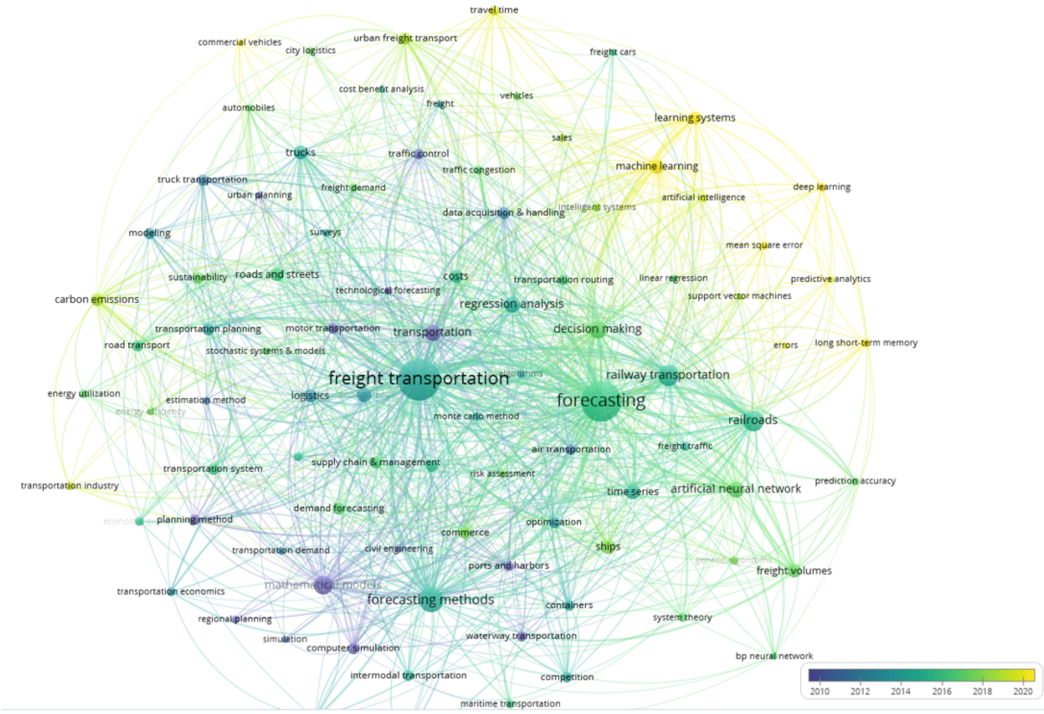

Figure 3.3: Temporal bibliographic map

or long short-term memory). It is remarkable that despite the recentness of these terms, they are already among the most recurrent in the field.

The use of a tool such as VOSviewer allows to easily identify the main research topics as well as new trends. After carrying out this bibliographic analysis, the trends mentioned in the literature chapter are reaffirmed with the growing concern for decarbonising transport, as well as the use of predictions as tools to help with decision-making.

Furthermore, the urban approach is also very present in freight transport research. Awareness of volatility and uncertainty also appears with the presence of terms such as risk assessment. It is also remarkable how the importance of research into artificial intelligence techniques has been growing in importance in recent years, for this reason, it forms an important part of this thesis. As well as other techniques that appear on the map and are evaluated in the next chapter.

Chapter 4

Systematic Comparison of Forecasting Techniques

Chapter 4 further elaborates on the systematic comparison of various forecasting techniques used in transport demand modeling, with a particular focus on freight transport. This chapter aims to provide a detailed analysis of the different methods, assessing their strengths and limitations through a structured evaluation framework.

Table 4.1: Forecasting techniques reviewed

Forecasting group	**Technique**
Time series	ARIMA
Econometric models	Regression analyses
	Gravity models
	Discrete choice models
	Equilibrium models
	4-stage model
	Cointegration and error correction models
	Vector autoregression
Simulation models	System dynamics models
	Agent-based models
AI/Machine learning models	Artificial neural network (ANN)
	Support vector machine (SVM)
	Random Forests (RF)

Table 4.1 is provided to categorize the different forecasting techniques into distinct groups, it serves as a roadmap for the chapter, guiding through the various methodologies that will be explored in detail. The techniques under review span across traditional approaches,

such as time series and econometric models, to more advanced methods, including simulation models, AI/Machine Learning models and optimisation techniques.

Each forecasting group is listed alongside representative techniques within each category. They will be examined in the context of their applicability to long-term freight demand forecasting within the European framework, as well as their potential to support the broader goals of decarbonisation and efficiency improvement in the transportation sector. The ultimate goal is to establish a comprehensive understanding of the state-of-the-art and identify the most suitable approaches for future development in freight demand forecasting.

4.1 Time Series

Time series forecasting is a foundational approach in the field of transport demand modeling. This method leverages historical data to project future demand based on time as the unique independent variable. Unlike other forecasting methods, time series analysis do not aim to explain the causal structure behind transport demand by establishing cause-and-effect relationships between various factors. Instead, it operates under the assumption that all factors influencing transport demand in the past will continue to remain with the same degree of influence in the future. For this reason, time series methods are most effective for short- to medium-term forecasting, where the assumption of continuity in influencing factors is more likely to hold true [11].

The general formula for a time series model can be expressed as follows:

$$Y_t = T_t + S_t + C_t + I_t \tag{4.1}$$

Where:

- Y_t is the observed value of the series at time t.
- T_t represents the trend component, reflecting the long-term progression in the data.
- S_t denotes the seasonal component, capturing regular, repeating short-term fluctuations.
- C_t is the cyclical component, which reflects medium- to long-term oscillations that are not of a fixed period.
- I_t represents the irregular or noise component, accounting for random variations that cannot be attributed to the other components.

The fundamental premise of time series forecasting is that the patterns observed in historical data such as trends, cycles and seasonal variations, are likely to persist. This assumption makes time series methods particularly suitable for scenarios where the external environment is relatively stable, and where the goal is to project future demand based on the continuation of past patterns.

Figure 4.1 below illustrates the key components of a typical time series, including the trend, cyclical component, and seasonal peaks. The trend represents the overall direction in which transport demand is heading. The cyclical component captures fluctuations around the trend , often in response to economic cycles. Seasonal peaks, on the other hand, are regular and short-term variations that repeat at specific intervals (monthly or quarterly time frames), typically driven by recurring events or conditions, such as holidays or weather patterns.

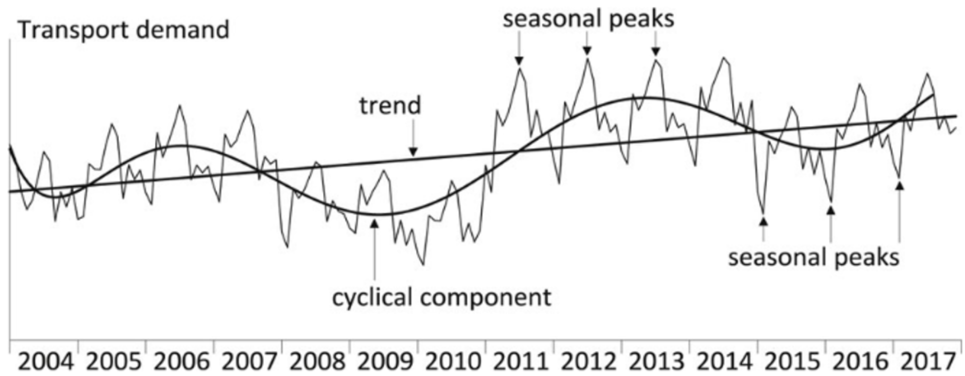

Figure 4.1: Time series components

As shown, time series models are able to accurately capture these components, making them valuable tools for understanding and forecasting transport demand within a defined time horizon. However, the reliance on historical data patterns also limits the applicability of time series due to the complexity and volatility of the freight transport system.

In the following section, it will be analysed the ARIMA time series, assessing its strengths and limitations in the context of freight transport demand forecasting. This analysis will provide a clearer understanding of when and how time series techniques should be applied, and how they can be integrated with other forecasting methods to improve accuracy and reliability.

4.1.1 ARIMA

Method Description

The ARIMA (AutoRegressive Integrated Moving Average) model is a powerful and versatile time series forecasting method that is widely used in various fields, including transport demand forecasting [11]. Although there are many types of time series, only ARIMA is analysed as it is the most commonly used and the most appropriate due to its ability to model a wide range of time series data with different characteristics, including non-stationary data, which is common in transport demand patterns.

The ARIMA model combines three key components: autoregression (AR), differencing (I for "Integrated"), and moving averages (MA) [11]. Each of these components plays a crucial role in capturing the temporal dependencies within a time series.

1. **Autoregressive (AR) Component**

   The AR component of the model represents a regression of the variable against its own previous values. The idea is that past values have a direct influence on future values.

   It is expressed as:

   $$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \epsilon_t \tag{4.2}$$

   where:

   - Y_t is the value of the time series at time t.
   - c is a constant term.
   - $\phi_1, \phi_2, \ldots, \phi_p$ are the coefficients of the autoregressive terms.
   - ϵ_t is the error term or white noise at time t.

   If p s the order of the autoregression, then the AR part of the ARIMA model can capture up to p lags of the time series data. This means that each Y_t is influenced by its previous p values.

2. **Integrated (I) Component**

   The integrated part of the ARIMA model is related to the differencing of the data to make it stationary. Stationarity is crucial for time series modeling as many statistical methods rely on the assumption that the time series is stationary.

   The differencing operation can be expresses as:

   $$\nabla^d Y_t = (1 - B)^d Y_t \tag{4.3}$$

   where:

   - $\nabla^d Y_t$ represents the differenced series at time t.
   - d is the order of differencing.
   - B is the backshift operator, where $BY_t = Y_{t-1}$.

Differencing removes trends and seasonality, which are non-stationary elements in the data. By differencing the data d times, the series becomes stationary, meaning that the mean, variance, and covariance are constant over time.

3. **Moving Average (MA) Component**

   It models the relationship between the observation and a residual error from a moving average model applied to lagged observations. It accounts for the noise in the series.

   This part is expressed as:

$$Y_t = c + \epsilon_t + \theta_1\epsilon_{t-1} + \theta_2\epsilon_{t-2} + \cdots + \theta_q\epsilon_{t-q} \tag{4.4}$$

   where:

   - Y_t is the value of the time series at time t.
   - c is a constant term.
   - $\theta_1, \theta_2, \ldots, \theta_q$ are the coefficients of the moving average terms.
   - ϵ_t is the error term or white noise at time t.

   The moving average part captures the impact of previous error terms on the current value. If q is the order of the moving average, the model accounts for q lagged error terms. This component helps in smoothing out the random fluctuations in the time series.

Combining these 3 components, the general ARIMA model can be expressed as:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \theta_1\epsilon_{t-1} + \theta_2\epsilon_{t-2} + \cdots + \theta_q\epsilon_{t-q} + \epsilon_t \tag{4.5}$$

If differencing is required, the complete ARIMA model is given by:

$$\nabla^d Y_t = c + \phi_1\nabla^d Y_{t-1} + \phi_2\nabla^d Y_{t-2} + \cdots + \phi_p\nabla^d Y_{t-p} + \theta_1\epsilon_{t-1} + \theta_2\epsilon_{t-2} + \cdots + \theta_q\epsilon_{t-q} + \epsilon_t \tag{4.6}$$

where:

- $\nabla^d Y_t$ is the differenced series at time t, where d is the order of differencing (I).
- c is a constant.
- $\phi_1, \phi_2, \ldots, \phi_p$ are the coefficients of the autoregressive terms.
- $\theta_1, \theta_2, \ldots, \theta_q$ are the coefficients of the moving average terms.

- ϵ_t is the error term (residual) at time t.

In notation, the model is often represented as *ARIMA(p,d,q)*, being the order of each component e.g. *ARIMA(1,0,2)*. Before applying this methodology, each of its parts must be identified and calibrated. To do this, first check whether the time series needs a differentiating part by performing a stationarity check, and then identify the degrees using the Autocorrelation function (ACF) and the partial Autocorrelation Function (PACF) [20][21].

On the other hand, the coefficients ϕ_i, θ_j and c have to be estimated, for which the Maximum Likelihood Estimation (MLE) is typically used. After fitting the model, the residuals are analysed to ensure that they behave like white noise, meaning that they have captured all the information from the data. For more information, this identification and calibration process is performed and explained in detail [11][20][21], this thesis focuses on the direct implication of the methodology, highlighting its strengths and weaknesses in freight demand forecasting.

Freight Forecasting Capabilities

Getting into the analysis of this technique, ARIMA models are relatively simple and interpretable, making them a practical choice for initial forecasting efforts in freight transport demand. Despite requiring some statistical knwoledge for the model's identification and calibration, the overall process is quite straightforward, allowing for easy interpretation of results as wells [22].

Regarding its accuracy, it can be a very precise method, considering its constraints. ARIMA models are particularly effective for short- to medium-term forecasts where the assumption that past patterns will continue holds true (relatively stable scenarios) [23]. Without being a very demanding method, it also requires sufficient samples of historical data to be efficient but it can be adapted to various types of time series data, including those with trends and seasonal patterns. This flexibility makes it a versatile tool in forecasting freight transport demand, which may exhibit seasonality due to economic cycles, holidays, or weather conditions.

While ARIMA models offer several strengths, particularly in their simplicity, statistical rigor and effectiveness for short- to medium-term forecasting, they are not without significant limitations. Firstly, in its limitation for long-term prediction. They are generally much less effective for long-term forecasting since they rely heavily on the assumption that historical patterns will persist into the future, which may not hold true over extended periods, especially in a dynamic environment like the EU, where policy changes, technological advancements and market shifts can significantly alter demand.

Its main strength, which is its simplicity, leads to these limitations. As it only uses the time variable, ARIMA models do not incorporate external variables that could influence freight demand such as economic indicators, fuel prices or policy changes, not being able to account for external shocks or structural changes that are not captured in the historical data.

Another major constraint is the need for stationarity (i.e., its statistical properties do not change over time). Many real-world time series, including freight transport demand, are non-stationary, requiring differencing or transformation before modeling, complicating the modelling procees and may reduce the model's effectiveness if not handled correctly. Attention must also be paid to the risk of overfitting the model to the historical data, especially if the model is overly complex (i.e., using a high number of AR or MA terms) since it can lead a great adjustment to the trainning data but poor performance with new data.

Taking into account all of these conditions, ARIMA can be effectively used to forecast short- to medium-term (over the next months up to $\approx$ 2 years) freight volumes on specific transport corridors or routes. Also as a tool for operational planning given its ability to model seasonality, companies involved in logistics and transportation can use ARIMA models for forecasting demand that fluctuates due to seasonal factors, such as increased freight volumes during holiday seasons or reduced demand during summer vacations helping companies to optimize fleet management, staffing levels, and inventory control.

There are some examples of ARIMA test scenarios [24], but in a stable environment and for the short-medium term, where the potential impact of minor regulatory adjustments can be estimated. Therefore, to further contribute to the main goal of this thesis, the only realistic option to use ARIMA models would be to integrate them into larger forecasting frameworks .

Therefore, to further contribute to the main goal of this thesis, the only realistic option to use ARIMA models would be to integrate them into larger models. The most viable options would be to integrate them with artificial intelligence techniques as in [20], in which ARIMA can be used to capture the linear structure of the data, and the machine learning component can handle the non-linear relationships. Or on the other hand, to econometric models (e.g. the 4-stage model) so that they predict demand based on economic theory, while ARIMA can model the residuals from these predictions to correct for any unmodeled time series patterns.

Multi-criteria Systematic Comparison

Table 4.2: Systematic evaluation of ARIMA

Accuracy ★★★⯪☆	+	ARIMA models are accurate for short- to medium-term forecasts in relatively stable environments.
	-	In long-term forecasting, their accuracy diminishes due to the model's reliance on historical data and its inability to predict structural changes in the system. Limited accuracy in dynamic environments like the EU transport sector.
Data Requirements ★★⯪☆☆	+	It doesn't require very specific data to model the demand, quite adaptable to different data set.
	-	It still needs a robust set of historical data to perform well. Its performance deteriorates if the historical data is incomplete or unrepresentative of future conditions.
Scalability ★★★☆☆	+	Geographically scalable, example of national forecast [24]. Always considering the stability and time horizon constraints.
	-	Despite being technically possible to have spatially and temporally a scalable model , its accuracy decreases that much in long-term that makes that not convenient. It doesn't perform well in complex systems with multiple variables (multivariate time series) and extending it to large datasets with many variables.
Complexity ★★⯪☆☆	+	Despite being more sophisticated than simple moving averages, it is quite simple compared to other forecasting methods. Practical solution for initiators in forecasting.
	-	Reasonable statistical background may required to correctly applied the model.
Cost-effective ★★★★⯪	+	Low computational power required. Simple model to develop and run with standard statistical software. Attractive option for organizations with limited resources.
	-	Since its short time horizon, it is required periodic re-calibration and validation with minimal additional cost.
Timeliness ★★★★⯪	+	Quickly to implement. It provides timely forecasts easily once the model is established. Suitable for constant short- to medium-term decision-making.
	-	Adjustments required if the model is not valid anymore due to external factors.

Robustness ★★⯪☆☆	+	ARIMA models are robust when applied to stable, well-understood systems.
	-	Their robustness is limited in long-term forecasting, where unforeseen changes in the external environment (e.g., regulatory changes, economic shifts) can lead to significant deviations from predicted values. This makes ARIMA less reliable for long-term strategic planning in a volatile European transport market.
Interpretability ★★★★★	+	One of the key strengths of ARIMA is its interpretability. The model's parameters have clear meanings (e.g., autoregressive terms, differencing order), which makes it easier for analysts to understand and communicate the results. Simplicity is key for interpretability.
	-	Limited tools to communicate uncertainty of results, but the core results are clear.
Integration ★★★⯪☆	+	ARIMA can be integrated with other models to enhance its functionality, such as combining it with machine learning models or econometric approaches to account for external variables. Many examples in literature research, interest in using ARIMA's accuracy and simplicity for short-term.
	-	Such integrations can be complex and require careful calibration. ARIMA struggles to handle multivariate time series without significant modifications.
Functionality ★★☆☆☆	+	ARIMA is highly functional for capturing trends and seasonality in time series data.
	-	It doesn't add any valuable information that could be use by decision-making apart from the forecast values of demand.

In conclusion, the ARIMA model has proven to be a powerful and versatile tool for time series forecasting in the context of freight transport demand. Its ability to model a wide range of data characteristics, including non-stationary time series, makes it particularly useful for predicting demand patterns that exhibit trends and seasonality. The ARIMA model is relatively simple to implement and interpret, which adds to its practicality in real-world applications, it makes ARIMA a good choice for initial or low resource practitioners (keeping in mind its constraints).

However, the ARIMA model is most effective for short- to medium-term forecasting, where the assumption that past patterns will continue into the future holds true. This limitation means that while it can provide accurate predictions in stable environments, it may struggle to account for sudden changes or disruptions in freight transport demand due to unexpected events or shifts in external conditions. Therefore, while ARIMA is still useful for forecasting, it is often best used as support tool in conjunction with other methods or models that can capture more complex, non-linear or dynamic behaviors in the data. This complementary approach can help provide a more comprehensive and robust forecasting solution, particularly in the face of increasing uncertainty in the global economic landscape.

4.2 Econometric Models

Econometric models are essential tools in transport demand forecasting, offering a methodical approach to understanding and predicting how various economic factors influence freight transport activity. These models are designed to establish a relationship between causes (driving forces) and their effects on transport demand, enabling researchers and policymakers to quantify the impact of key economic indicators such as GDP, fuel prices, industrial production, and trade volumes on freight transport systems. By incorporating economic theory into the modeling process, econometric models aim to establish cause-and-effect relationships, building a deep analysis of the interactions between these variables, to provide valuable insights for long-term forecasting and policy planning [11].

In the context of freight transport, the application of econometric models is particularly valuable due to the sector's close ties to economic activities. Freight transport demand is inherently influenced by the production and consumption patterns that drive the movement of goods [25]. Therefore, understanding how these economic indicators interact with freight demand is crucial for making informed decisions about infrastructure investments, logistics planning, and policy development.

One of the notable advantages of econometric models in freight transport forecasting is their ability to achieve high accuracy with a relatively small number of independent variables. Research has shown that a well-constructed econometric model, with carefully selected variables, can offer robust forecasting capabilities while maintaining simplicity [26]. As previously explained, as the number of variables and the complexity of the model increase, so does the risk of systematic error due to the assumptions required to build the model, making crucial to balance complexity and simplicity to minimise errors and improve the model's reliability [12].

These models are particularly well-suited for scenarios where there is a strong and demonstrable relationship between independent variables (such as economic indicators) and the dependent variable (freight transport demand). For example, a clear link between GDP growth and increased demand for freight services can provide a solid foundation for forecasting. However, for these models to be effective in long-term predictions, it is essential that future values of each independent variable can also be forecasted accurately (it is required not only quality historical data, but also quality projections of these variables). This requirement highlights the need for specialised staff who can not only build and calibrate these models but also ensure the availability and accuracy of data over a long period, as well as the accuracy of the underlying assumptions.

As it can be noticed, building an econometric model for freight transport is a resource-intensive process, requiring substantial effort, expertise, and accurate data. Therfore, econometric models should be employed primarily in situations where simpler methods do not provide satisfactory results. They are best utilized in complex freight transport scenarios where the relationships between variables are clear, the data is reliable, and the stakes of the forecast are high, such as in strategic planning for freight corridors, logistics optimisation and national infrastructure development.

Throughout this chapter, several key econometric models will be reviewed, including regression analysis, which forms the basis for many econometric techniques by modeling the relationship between dependent and independent variables. We will also explore discrete choice models, which are particularly useful for understanding and predicting the choices made by stakeholders within the transport sector, such as mode choice or routing decisions. Additionally, gravity models will be discussed, which are commonly used to forecast the flow of goods between different regions based on economic size and distance. Vector Autoregression (VAR), which allow for the simultaneous analysis of multiple relationships between variables, and cointegration and error correction models, which help in understanding long-term equilibrium relationships, will also be covered. These models, together, provide a comprehensive toolkit for analysing and forecasting freight transport demand, each offering unique strengths depending on the specific context and objectives of the study.

The complexity and size of econometric models can vary significantly depending on the specific problem being addressed. It is important to note that econometric models typically integrate more than one of the techniques discussed in this chapter. These methods are not independent solutions but are often complementary, working together to provide a more comprehensive and accurate analysis. By combining these techniques, econometric models can better capture the multifaceted relationships that influence freight transport demand, ultimately leading to more robust and reliable forecasts.

4.2.1 Regression Analyses

Method Description

Regression analysis is a fundamental technique within econometric models, widely used in the field of transport demand forecasting to explore and quantify the relationship between dependent variables, such as freight transport demand and one or more independent variables, such as economic indicators, fuel prices or industrial output. This statistical method is key for understanding how changes in specific factors influence transport demand, allowing for the development of predictive models that can inform decision-making and policy development in the transport sector.

In the context of freight transport, regression analysis is used as a powerful tool to identify and measure the impact of key drivers of demand. For instance, by analyzing historical data, a regression model can help determine how fluctuations in GDP, trade volumes, or fuel costs affect the volume of goods transported by road, rail, or sea. This understanding is critical for forecasting future demand, optimizing logistics operations, and planning infrastructure investments.

Depending on the number of variables, the need to linearize or the interaction between variables there are various types of regression techniques [11]. These are one of the most common:

1. **Simple Linear Regression**

   In its simplest form, regression analysis can be applied to model the relationship between a single independent variable and a dependent variable. For instance, modelling the relationship between GDP and freight transport demand:

   $$Y_t = \beta_0 + \beta_1 X_t + \epsilon_t \tag{4.7}$$

   where:

   - Y_t is the dependent variable (e.g., freight demand) at time t.
   - X_t is the independent variable (e.g., GDP) at time t.
   - β_0 is the intercept of the regression line, representing the baseline level of Y_t when X_t is zero.
   - β_1 is the slope of the regression line, indicating the change in Y_t for a one-unit change in X_t.
   - ϵ_t is the error term, capturing the influence of other factors not included in the model.

2. **Multiple Linear Regression**

   Normally, freight demand is influenced by multiple factors simultaneously. A multiple linear regression model extends the simple regression by including more independent variables. In this case, the freight transport demand is model based on multiple variables such as GDP, fuel prices, population, etc.

   $$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \cdots + \beta_n X_{nt} + \epsilon_t \tag{4.8}$$

   where:

   - Y_t is the freight transport demand at time t.
   - $X_{1t}, X_{2t}, \ldots, X_{nt}$ are the independent variables at time t (e.g., GDP, fuel prices, industrial output).
   - β_0 is the intercept of the regression line.

- $\beta_1, \beta_2, \ldots, \beta_n$ are the coefficients of the independent variables to be estimated, indicating the change in Y_t for a one-unit change in each corresponding X_{it} while holding other variables constant.
- ϵ_t is the error term.

3. **Log-Linear Regression**

   When there is no linear relationship but exponential, it is possible to logarithmize it. For instance, the impact of GDP growth on freight demand might increase at an increasing rate. A log-linear regression model is useful in such scenarios.

$$\ln(Y_t) = \beta_0 + \beta_1 \ln(X_{1t}) + \beta_2 \ln(X_{2t}) + \cdots + \beta_n \ln(X_{nt}) + \epsilon_t \tag{4.9}$$

   where:

   - $\ln(Y_t)$ is the natural logarithm of the dependent variable at time t.
   - $\ln(X_{1t}), \ln(X_{2t}), \ldots, \ln(X_{nt})$ are the natural logarithms of the independent variables at time t.
   - β_0 is the intercept.
   - $\beta_1, \beta_2, \ldots, \beta_n$ are the elasticities,meaning they show the percentage change in freight demand for a 1% change in each corresponding X_{it}. This type of model is particularly useful when the relationship between the variables is multiplicative rather than additive.
   - ϵ_t is the error term.

Having presented the different types of regression, the process of calibration and validation of these regressions is briefly explained. If a more detailed clarification is needed, it is explained extensively in [11].

Calibration is the process of estimating the parameters (β coefficients) of the regression model. This involves using historical data to find the values of the coefficients that minimize the difference between the observed data and the model's predictions. The most common method for calibration is Ordinary Least Squares (OLS), which minimises the sum of the squared differences between the observed and predicted values. However, it can be used more complex method if OLS doesn't meet the statistical requirements [27].

Steps in calibration include:

- **Data preparation:** Collecting and organizing historical data on both dependent and independent variables.
- **Model specification:** Choosing the appropriate form of the regression model based on the nature of the data and the relationships being studied.

- **Estimation of coefficients:** Using statistical software to apply the OLS method and estimate the coefficients $\beta_1, \beta_2, \ldots, \beta_n$.
- **Diagonistic checks:** After estimation, it's crucial to check the assumptions of the regression model, such as linearity, homoscedasticity (constant variance of errors), and absence of multicollinearity (independence among predictors) by a statistical validation.

Statistical validation is essential to ensure that the regression model is reliable and that the estimated relationships are not due to random chance. Key steps in validation include:

- **Goodness-of-fit:** R-squared (R^2) measures the proportion of variance in the dependent variable that is predictable from the independent variables. A higher (R^2) value indicates a better fit.
- **Significance test:** t-tests is used to assess whether individual regression coefficients ($beta_i$) are significantly different from zero, indicating a meaningful relationship between the independent and dependent variables.
- **Residual Analysis:** Plotting residuals (the differences between observed and predicted values) helps to check for patterns that indicate issues like non-linearity or heteroscedasticity.
- **Multicollinearity:** Variance Inflation Factor (VIF) measures the extent to which the variance of a regression coefficient is inflated due to multicollinearity. High VIF values suggest that independent variables are highly correlated, which can distort the model.

A reminder that training data to calibrate the model must be different to the data to tests its forecasting accuracy. Once a regression model has been calibrated and validated, it can be used to make predictions and inform decision-making. The interpretation of the regression coefficients provides insights into the magnitude and direction of the impact that each independent variable has on the dependent variable. For example, in a freight demand model, a positive coefficient for GDP would indicate that as GDP increases, freight demand is expected to rise.

Freight Forecasting Capabilities

As time series, regression models, particularly simple linear regression (SLR) and multiple linear regression (MLR), are straightforward to implement and interpret. These models provide clear insights into the relationships between independent variables such as economic indicators, and dependent variables like freight demand [28]. This simplicity and interpretability makes them accessible to a wide range of users, from policymakers to analysts [29].

Regression models provide quantitative measures of the relationships between variables, such as the strength and direction of influence (e.g., coefficients in MLR). These insights can be used to optimise decision-making processes and allocate resources effectively. Also, these techniques are versatile and can be applied across different regions and contexts, making them a reliable tool in various scenarios.

Referring to its accuracy, it is highly effective for short- to mid-term forecasting, where historical relationships between variables are expected to remain stable. This makes regression techniques particularly useful for operational and tactical planning in freight transport. However, while MLR can handle multiple variables, it may struggle to capture the complexity of freight demand, influenced by countless amount of non-linear socio-economic and environmental factors, limiting their effectiveness for long-term strategic forecasting. Additionally, environments where structural changes and external shocks are likely, regression models may not perform well due to their reliance on historical data.

This reliance also makes regression models potentially sensitive to outliers, which can disproportionately affect the model's predictions. This is particularly problematic in freight transport, where unexpected events (e.g., natural disasters, economic crises) can create significant outliers in data. Taking into account these limitations, regression analyses are still valid for plenty uses.

They can act as a tool to establish baseline forecasts for freight demand based on economic indicators like GDP, industrial production, or fuel prices. These baseline forecasts can be used to compare the performance of more advanced models, serving as a benchmark. Scenario analysis is another possibility since regression models are well-suited for scenario analysis, where you explore how changes in key variables impact freight demand. Sensitivity analysis as well, since they can further identify which variables have the most significant effect on demand, providing insights into potential risks and uncertainties.

These regression techniques are the foundation because of their simplicity and adaptability. This is reason why often they are found as an integrated tool in larger models rather than being used alone. They can be integrated into bigger econometric model such as the 4-stage model, being used for the freight generation in the first step or they can be integrated into more sophisticated models like Vector Autroregression (VAR), to analyse the impact of policy changes or economic shocks on freight demand.

Also, regression analysis can be integrated with machine learning techniques to create hybrid models that leverage the strengths of both approaches. Regression can serve as a feature selection tool, identifying the most relevant variables for inclusion in a machine learning model, which can capture more complex, non-linear relationships. In the same way, it can be part of simulation models, participating in the economic factors projections.

Finally, regression analysis can also combine with ARIMA to create a more complex time series model like ARIMAX (ARIMA with exogenous variables, external factors that can affect the dependent variable like economic indicators). These models considers both historical trends and external influences improving the performance of ARIMA and even outperforming the more sophisticated model VAR in certain cases [30].

Multi-criteria Systematic Comparison

Table 4.3: Systematic evaluation of regression analyses

Accuracy ★★★☆☆	+	Reasonably accurate short- to mid -term forecasts when the relationships between the dependent and independent variables are well understood and stable.
	-	Its accuracy can diminish over the long term, especially if the underlying relationships change over time or if the model is overfitted to historical data.
Data Requirements ★★⯪☆☆	+	The common variables used are reasonably available. Its accessibility depend on the scope and specific variables. European economic indicators should be accessible.
	-	It requires a significant amount of historical data to identify and quantify relationships between variables. High quality data is required for better precision and reliability. Missing or noisy data can significantly affect performance.
Scalability ★★★☆☆	+	Regression models are relatively scalable in terms of geographical scope, being able to use it across regions. They can handle a broad range of operational scales
	-	They may struggle with scaling over time, particularly for long-term forecasts. When handling with broad range of operational scales (Different types of commodities, for instance), it might be limited when dealing with highly complex networks or extremely large datasets.
Complexity ★★★☆☆	+	It requires more knowledge and effort than simple time series but the implementation is relatively straightforward. Transparency high, easy to interpret its dynamics.
	-	Its complexity increases with MLR or non-linear ones. As the number of independent variables increases, multicollinearity and overfitting can become significant challenges, adding to the model's complexity
Cost-effective ★★★★⯪	+	It requires fewer computational resources and is relatively inexpensive to develop and maintain, especially when the data is readily available, making it accessible for most applications
	-	Depending on the scope, some minimal data collection should be done and a bit more expertise in transport forecasting than in time series.

Timeliness ★★★★★	+	Regression models can provide results relatively quickly, especially for short- and mid-term forecasts. They require less computation time compared to more complex models.
	-	Updating might be necessary due to its long-term limitation, but are also relatively easy.
Robustness ★★★☆☆	+	Robust in short- to medium- term well-understand systems. Moderate sensitivity analysis could be done due to the elasticity concept, but may require frequent recalibration.
	-	Regression models may not be highly robust in the face of significant variability or uncertainty in the data. They are sensitive to outliers and may not perform well in highly dynamic environments without frequent recalibration. Limited adaptability to structural changes.
Interpretability ★★★★★	+	One of the main strengths of regression analysis is its interpretability. The model's results are easy to understand and can be communicated effectively to stakeholders, making it a user-friendly tool.
	-	Limited tools to communicate uncertainty of results, but the core results are clear.
Integration ★★★★☆	+	Regression models can be easily integrated with other methods, such as time series models or more complex econometric models, to improve forecasting accuracy.
	-	However, their integration with non-linear models or simulations can be challenging due to the different underlying assumptions.
Functionality ★★☆☆☆	+	Regression models provide detailed results in terms of the relationship between variables, elasticities.
	-	Lack granularity in terms of predicting specific outcomes like shipment routes or types of goods. Their scope is generally limited to the variables included in the model.

Regression analysis is a practical and cost-effective tool for short- to mid-term freight transport demand forecasting, particularly when relationships between variables are well-understood and stable. However, its limitations in handling variability, long-term forecasting, and complex interactions suggest that it is best used in conjunction with other methods, particularly in more dynamic and uncertain environments. As time series, they are not robust enough to be used as single method, so they should be limited to complementary tools particularly within the broader framework of long-term freight demand forecasting in the European Union.

4.2.2 Gravity Models

Method Description

Gravity models are widely used in various fields, including economics, geography, and transportation, to predict and analyze flows between different locations [11]. The model is inspired from Newton's law of gravitation, which states that the gravitational force between two objects is directly proportional to their masses and inversely proportional to the square of the distance between them. Analogously, in the context of freight transport, the flow of goods between two locations is considered to be directly proportional to the economic "mass" (such as population, GDP, or industrial output) of these locations and inversely proportional to the distance between them. This method has been traditionally used for transport forecasting since the last century and particularly for freight transport as its main drivers are economic, in line with the nature of this model.

Adapting the original formula to the freight transport context [13]:

$$F_{ij} = G \times \frac{M_i \times M_j}{D_{ij}^n} \tag{4.10}$$

where:

- F_{ij} is the flow of goods between region i and region j.
- M_i is the economic mass of region i (e.g., GDP, population, industrial output).
- M_j is the economic mass of region j.
- D_{ij} is the distance between region i and region j, which may also represent generalized transport costs, travel time, or other measures of separation.
- G is the proportionality constant that scales the relationship between the masses and distance to fit the observed data.
- n is the distance decay exponent, indicating how sensitive the freight flow is to changes in distance.

Freight transport is often driven by economic considerations—such as cost minimization and efficiency—distance (or more broadly, the cost associated with moving goods) plays a critical role in determining the volume of trade between regions. Gravity models' inclusion of distance as a key variable captures the economic trade-offs inherent in freight transport decisions, where longer distances typically reduce the volume of goods traded due to higher transportation costs.

Freight Forecasting Capabilities

Gravity models are known for their simplicity and ease of use, their straightforward mathematical framework links economic mass, such as GDP or population, and distance to predict the flow of goods between regions. This simplicity not only makes gravity models accessible to a wide range of users, including policymakers and planners, but also allows for quick insights when data availability is limited. Additionally, gravity models have been extensively validated across different contexts, particularly in trade and transport studies, which reinforces their reliability and trustworthiness.

Another significant advantage of gravity models is their scalability. They can be easily adapted to different geographical levels, whether analyzing inter-city, inter-regional, or international freight flows. This scalability makes them versatile and applicable to various stages of transport planning, from local infrastructure development to the assessment of international trade agreements. Moreover, gravity models align well with the economic factors that drives freight transport, enhancing the model's relevance, especially in scenarios where economic considerations dominate freight movement, such as in trade corridors or regional logistics planning.

However, gravity models also have limitations. They may oversimplify the complexities of freight transport by focusing mainly on distance and economic mass, potentially overlooking other critical factors such as infrastructure quality, transport modes, or regulatory environments. This can lead to inaccuracies, especially in diverse regions like the European Union, where transport infrastructure and regulations vary significantly.

Traditional gravity models are also static, meaning they do not account for changes over time unless specifically modified, limiting their usefulness in long-term forecasting or rapidly changing environments. Furthermore, gravity models often assume that all regions and flows are homogeneous, an assumption that may not hold true in reality. Different goods, transport modes, or regional characteristics can significantly influence freight flows.

Additionally, gravity models do not account for the decision-making processes of individual agents, such as shippers or carriers, who may be influenced by various factors beyond economic mass and distance. This lack of behavioral insights limits the model's ability to predict changes in behavior due to policy interventions, economic shocks, or technological advancements.

As regression analyses, gravity models can serve as a valuable baseline forecasting tool, establishing a reference point for comparing more complex models and conducting scenario analysis. For example, gravity models can be used to explore how changes in economic mass such as GDP growth, population changes or distance-related costs like fuel price changes or infrastructure improvements, might affect freight demand. This makes them particularly useful in analyzing the impact of trade barriers or new infrastructure in the European Union.

Gravity models can also be integrated with other forecasting techniques to address some of its limitations. For instance, econometric techniques can help to include exogenous variables like tariffs, exchange rates, or policy changes. This integration is already well-developed and commonly used in trade and transport economics, incorporating more detailed relationships and improving the overall accuracy [31]. Also, the static nature of traditional gravity models, they can be integrated with dynamic models that account for changes over time (adding a time component or as a part of a dynamic simulation model). Dynamic gravity models are an emerging area of research, increasingly applied in long-term transport planning and forecasting [32].

Regarding a possible integration with AI techniques, it could be used to adjust the gravity model's parameters in real-time or identify complex patterns in freight demand data that can be incorporated into the model. This integration is still experimental but shows promise, particularly in complex and dynamic environments like multimodal transport systems.

Multi-criteria Systematic Comparison

Table 4.4: Systematic evaluation of gravity models

Accuracy ★★☆☆☆	+	Moderate accuracy for short- to medium- term, particularly for regional or national freight forecasting where economic mass and distance are primary determinants.
	-	Accuracy dependent on stability of economic and distance factors, also it is potentially lower for long-term, especially if key factors change over time. Their accuracy can be compromised in cases where other significant factors, such as infrastructure quality or political barriers, are not accounted for.
Data Requirements ★★☆☆☆	+	Economic indicators (e.g., GDP, population) and distances between regions are generally accessible and straightforward to collect.
	-	Necessary some disaggregation of data to take into account distance factor (disaggregation at a regional or national level). Generalized transport costs and other measures of distances becomes a bit harder to collect, for a gravity model type more complex
Scalability ★★★★☆	+	Highly scalable across different geographical scales, from local to global. Easily adapted to different regions, making them versatile tools in freight transport forecasting. Effective for various types of goods and modes of transport.
	-	It is not temporally scalable due to its limitations in capturing temporal dynamics over long periods.
Complexity ★⯪☆☆☆	+	Simple in terms of structure and implementation. Their assumptions are easy to understand, making them accessible to policymakers and practitioners.
	-	Recent models such as dynamic gravity models implies more complexity but it remains being more simple than most of the models.

Cost-effective ★★★★★	+	Gravity models are cost-effective due to their simplicity and the low data and computational requirements. They can be implemented quickly with existing data, making them a practical choice for initial analyses. Model does not require extensive recalibration due to its static nature.
	-	
Timeliness ★★★★★	+	Gravity models provide forecasts quickly, given their straightforward structure. They are suitable for generating timely insights, particularly when quick decisions are needed based on readily available data. Easy to update with new data.
	-	
Robustness ★★☆☆☆	+	Gravity models are moderately robust.
	-	Limited capturing complexity. No uncertainty assessment, primarily deterministic. The assumption that distance always inversely affects freight flows may not hold in all cases, particularly in complex, multimodal networks.
Interpretability ★★★★★	+	The relationship between economic size, distance, and freight flow is intuitive and easy to communicate, making the model results accessible to non-experts.
	-	Limited tools to communicate uncertainty of results, but the core results are clear.
Integration ★★★☆☆	+	Gravity models can be integrated with other methods, such as econometric models or simulation techniques
	-	Integration possible but may require adjustments.
Functionality ★★☆☆☆	+	Gravity models are functional for estimating flows of different commodities between regions based on economic mass and distance.
	-	No additional features for stakeholders. Basic degree of details in its outcomes, focusing on macro-level (aggregate) interactions. Effective for broad predictions but lacks specificity in complex scenarios.

The gravity model has established itself as a tool in freight transport demand forecasting due to its simplicity, empirical validation, and alignment with economic drivers. It effectively captures freight demand in well-suited for scenarios where economic activities are the primary drivers of freight flows. However, the model's simplicity can also be a limitation, as it may oversimplify complex real-world factors, such as infrastructure quality and behavioral aspects.

While the gravity model provides valuable baseline predictions, its static nature and assumptions of homogeneity necessitate integration with more sophisticated models for long-term forecasting, therefore it remains valuable component of a broader forecasting strategy.

4.2.3 Discrete Choice Models

Method Description

Discrete choice models are a vital tool in transport demand forecasting, offering a detailed and disaggregate approach to understanding and predicting the decision, making behavior of individual agents, such as shippers, carriers or consumers. These models are based on the concept of utility maximisation, in freight transport, decision-makers are assumed to select the transport option that provides them with the highest utility, considering factors like cost, time, reliability and service quality [11].

Therefore, what distinguishes discrete choice models is their disaggregate approach, which focuses on individual decision-making processes rather than aggregate trends, allowing for a deeper analysis of how different factors influence choices at micro-level. These models are able to incorporate qualitative data from sources such as State Preferences/Revealed Preferences (SP/RP) surveys, providing detailed insights into the preferences and motivations of decision-makers, which can then be quantified and integrated into the model. Thus, discrete choice models can better capture the subjective aspects of decision-making that are not easily observed in quantitative data alone.

The general form of a discrete choice model can be expressed as:

$$P_i = \frac{e^{V_i}}{\sum_{j=1}^{J} e^{V_j}} \tag{4.11}$$

where:

- P_i is the probability that a decision-maker chooses alternative i from a set of J alternatives.
- V_i is the systematic or deterministic component of the utility associated with alternative i. It is typically modeled as a linear combination of the attributes of the alternative:

$$V_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_k X_{ik}$$

- $X_{i1}, X_{i2}, \ldots, X_{ik}$ are the attributes of alternative i (such as cost, time, reliability).
- $\beta_1, \beta_2, \ldots, \beta_k$ are the coefficients representing the importance or weight of each attribute in the decision-making process.
- e is the base of the natural logarithm.
- J is the total number of alternatives available to the decision-maker.

Additionally, the total utility U_i of alternative i is composed of:

$$U_i = V_i + \epsilon_i \tag{4.12}$$

where:

- U_i is the total utility of alternative i.
- V_i is the deterministic component of utility (as described above).
- ϵ_i is the stochastic or random component of the utility, which captures the unobserved factors affecting the decision.

Some of the most common discrete choice models are:

- **Multinomial Logit Model (MNL):** It is the most widely used type of discrete choice model. It assumes that the probability of choosing a particular alternative is based on the relative utility of that alternative compared to others. It is computationally efficient and commonly used for mode choice analysis [33].
- **Nested Logit Model (NL):** The NL model relaxes the independence of irrelevant alternatives (IIA) assumption by grouping similar alternatives into "nests." This model is particularly useful when the choices are not independent but rather share some common factors or characteristics [33]. Alongside MNL, these are the most commonly used methods for the freight transport.
- **Mixed Logit Model:** Also known as the Random Parameters Logit Model, it allows for random variations in preferences across individuals. The coefficients change across decision-makers, capturing unobserved heterogeneity. They are used in situations where individual preferences vary significantly, for instance, passenger transport.

Comparing with previous described techniques which were generally deterministic and using and aggregate approach, discrete choice models is a micro-modelling approach (disaggregate) with some degree of stochasticity. They are particularly useful for modeling choices such as mode choice, size choice, route selection and carrier choice, being able to predict, for instance, how changes in fuel prices or the introduction of new regulations will influence the choice between different transport modes [34][35].

Freight Forecasting capabilities

Discrete choice models plays a main role in disaggregate freight transport modelling as they provide deep insights into the decision-making processes of various stakeholders in freight transport, such as shippers, carriers, and logistics providers. One of its main strengths is the ability to incorporate behavioural factors to the forecasting (particularly useful in freight transport because of the difficulty of modelling subjective aspects from data) by using sources such as the Swedish Commodities Flows Survey (CFS) [36], quantifying the influence of different factors in the choice.

This behavioural insights becomes vital in complex logistic environments since by modeling the choices between different alternatives (e.g., mode of transport, route selection), these models help in understanding the trade-offs that decision-makers consider, such as cost versus time or reliability versus flexibility. This approach is really powerful for micro-simulation approaches and for having a model with strong robustness.

As stated, these models can be applied to a wide range of decision-making scenarios (mode, size, route, shipper, etc.), this flexibility makes them particularly valuable for capturing the complexities of the freight transport system. Furthermore, it gives them the ability to be highly effective for evaluating the impact of policy changes, for instance, they can be used to predict how changes in fuel prices, new regulations or infrastructure investments will affect the mode choice behavior of shippers, thereby influencing overall transport demand.

However, this micro-approach leads to the two main disadvantages of this kind of tool, the data requirements and the increasing complexity. Modelling the decision choice requires detailed data on the attributes of all alternatives and the preferences of decision-makers. Not only collecting and maintaining this data can be challenging, especially in freight transport, where data may be distributed across various private stakeholders, but also this micro-simulation approach implies modelling single decision, leading to bigger computation requirements and increased complexity. This complexity can make the models difficult to interpret and validate, especially when integrating them with other forecasting techniques.

This type of model is currently one of the main research topics in freight transport demand forecasting due to its behavioural and micro-simulation approach, which is why its integration with other models has also been developed, to take advantage of these two major assets. Currently, the integration of discrete choice models into broader econometric and simulation models are both well-developed and commonly used in both academic research and practical applications and this integration is increasingly sophisticated since they are still working on that.

On the hand, integrating with econometric models is valuable due to providing a more comprehensive understanding of how macroeconomic variables influence individual decision-making processes. This integration allows researchers to capture both the broader economic trends and the specific choices made by individual actors within the transport system.

On the other hand, the integration with simulation models is useful to explore the dynamic interactions between different stakeholders in the freight transport system. Therefore, discrete choice models are used to determine how individual agents (e.g., shippers, carriers) make decisions in response to changes in the environment, such as policy interventions or infrastructure developments, allowing a detailed analysis of how individual choices aggregate to influence overall system behavior. This approach is gaining importance, especially in studies focused on long-term strategic planning an scenario analysis, suiting with the objective of this thesis.

Both approaches have promising characteristics for long-term analysis, which is the reason they are already implemented in many of the current models in practice and research is ongoing to improve their performance. This integration and applicability will be discussed in detail in the following chapter, analysing the contributions of the different techniques in the current models, describing the functionalities of these models to determine the current capabilities of the state-of-the-practice in freight transport demand for long-term planning.

To conclude the analysis of this technique, it is also worth mentioning that the integration with machine learning techniques is an emerging area of research. They are being used to enhance the predictive accuracy of discrete choice models by identifying complex, non-linear patterns in data that traditional approach might miss. While this area is still in a developing stage, early results suggest that combining the strengths of both methodologies could lead to more robust and accurate forecasts, particularly in complex environments like freight transport.

Multi-criteria Systematic Comparison

Table 4.5: Systematic evaluation of discrete choice models

Accuracy ★★★★☆	+	Discrete choice model perform well in short- to medium forecasting due to their ability to capture current decision-making behaviour based on available data. In long-term forecasting, the accuracy will depend by how well the model accounts for changes in preferences and external conditions over time (Incorporate dynamic elements). Still better accuracy than previous techniques since the behaviour modelled will adapt to the environment long-term external factors.
	-	Accuracy can diminish if there are sudden, unforeseen changes in the transport environment that are not captured by the model. Another reason for a decrease in accuracy, particularly in long-term, would be with a static modelling as new factor emerge or as preferences evolve.

Data Requirements ★★★⯪☆	+	This data is often available for specific studies such as public datasets, industry reports, and collaboration with stakeholders.
	-	The effectiveness of this models is highly dependent on the availability of detailed data on the attributes of alternatives and the characteristics of decision-makers to accurately capture decision-making behavior. It is required a high-quality, reliable and large amount of data. Inconsistent or incomplete data can lead to biased estimates and reduce the model's predictive power so ensuring data consistency and completeness, possibly through data cleaning and validation processes, is critical. Subjective data is harder to get, also data may be fragmented or private proprietary, which can limit the model's application.
Scalability ★★★★☆	+	Geographically scalable, meaning they can be applied to local, regional, national, or even international transport networks. Incorporating temporal dynamics can enhance their scalability over different time horizons. It can include a wide range of transport modes, routes, and service providers, being particularly useful in multimodal freight transport systems.
	-	Scaling up requires a proportional increase in data availability and computational resources, which can be a challenge when working across large or diverse regions. It can struggle with the complexity of large, diverse systems like national freight networks.
Complexity ★★★⯪☆	+	Despite their complexity, they are relatively transparent compared to some machine learning methods. he relationships between inputs (e.g., transport costs, time) and outputs (e.g., choice probabilities) are explicit, which helps in model interpretation and validation. User-friendly software tools and detailed documentation can non-technical user to understand the interal dynamics of the model.
	-	Implementation requires careful specification of the utility functions and consideration of various attributes. The complexity increases with the inclusion of advanced models like Nested Logit, which address specific limitations but add to the model's computational load. While the underlying behavioural theory is easy to understand, its practical application can be complex, particularly for users without a strong background in econometrics or statistics.

Cost-effective ★★★☆☆	+	Once established, they can be cost-effective to maintain, especially if the required data is continuously available. The detailed insights provided can justify their costs, particularly when used for policy analysis or strategic planning where understanding the drivers of transport demand is crucial.
	-	Developing discrete choice models means significant initial costs, including data collection, model specification and calibration, since high-quality data and expert knowledge are needed in the model design. Regular updates and recalibrations may be necessary to keep the model accurate, especially in dynamic environments. A large model could require significant computational resources.
Timeliness ★★★⯪☆	+	Once the model is set up, generating forecasts can be relatively quick, depending on the complexity of the scenarios being analysed.
	-	Developing these models an be time-consuming, particularly in the initial stages of data collection, model specification and calibration, not suitable if quick results are needed. Running the model, especially for large-scale applications, can require significant computational resources.They need to be updated periodically to reflect changes in the transport environment or in decision-makers' preferences, the frequency of updates depends on the volatility of the environment and behaviours being modeled (as new factors or behavioural influences could appear).
Robustness ★★★★☆	+	Generally robust to variations in input data. They can be adapted to accommodate structural changes in the transport network or in the preferences of decision-makers, making them valuable for scenario analysis and long-term forecasting. Discrete choice models can incorporate stochastic elements to handle uncertainty, particularly in situations where decision-makers face incomplete information or where choices are influenced by random factors, enhancing the model's robustness in uncertain environments.
	-	Their accuracy can be compromised by significant outliers or non-standard conditions that were not included in the model calibration. Careful calibration and specification is required, some bias included in the model could compromise robustness.

Interpretability ★★★★★	+	User-friendly in terms of interpretation, as they provide clear insights into how specific factors influence decision-making, making them accessible to a wide range of stakeholders. The assumptions underlying, such as utility maximization and the independence of irrelevant alternatives, are explicit and well-documented, allowing a clear understanding of the model's limitations and the conditions under which it is most applicable. The results, particularly the choice probabilities and the relative importance of different attributes, are easy to communicate to non-technical audiences being this transparency a key strength in policy and decision-making contexts.
	-	Complexity of the model, if it is not addressed correctly by documentation and software, could potentially reduce the interpretability for non-technical stakeholders
Integration ★★★★☆	+	They are highly compatible with other modelling approaches, particularly econometric models and simulation frameworks with many examples at research and practical level. They can be designed to accommodate various extensions, such as dynamic components or interactions with other models (e.g., gravity models, 4-stage models, agent-based models), enhancing flexibility improve their applicability in complex forecasting environments.
	-	The current state of integration is the result of a major research effort in previous years, not because of its ease of integration itself.
Functionality ★★★★☆	+	High degree of detail in modeling by offering different possible outcomes in specific aspects of transport demand, such as mode choice, loading size choice or route selection. Discrete choice models are perfectly suitable with scenario planning. Practical tool for policymakers and planners, particularly in the context of evaluating the impact of policy changes or infrastructure investments. Their outputs are directly applicable to decision-making processes, making them highly functional by incorporating behavioural factors. [34][37][38]
	-	While they are highly effective for specific choice scenarios, their scope may be limited when broader system-level dynamics need to be captured, this limitation could be address by integrating with other models.

Discrete choice models are a promising tool within the framework of this thesis, particularly for forecasting long-term freight transport demand in the European context, not without requiring significant data and careful model specification. Their strength lies in their ability to capture individual decision-making processes with a high degree of detail, making them invaluable for understanding complex choices such as mode and route selection. The flexibility coupled with their potential for integration with other models, makes them a key component of a comprehensive forecasting framework, offering detailed insights that align well with the strategic goals of this research.

4.2.4 Equilibrium Models

Method Description

Equilibrium models are essential tools in transport demand forecasting, particularly for analyzing how freight transport systems achieve balance between supply and demand across a network. These models are based on the fundamental principle of equilibrium, where all participants in the transport network such as shippers, carriers and consumers make optimal decisions given the conditions and the choices of others [11][13]. In this balanced state, no individual actor has an incentive to change their behavior, as doing so would not improve their situation.

Equilibrium models are based on economic theory, particularly in the concepts of general equilibrium and game theory. These models consider the interactions between various agents within the transport system such as shippers selecting transport routes or carriers optimizing their logistics operations. The goal is to find a state where the transport network operates efficiently, with freight flows distributed in a way that minimizes costs and maximizes system-wide utility [39].

The general form of an equilibrium model in transport can be expressed as:

$$\text{Minimize } Z = \sum_{a \in A} \int_0^{f_a} c_a(x)\, dx \tag{4.13}$$

Subject to:

$$\sum_{p \in P_i} \delta_{ap} x_p = f_a \quad \forall a \in A \tag{4.14}$$

$$\sum_{i \in N} x_p = d_i \quad \forall p \in P \tag{4.15}$$

where:

- Z: The total system cost, which the model seeks to minimize. This cost could represent total travel time, congestion costs, or any other cost metric relevant to the transport system.
- $a \in A$: A set representing all links in the transport network.
- f_a: The flow on link a, which is the sum of the flows on all paths that use link a.
- $c_a(x)$: The cost function associated with flow on link a. This function typically represents the cost as a function of the flow, such as travel time increasing with congestion.
- $p \in P_i$: A set representing all possible paths available for the flow i.

- x_p: The flow on path p, determined by the decisions of shippers or carriers in the network.
- δ_{ap}: A binary indicator, where $\delta_{ap} = 1$ if path p uses link a, and $\delta_{ap} = 0$ otherwise.
- d_i: The demand from origin i to destination i, which must be met by the flow on the network.

Some types of equilibrium models:

- User equilibrium: In a user equilibrium state, all shippers or carriers have optimized their routes to the point where no one can reduce their costs by choosing a different route, given the choices of others.
- System Optimal: System optimal models aim to minimize the total cost of the transport system as a whole, even if it means that some individuals or entities incur higher costs. Particularly relevant in policy planning, where the goal is to optimize the overall efficiency of the transport network
- Dynamic traffic assignment: They extend equilibrium concepts into a dynamic context, modeling how freight flows evolve over time in response to changing conditions. They are commonly used in combination with micro-simulation modes to model the urban flows, where congestion and demand fluctuate throughout the day.

These models are particularly valuable for forecasting how changes in the transport network such as new infrastructure, policy interventions or shifts in market conditions will impact the distribution of freight flows [40]. By simulating the effects of policies such as congestion pricing or low-emission zones, equilibrium models provide insights into how freight flows might shift, helping policymakers design more effective interventions.

Equilibrium models are a crucial component of transport demand forecasting, offering robust tools for analyzing how freight flows are distributed across a network in response to various factors. Their ability to model the interactions between different agents and predict how changes in the transport environment will impact these interactions makes them particularly valuable for long-term strategic planning.

Freight Forecasting Capabilities

Analysing equilibrium models, they are highly effective in capturing the way freight flows naturally distribute themselves across a transport network due to the principle of cost minimization, reflecting the actual behaviour in transport systems (in freight transport, shippers and carriers) where each participant seeks to optimize their route or mode choice to minimize costs [39].

Regarding its scalability and flexibility, equilibrium models can be scaled to analyze both local networks (e.g., urban freight routes) and larger, inter-regional networks (e.g., trans-European corridors) [40]. They are flexible enough to incorporate various transport modes and commodities, making them adaptable to different scales of analysis [41].

They are also well-suited for testing the impact of various policy measures or infrastructure changes, making them a valuable tool for long-term planning.hey allow policymakers and planners to simulate different scenarios, such as the introduction of tolls, the construction of new infrastructure, or changes in fuel prices, and observe how these changes might redistribute freight flows across the network.

Their main limitations are its static nature, meaning they provide a snapshot of the transport system at equilibrium but do not account for changes over time, needing a dynamic approach to better capture the evolution of transport demand and network conditions.

Another issue is the assumption that all users have perfect information and behave rationally to minimize costs. In reality, decision-makers may not have complete information or may behave differently due to constraints or preferences, leading to discrepancies between model predictions and actual outcomes. Other type of equilibrium models that have stochasticity within the optimization could potentially deal with this limitation.

Modelling a detailed networks implies that equilibrium models are mathematically complex and require detailed, high-quality data on network conditions, costs and demand. The complexity increases when extending the model to include multiple modes, different commodities, stochastic elements, or dynamic factors.

Equilibrium models' forecasting capabilities makes them valuable assets for scenario analysis and risk management since they allow allow for the exploration of various "what-if" scenarios, providing insights into how different risk factors (e.g., economic downturns, policy changes) or changes in the network (cost changes, restructure of the supply chain or infrastructure investments) might impact freight transport demand and flows. Naturally, they are useful tools in planning and optimizing transport networks. By predicting how freight will flow under different conditions, these models help in designing infrastructure that meets demand efficiently while minimizing costs and congestion [41].

Regarding its integration with other models, there has been significant progress in integrating equilibrium models with dynamic models using the DTA equilibrium model type. This integration allows for the analysis of how equilibrium conditions change over time, making it possible to model the evolution of traffic flows under varying conditions, being essential for long-term analysis. This dynamic approach have been already implemented in various agent-based models as it will be mentioned in the discussion.

Another possibility is the integration with further economic models, which commonly is presented in current models. It incorporate the effects of economic variables such as GDP, trade volumes or fuel prices on transport demand, allowing a more robust analysis that considers both economic and network factors.

Multi-criteria Systematic Comparison

Table 4.6: Systematic evaluation of equilibrium models

Accuracy ★★★☆☆	+	Equilibrium models generally offer high short-term accuracy, particularly in predicting the immediate distribution of freight flows across a transport network.
	-	The assumption of equilibrium reflects the optimal behavior of agents in the system, leading to reliable short-term predictions, but it might not be always the same (users don't have perfect information and decision-making). Their long-term accuracy can be limited by their static nature since they may not fully capture evolving dynamics over time unless integrated with dynamic models.
Data Requirements ★★★★☆	+	Public datasets, industry reports, and collaboration with stakeholders can help in the collecting process.
	-	It is required high-quality data on the transport network, including costs, capacities and demand levels for accurate predictions. Inaccuracies in cost functions or demand estimates can lead to significant deviations in the model's output. Ensuring data quality is crucial and since the availability of such data can vary, the lack of comprehensive data can limit the model's applicability.
Scalability ★★★★☆	+	Scalable across different geographical contexts, from local urban networks to regional or international transport systems. They can also handle multiple transport modes and routes, making them versatile for analyzing complex, multimodal freight transport systems, making them suitable for the European analysis.
	-	Its single weak point in terms of scalability is the time horizon, while traditional equilibrium models are static, they can be scaled temporally by integrating with dynamic traffic assignment, enhancing their applicability for long-term forecasting.
Complexity ★★★⯪☆	+	Despite their complexity, equilibrium models are relatively transparent compared to some other advanced forecasting techniques. Relationships between inputs (e.g., costs, demand) and outputs (e.g., traffic distribution) are explicit, which aids in interpretation and validation.
	-	Implementing equilibrium models requires a sophisticated understanding of network theory, optimization techniques, and transport economics. The practical application of equilibrium models can be challenging, particularly for those without specialized training, however, the availability of software tools that implement these models can help mitigate this weakness.

Cost-effective ★★★☆☆	+	Once established, equilibrium models can be cost-effective to run, especially if the necessary data is readily available, the ongoing costs are generally lower than the initial setup costs. These costs can be justified by the detailed insights the model provides and their ability to simulate and test various scenarios.
	-	Initial costs of setting up an equilibrium model can be high due to the need for extensive data collection, model calibration, and computational resources. Regular updates may be needed to maintain accuracy. Large networks with multiple scenarios can require significant computational resources.
Timeliness ★★★⯪☆	+	Once set up, the model can provide timely insights for policy analysis and planning.
	-	Developing an equilibrium model can be time-consuming, especially in the initial stages of data collection, network modeling, and calibration, becoming a limiting factor if quick results are required. These models need to be updated periodically to reflect changes in network conditions, costs, or demand.
Robustness ★★★★☆	+	Generally robust to variations in input data, particularly when well-calibrated. They are able to adapt to structural changes in the transport network or in demand patterns, making them useful for scenario analysis. While traditional equilibrium models assume deterministic conditions, they can be extended to include stochastic elements to handle uncertainty. Generally robust to variations in input data. Highly effective for sensitivity analysis.
	-	Uncommon data or unplanned conditions could affect the accuracy. Significant changes might require re-calibration of the model to maintain accuracy if the network conditions change.
Interpretability ★★★⯪☆	+	Concept of equilibrium is easy to understand. Visual tools and clear explanations help often stakeholders to interpret the results.
	-	Results of equilibrium models can be difficult to interpret for non-experts, especially in complex systems. The mathematical formulations and assumptions behind the equilibrium can obscure how different factors influence the outcomes.
Integration ★★★★☆	+	Highly compatible, especially with econometric models and dynamic models. Flexibility that enhances their applicability in complex forecasting environments, designed to accommodate various extensions, such as dynamic components or interactions with other models.
	-	Its complexity makes it necessary expertise to handle the integration. There has been research focus behind this integration.

Functionality ★★★★☆	+	Powerful tool for scenario analysis and uncertainty analysis since it links the demand of transport with the supply conditions of the network, being highly valuable for policy-making (impact evaluation of policy changes or infrastructure investments). Highly effective for sensitivity analysis. High degree of detail and granularity in modeling specific aspects of transport demand such as route, mode choice, multicommodity, congestion, environmental impact, supply chain, etc. [39][41]
	-	While equilibrium models are highly effective for specific scenarios, their scope may be limited when broader system-level dynamics need to be captured, needing the integration with broader econometric models.

Equilibrium models play a critical role in the field of freight transport demand forecasting, especially within the European context. Their ability to simulate the distribution of freight flows across transport networks under varying conditions makes them highly valuable for strategic planning, infrastructure optimization and policy evaluation.

However, equilibrium models face certain limitations, particularly their static nature and high data requirements. To address the dynamic and evolving nature of freight transport demand, integrating equilibrium models with other forecasting methods such as dynamic traffic assignment or econometric models, is essential. Overall, these models offer robust functionality and serve as a cornerstone in forecasting methodologies, particularly when assessing the long-term sustainability and efficiency of the European transport network.

4.2.5 4-Stage Models

Method Description

Having looked at the most commonly used models historically, it is possible to return to the 4-stage model to further analyse this traditional approach to demand forecasting. As previously explained, the four-stage model is a typical tool in transport demand forecasting, widely used to analyze and predict both passenger and freight transport flows [11]. This model follows a sequential process that involves four key stages: Trip Generation, Trip Distribution, Mode Choice, and Traffic Assignment. Each stage builds on the output of the previous stage to create a comprehensive forecast of transport demand across a network.

As these models have already been described, it can then be explained what type of model is involved at each stage in a standard 4-stage model:

1. **Trip Generation Stage** Firstly, econometric models, often based on regression analysis, are typically used in the trip generation stage, estimating the number of trips origination from and attracted to different zones as a function of socioeconomic variables.

2. **Trip Distribution** Once trips are generated, the next stage is to distribute them across origin-destination pairs (O-D matrix, in freight forecasting by transforming P-C matrix), which is typically done using a gravity model.

3. **Mode Choice** The mode choice stage predicts how many of the trips between zones will be carried out by each transport mode (e.g., road, rail, sea, air). Discrete choice models like the multinomial logit (MNL) model are typically used to model this behavior, with factors such as cost, time, and reliability influencing the decision.

4. **Traffic Assignment** The final stage, traffic assignment, allocates the trips from the mode choice stage to specific routes in the transport network, taking into account the relationship between the transport demand and the supply of the network condition. This stage typically uses equilibrium model, to bring the system to balance state.

Forecasting Capabilities

While the traditional four-stage model provides a structured approach to forecasting transport demand being able to provide reliable results, its static nature and simplifications limit its applicability, particularly in the context of long-term freight transport forecasting. These type of models provides a snapshot of the transport system under specific conditions, without accounting for temporal changes in demand or supply. This is a major limitation for long-term forecasting, where economic conditions, transport technology, and infrastructure evolve over time.

The lack of behavioural realism(discrete choice take into account behavioural factor but the input data for that stage is conditioned by previous ones) oversimplifies real-world decision-making in freight transport where other factors such as regulatory constraints, logistics strategies, and contractual agreements play a significant role.

One of the main constraints of this methodology are the feedback inconsistencies since the four stages are applied sequentially. For example, changes in traffic assignment (e.g., congestion, travel cost, capacity of network) may alter mode choice or trip distribution, but in the traditional model, these stages are treated as independent, therefore it can lead to inaccuracies [13]. Taking into account these constraints, this methodology is analysed based on the multi-criteria as previous models.

Multi-criteria Systematic Comparison

Table 4.7: Systematic evaluation of 4-stage models

Accuracy ★★★☆☆	+	The four-stage model performs relatively well in short-term forecasts, especially for estimating demand and flow distribution based on existing network conditions.
	-	In freight transport, where decisions are influenced by more factors than passenger transport, accuracy may be somewhat lower. In the long term, the accuracy decreases as it is a static model, it could be partially fixed using some dynamic modelling or extra feedback mechanisms.
Data Requirements ★★★★⯪	+	When high-quality is available or collected, the model uses it effectively to generate forecast.
	-	Freight transport data often come from diverse sources, increasing the risk of inconsistencies. Poor data quality or missing data at any stage can significantly reduce the model's accuracy. Accurate forecasting relies heavily on the quality of the input data, requiring granular data at each stage. In freight transport, obtaining such detailed data for all transport modes can be challenging.
Scalability ★★★⯪☆	+	The four-stage model can be scaled geographically, making it useful for regional, national, and international transport systems. It can handle different transport modes and various operational scales.
	-	While the model can be applied over different time periods, it does not easily accommodate dynamic changes in demand or network conditions over time. For long-term forecasting, this temporal limitation can reduce its effectiveness. The model becomes more complex as the scope of the study area increases, making it difficult to scale efficiently for large-scale, long-term forecasting like at the European level.
Complexity ★★★★☆	+	Once set up, the model is relatively easy to use for repeated analysis. It is the outcome of the combination of several models. The four-stage model is transparent in its approach, making it easier for users to understand how inputs affect outputs.
	-	It requires significant effort in model calibration, especially in multi-modal freight systems, growing its complexity as more modes or network details are added to the model. The main challenges are initial model design, calibration, and data collection.
Cost-effective ★★★☆☆	+	The methodology is well-established, and the tools to run it are widely available. Once the model is established, running it for new scenarios or updating forecasts is relatively cost-effective, as the structure is already in place.
	-	The model's setup can be costly due to the extensive data collection, calibration, and validation processes required, especially for large freight networks across Europe. It requires high expertise in freight forecasting and the different models applied.

Timeliness ★★★☆☆	+	The model runs relatively quickly once calibrated, not being the computational time a problem.
	-	Developing the model for a complex freight system takes significant time during the initial phases of data collection and calibration, not being suitable for quick analysis. Dynamic changes require recalibration and updates, which can delay results.
Robustness ★★⯪☆☆	+	The four-stage model is relatively robust to input variations when well-calibrated.
	-	Significant changes in network conditions (e.g., new infrastructure) or external factors (e.g., fuel prices) may require recalibration to maintain robustness. Traditional four-stage models do not handle uncertainty well, as they assume deterministic inputs and outputs. The model's sequential nature introduces potential weaknesses such as being highly sensitive to the assumptions in each stage
Interpretability ★★★★⯪	+	The model is user-friendly, with a clear sequence of stages that are easy to interpret. Its outputs are straightforward, which helps non-technical stakeholders understand the forecasts. Assumptions and results are explicit and easy to communicate, making it easier to understand and giving a important transparency which is beneficial when discussing outputs with policymakers.
	-	The deterministic approach can lead to inaccuracies, not helping to take optimal decisions.
Integration ★★★☆☆	+	The four-stage model can be integrated with other techniques, such as dynamic traffic assignment models or economic models. It can be adapted to different contexts, such as multimodal freight networks.
	-	Its lack of internal feedback mechanisms makes integration more challenging compared to more advanced models. It lack of some flexibility since it is already an assembled model, needing effort to ensure consistency (taking into account the assumptions made and the principles of the methods).
Functionality ★★★☆☆	+	The model offers a reasonable degree of detail, particularly in mode choice and trip distribution. Applicable across a wide range of scenarios. Practical for transport planning and policy-making, mainly for short-term and static scenarios.
	-	It may oversimplify certain freight behaviors due to its sequential and static nature. Its static nature limits its ability to capture real-time dynamics or long-term structural shifts in the market.

As the challenges of freight transport forecasting grow more complex, especially in the context of long-term, multimodal and dynamic systems within Europe, more sophisticated models are required.

The four-stage model's limitations, such as its static nature, lack of feedback mechanisms, and oversimplification of behavioral dynamics, suggest that while it is a solid baseline, future freight transport planning will demand models that integrate dynamic, economic, and behavioral components. The growing complexity of global logistics, technological advancements, and evolving policy goals will require ore accurate and responsive forecasting for the challenges ahead.

4.2.6 Cointegration and Error Correction Models

Method Description

Cointegration and Error Correction Models (ECM) are critical econometric tools that address time series data with both short-term fluctuations and long-term relationships. These models are essential for understanding how multiple economic variables such as GDP, industrial output and fuel prices are interconnected with freight demand over time.

For this purpose, causality tests are carried out to identify whether one variable is the cause of the other, or the other way around, e.g. it can be studied whether road transport investment promotes economic growth or the vice versa [42]. Therefore, by capturing both equilibrium relationships and dynamic adjustments, these models offer a comprehensive approach in the relationship between economic variables and transport demand, being particularly useful for long-term planning.

Cointegration

Cointegration identifies long-term relationships between non-stationary time series variables, meaning that while each variable may show short-term deviations, they maintain a stable relationship over time. So, by performing a cointegration test, it is determined whether there is a long-term relationship between the series after the stationary study between the series [43]. For instance, economic growth (GDP) and freight demand may fluctuate due to market conditions but tend to move together in the long run [11].

The basic formula for understanding this concept is expressed as:

$$y_t = \alpha + \beta x_t + u_t \tag{4.16}$$

where:

- y_t: Dependent variable at time t (e.g., freight demand).
- x_t: Independent variable at time t (e.g., GDP or industrial output).
- α: Constant term representing the intercept of the long-term relationship.
- β: Coefficient that captures the strength of the long-term relationship between x_t and y_t.
- u_t: Error term, which should be stationary if y_t and x_t are cointegrated.

Error Correction Model (ECM)

This model usually complements cointegration, by capturing the short-term dynamics and adjustments that bring variables back into long-term equilibrium [44]. When variables deviate from their long-run relationship due to temporary shocks (e.g., fuel price spikes, policy changes), ECM quantifies how these deviations are corrected over time. For instance, if a policy change causes a short-term increase in freight costs, ECM helps model how demand will gradually adjust to restore equilibrium.

The general ECM equation can be expressed as:

$$\Delta y_t = \alpha + \beta_1 \Delta x_t + \lambda(y_{t-1} - \gamma x_{t-1}) + \epsilon_t \tag{4.17}$$

where:

- Δy_t, Δx_t: Change in the independent x and dependent y variables at time t.
- $y_{t-1} - \gamma x_{t-1}$: Error correction term, representing the deviation from the long-run equilibrium.
- λ: Speed of adjustment, indicating how quickly the system returns to equilibrium.
- α: Constant term.
- β_1: Coefficient of the change in the independent variable x_t.
- ϵ_t: Error term representing short-term shocks.

Additionally, an extension of ECM is the Vector Error Correction Model (VECM) which is able to anlyse many variables simultaneously [43]. It is used when multiple variables influence freight demand and each variable interacts with others in a dynamic manner. For example, changes in fuel prices, economic output and freight demand all influence each other over time, and VECM provides a comprehensive way to model these interdependencies [44]. Then, VECM captures how these economic variables and freight demand adjust together toward their long-run equilibrium while modeling short-term deviations across all these variables.

The general form of a VECM is [44]:

$$\Delta \mathbf{y}_t = \Pi \mathbf{y}_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta \mathbf{y}_{t-i} + \epsilon_t \tag{4.18}$$

where:

- $\Delta \mathbf{y}_t$: Vector of changes in the variables at time t (e.g., changes in GDP, trade volume and freight demand).
- $\mathbf{y}_{t-1}$: Vector of variables at time $t-1$ (e.g., lagged values of GDP, freight demand, fuel prices).

- Π: Matrix representing the long-term relationships between the variables (cointegration relationships).
- Γ_i: Short-term adjustment coefficients for the lagged differences.
- ϵ_t: Vector of error terms at time t, capturing short-term shocks.

These models are valuable tools for long-term forecasting in freight transport since they allow for the analysis of how economic and policy changes influence transport demand both in the short and long term. By applying these models, it is possible to predict how freight demand will evolve in response to fluctuations in economic conditions or policy interventions in the European context.

Forecasting Capabilities

These techniques allow for the identification of long-term equilibrium relationships between non-stationary time series variables. For freight transport, this means identifying how key economic drivers such as GDP growth, industrial output, or fuel costs trend together with freight demand over time by capturing the inherent relationship between economic activity and freight transport demand, even if short-term deviations exist.

Taking into the framework of this thesis on long-term forecasting, the ability to capture these stable relationships provides valuable insights into how freight demand evolves with macroeconomic trends in Europe, forecasting how European economic integration, changes in trade policies, and regional developments will impact long-term freight transport demand.

Simultaneously, Cointegration and ECM models are able to forecast how short-term deviations from the long-term equilibrium are corrected over time. Therefore, capturing how different economic variables interact and adjust together in the short run, while moving toward long-term equilibrium. This approach is crucial for understanding how freight transport system in Europe responds to to short-term economic shocks (e.g., fuel price spikes or trade policy changes) and adjusts over time to return to its long-term trajectory, becoming a key tool to perform policy impact assessment and scenario analysis, capturing both short- and long-term consequences.

Using the extension VECM, it allows for simultaneous analysis of multiple variables and their relationships, captures the dynamic interactions between several variables (e.g., GDP, industrial production, transport costs and freight demand) and how they jointly adjust to restore equilibrium. So, it offers a more realistic and holistic forecasting approach of the complex European transport network, where freight demand is influenced by a variety of economic and regulatory factors.

However, this approach is very data demanding since it requires long-term, high-quality time series data to accurately estimate relationships between variables and without sufficient data, especially for long-term historical trend, these models may not reach their full potential, compromising its accuracy. At the same time, their complexity requires deeper statistical knowledge and more careful model specification, especially when determining the number of cointegrating relationships. This complexity makes it more difficult to implement them, particularly when integrating it with other models. Interpreting results can also be more challenging, particularly when dealing with multiple variables with feedback effects.

Moreover, cointegration and ECM models assume linear relationships between variables which may not always reflect the real-world dynamics of freight transport demand, where non-linearities such as policy shifts or technological advancements, may have significant impacts. This assumption may limit the model's ability to capture more complex dynamics in the European freight market.

Regarding the possibilities of integration with further forecasting models, cointegration and ECM models are frequently integrated with ARIMA time series. Despite the fact that ARIMA assumes stationartiy, meaning it cannot effectively model long-term trends, by integrating it with these models, it is possible to handle both short-term volatility (with ARIMA) and long-term equilibrium relationships (with cointegration and ECM).

They are also commonly integrated with broader econometric models, incorporating the strengths of these models with previously explained methods such as gravity, equilibrium or 4-stage models, enabling a detailed understanding of both structural changes and cyclical variations in the freight transport sector. Furthermore, they can also be integrated with simulation-based models, providing both a macro-level view of how economic trends affect freight demand and a micro-level understanding of how individual decision-makers in the transport system react.

Multi-criteria Systematic Comparison

Table 4.8: Systematic evaluation of cointegration and error correction models

Accuracy ★★★★⯪	+	This joint method provides a higher level of accuracy in scenarios where both short-term volatility and long-term trends matter. It allows for dynamic adjustments, which is particularly important for freight demand forecasting, where short-term shocks (e.g., changes in fuel prices, trade policies) can disrupt demand, but long-term economic trends remain consistent.
	-	The accuracy of this model depends heavily on the quality and quantity of data available, being reduced its effectiveness due to incomplete or noisy data.
Data Requirements ★★★★☆	+	When sufficient, accurate, and granular data are available, these models offer significant predictive power.
	-	They are data-intensive models, requiring high-quality, long-term time series data for key economic indicators, being a challenge to gather sufficient time series data across different regions. Missing data, measurement errors, or inconsistencies between data sources can severely affect the accuracy of these models.
Scalability ★★★⯪☆	+	Cointegration and ECM models are highly scalable in both temporal and geographical contexts. They can handle both regional and international freight system effectively taking into account both short- and long-term.
	-	Although scalable, the complexity of the model increases with the number of variables and the time span, requiring more extensive data collection, model calibration, and computational power. They work best in systems where a few key variables drive long-term trends.
Complexity ★★★★☆	+	The complexity of the model allows for a detailed and deep understanding of the relationships between variables, particularly in how short-term shocks are corrected and how long-term trends are sustained.
	-	The increased complexity may require a higher level of expertise and longer time for implementation. Moreover, interpreting the results, especially with multiple interdependent variables, can be challenging, particularly when communicating the results to non-experts such as policymakers.
Cost-effective ★★★⯪☆	+	Once the models are built, they can be run relatively cost-effectively for various scenarios, particularly when applied to well-maintained datasets.
	-	They can be costly to implement, primarily due to the data requirements (data needs to be collected or acquired) and the need for specialized expertise. Regular updates and recalibration are also required as new data becomes available.

Timeliness ★★★☆☆	+	Once built, these models can be run fairly quickly for scenario testing or policy analysis. Capable of providing insights into both short-term changes and long-term trends in a timely manner.
	-	Developing phase is time-consuming due to complexity and data requirements. Calibration and validation also adds time to the process.
Robustness ★★★★☆	+	The joint method of using Cointegration and ECM/VECM ensures that long-term trends are stable while short-term deviations are corrected, providing robustness in uncertain or volatile economic conditions.
	-	Although robust, the models are sensitive to structural breaks, requiring recalibration in economic events that cause permanent shifts such as the Covid-19.
Interpretability ★★★⯪☆	+	For long-term relationships, the models provide valuable insights into how variables like GDP and freight demand evolve together over time, this being potentially used for policymakers and planner.
	-	Understanding how short-term shocks are corrected across multiple variables can be a challenge. ECM and particularly VECM add complexity, making the interpretation of the results more difficult, especially when modeling multiple variables, for non-technical stakeholders.
Integration ★★★★☆	+	These models integrate well with other forecasting methods. They are commonly used alongside time series models like ARIMA to capture both short-term trends and long-term relationships. Its flexibility makes it suitable for integration with other econometric and simulation models, enhancing its functionality.
	-	Integration requires careful calibration, and combining VECM with other models (e.g., ARIMA) can be computationally intensive.
Functionality ★★★⯪☆	+	Long-term forecasting and scenario analysis, making them suitable for strategic planning and policy evaluation in transport systems. They are particularly effective in analyzing the dynamic interactions between multiple economic variables for both long-term and short-term forecasting.
	-	Their functionality is limited by the need for high-quality data and the time required for model development. They don't have a disaggregate approach.

As a conclusion, cointegration and error correction models are highly valuable for capturing both long-term equilibrium and short-term fluctuations in the relationships of key economical variables and freight transport demand. This combination is particularly well-suited for the European context, where economic volatility and policy shifts require a forecasting model that accounts for both steady trends and transient changes.

Despite their complexity and high data requirements, these models offer robust predictive power and scalability across different regions and time periods. Therefore, they form an essential part of any strategic, long-term forecasting framework, especially in environments where multiple economic variables influence demand, being used in scenario analyses and policy impact assessments.

4.2.7 Vector Autoregression

Mehtod Description

Vector Autoregression (VAR) is a widely used econometric model for analysing the dynamic relationships between multiple time series variables, each influencing the others [45]. Unlike univariate models like ARIMA, VAR models allow multiple variables to be interdependent, where each variable is modeled not only by its own past values but also by the past values of all other variables in the system. This multivariate approach is well-suited for studying the connection of economic factors influencing freight transport demand, providing a flexible framework for capturing these dependencies in the European context.

They provide a robust method for examining how these interrelated factors evolve together over time, particularly in scenarios of economic volatility or policy shifts like those planned for the environmental targets [46]. This multivariate approach allows for forecasting the evolution of multiple variables simultaneously, offering insights into how shocks in one factor (e.g., a sudden rise in fuel prices) can propagate through the system to influence other factors (e.g., freight demand) [47]. Regarding the goals of this systematic comparison, this capability is crucial for understanding the medium-term dynamics of freight demand under shifting economic conditions and policies.

The general form of a VAR(p) model, where p is the number of lags, is given by:

$$\mathbf{y}_t = A_1\mathbf{y}_{t-1} + A_2\mathbf{y}_{t-2} + \cdots + A_p\mathbf{y}_{t-p} + \mathbf{u}_t \tag{4.19}$$

where:

- $\mathbf{y}_t$: A $k \times 1$ vector of endogenous variables at time t (e.g., freight demand, GDP, fuel prices).
- $A_1, A_2, \ldots, A_p$: $k \times k$ coefficient matrices for each lag, where p is the number of lags.
- $\mathbf{y}_{t-1}, \mathbf{y}_{t-2}, \ldots, \mathbf{y}_{t-p}$: Lagged values of the endogenous variables.
- $\mathbf{u}_t$: A $k \times 1$ vector of error terms or innovations at time t (representing unexpected shocks).
- k: The number of variables included in the system.
- p: The number of lags.

The main difference between VAR and the previously explained cointegration and error correction model is based on their treatment of long-term relationships and stationarity. While VAR assumes all variables are stationary and models short- and medium-term interactions without accounting for long-term equilibrium relationships, cointegration focuses on long-term relationships between non-stationary variables that tend to move together. This cointegrated approach with the addition of the ECM, it incorporates an error correction mechanism that allows it to handle both short-term dynamics and long-term equilibrium relationships.

Forecasting Capabilities

Once anlysed this technique, it is underlined as one of the main strengths of VAR, its ability to capture dynamic realtionships and model the interdependencies between multiple time series variables [46]. Treating all variables as endogenous, meaning each variable in the system can influence and be influenced by all other variables, makes VAR valuable for systems with complex interactions, such as freight transport demand, where variables like GDP, fuel prices, and trade volumes interact with each other. Therefore, this technique is highly effective for short- to medium-term forecasts, being able to predict short-term volatility in variables based on recent trends in economic indicators [48].

This capability to forecast volatile makes VAR models well-suitable, particularly in short- to medium-term, for scenario analysis. They can be used to test hypothetical situations (policy evaluation, impact assessment of economic shocks, etc.), simulating how changes in certain variables such as fuel prices or trade volumes will affect freight demand or how a recession propagates through the freight transport system, considering the lagged relationships between variables [47].

Another main characteristic of VAR models is their simplicity in application since they are relatively straightforward to implement compared to more sophisticated econometric models like VECM. They do not require complex assumptions about the causal relationships between variables, making them easier to interpret and apply in various forecasting scenarios. At the same time, they can handle multiple variables simultaneously, being able to carry out analyses of how different transport modes (e.g., road, rail, sea) and related economic drivers (e.g., fuel prices, industrial output) interact over time. This makes them scalable to systems with freight multimodality as the European transport network.

However, the assumption of stationarity is one of their main limitation since they assumes that past relationships between variables will remain stable, which may not hold in the long run. Therefore, this makes them ineffective for long-term forecasting, especially in systems where structural changes (e.g., technological advances, policy shifts) may alter the relationships between variables over time.

Moreover, while VAR models are conceptually simple, the complexity increases with the number of variables and time lags included. More variables lead to larger systems of equations, which require more computational resources and can be difficult to interpret, particularly in high-dimensional settings. Having to add that VAR models also require long, high-quality time series data for each variable in the system since incomplete or noisy data can significantly impact the model's accuracy. Therefore, data requirements is challenging in freight transport systems, where reliable data on factors like demand, fuel prices and regulatory impacts may not always be available.

Regarding their compatibility with other methods, VAR models can be extended with cointegration techniques to model long-term relationships between non-stationary variables [49]. Such a integration with cointegration and VECM models, becomes essential for improving long-term forecasting accuracy. In parallel, they are often integrated with ARIMA models to improve forecasting accuracy. ARIMA handles the univariate forecasting for individual time series variables, while VAR captures the dynamic interdependencies between multiple variables. This combination is particularly useful when short-term and individual variable dynamics are of interest.

Furthermore, they can be integrated with further econometric models and simulation models to improve the volatility forecasting prediction of this models. About its degree of integration with AI techniques, it is growing with the aim of providing more accurate (also for long-term), dynamic, and adaptable forecasting by handling non-linearities, complex datasets and adapting to real-time changes with the support of AI tools.

Multi-criteria Systematic Comparison

Table 4.9: Systematic evaluation of vector autoregression models

Accuracy ★★★⯪☆	+	Highly effective at capturing short- to medium-term interactions between multiple variables. By accounting for the past values of all variables in the system, VAR can model how changes in one variable impact the other variables, making it highly accurate for short-term forecasts.
	-	They struggle with long-term forecasting because they rely on historical relationships, which may not remain stable over long periods (assumption of stationarity). VAR not account for structural changes or trends over time unless integrated with other methods like cointegration reducing its long-term suitability.
Data Requirements ★★★⯪☆	+	VAR models use readily available time series data and do not require extensive assumptions about the underlying structure of the relationships between variables. They work well when reliable, high-frequency data is available for all relevant variables (e.g., GDP, freight demand, fuel prices).
	-	VAR requires long, high-quality time series data for each variable, and missing or inconsistent data can greatly affect the model's accuracy. In the European context, where data from multiple countries and regions must be integrated, data quality and availability may become an issue, particularly for freight-specific variables since they might be of private property.

Scalability ★★★½☆	+	VAR models are scalable in that they can handle multiple variables and can be adapted to both national and international freight transport systems, being suitable for analysing large-scale systems.
	-	As the number of variables and lags increases, the complexity, data collection and computational intensity of the model also rise. Increasing the number of variables to capture multi-modal transport systems or complex policy interactions requires greater data processing power and more advanced statistical skills. Its scalability is also constrained due to its long-term forecasting.
Complexity ★★★½☆	+	Relatively simple model compared to more sophisticated econometric models, as it does not require complex assumptions about the structure of relationships between variables, making it easier to implement and interpret in comparison to methods like VECM or structural econometric models.
	-	Despite being simple in structure, it grows complex with additional variables.The more variables and lags included in the model, the more complex it becomes, since interpreting the dynamic interactions between variables in large-scale systems with many time periods can become difficult.
Cost-effective ★★★★☆	+	Cost-effective tool for medium-term forecasting, particularly in systems with stable, reliable data. VAR models are relatively inexpensive to develop and implement when data is readily available, as they do not require complex structural modeling.
	-	The costs rise as the model becomes more complex and requires more data processing. The implementation is not that effort-demanding,it is mainly the data collection.
Timeliness ★★★½☆	+	Once built, VAR models can be run relatively quickly and provide timely results, making them suitable for regular updates to forecasts based on new data. Particularly useful for forecasting in rapidly changing markets, such as the freight transport industry in Europe, to face short- to medium-term volatility.
	-	Initial model development phase can take time, particularly when many variables and lags are involved. Frequent recalibration may also be necessary when the model is applied to long-term forecasting or when structural changes occur in the economic environment.
Robustness ★★★½☆	+	They are robust for short-term shocks, being able to perform scenario anlysis, policy assessment or uncertainty analysis in this time horizon. The ability to account for the past values of all variables in the system increases the model's resilience to shocks in individual variables.
	-	Despite being robust for short-term shocks, they are sensitive to structural changes in the system over time. If significant regulatory or technological changes occur in the transport sector, the model may fail to accurately capture their long-term effects without recalibration.

Interpretability ★★★★☆	+	Relatively easy to interpret, as they provide clear insights into how each variable affects the others over time. Accessible to both technical experts and policymakers who need to understand the relationships between variables influencing freight demand.
	-	Interpretation becomes more difficult when many variables are included, as the dynamic interactions between variables can be complex. Scaling the model affects its interpretability.
Integration ★★★★★	+	VAR models can be integrated with other time series models, such as ARIMA and Cointegration models (e.g., VECM), to handle both short-term volatility and long-term relationships. Also compatible with structural econometric models and can be used to complement simulation models like agent-based models in transport forecasting.
	-	Integration requires careful calibration and model alignment, which can increase complexity and computational cost.
Functionality ★★★⯪☆	+	Strong for short- and medium-term forecasting, allowing for the exploration of how different economic variables (e.g., GDP, fuel prices) affect freight demand, making them useful for scenario analysis, policy evaluation, and real-time forecasting. Suitable for multimodality.
	-	They typically focus on volume prediction and may not provide detailed insights into other aspects of freight transport, such as mode choice or environmental impact.

The systematic evaluation of VAR within this thesis highlights its strengths in capturing the short-term dependencies and providing accurate predictions in scenarios where variables are interdependent. However, the model's complexity and data requirements may limit its scalability, particularly in long-term forecasting or when data is scarce. Despite these limitations, the VAR model remains a valuable method, particularly when dealing with volatility, also, when integrated with other forecasting techniques to enhance its predictive power and applicability in the European transport context.

4.3 Simulation Models

Simulation models play a crucial role in the field of freight transport demand forecasting, particularly when complex systems need to be analysed dynamically over time [50]. As part of the broader category of forecasting techniques, simulation models allow for a detailed exploration of how various components within a system interact. Their distinguishing feature lies in their ability to model the behavior of systems over time, capturing the evolving nature of transport demand under different conditions. Unlike statistical approaches, which rely heavily on historical data, simulation models focus on replicating real-world processes, offering a flexible framework to explore various future scenarios.

One of the most important characteristics of simulation models is their ability to handle complexity. Freight transport systems are inherently complex, involving numerous stakeholders, from shippers and carriers to regulatory bodies [16]. Simulation models excel at representing the interactions between these actors, as well as the non-linear relationships that exist between different variables [51]. By simulating such interactions, these models provide valuable insights into the emergent behavior of the system as a whole. This is particularly relevant in the context of long-term forecasting, where the goal is to understand not just a single outcome but a range of potential futures based on varying assumptions.

Another defining feature of simulation models is their ability to incorporate dynamic feedback loops [51]. In freight transport systems, feedback mechanisms, such as how an increase in demand affects infrastructure capacity or how regulatory changes influence operational costs [52], play a significant role in shaping future demand. Simulation models can capture these dynamic processes, allowing researchers and policymakers to see how interventions or changes in one part of the system evolve and affect the entire network. This capability makes simulation models particularly useful for scenario analysis, enabling decision-makers to explore "what-if" questions and assess the potential impacts of different policies or strategies, as in [53], where several scenarios are compared to a baseline one.

Among simulation models, two approaches stand out: Agent-Based Models (ABM) and System Dynamics (SD). While each method has its own strengths, they share the overarching goal of representing system dynamics through a simulation framework. ABM focuses on the interactions of individual agents such as firms, logistics providers or consumers within the transport system. Each agent operates according to a set of rules, and through their interactions, system-wide patterns emerge [54]. This bottom-up approach allows for a detailed representation of the behavior of different actors, making ABM well-suited for modeling complex and heterogeneous systems like freight transport where the decision process is more complex than in passenger transport since multiple stakeholders play a role in the supply chain, as previously mentioned through the thesis.

On the other hand, SD models adopt a top-down perspective, focusing on the feedback loops and accumulations within the system. SD models represent the system in terms of stocks and flows, capturing the continuous interactions between variables such as transport capacity and demand [52]. This method excels in long-term forecasting, where understanding how factors such as economic growth, fuel prices or environmental regulations evolve over time is critical, being able to model structural changes and, therefore, increase its suitability for long-term prediction.

In both models, the flexibility to simulate a wide range of variables, whether they refer to behavioral changes, economic policies or technological shifts, makes them indispensable tools in transport forecasting. By integrating these insights into the broader explanation of simulation models, we can highlight their essential role in addressing complex, long-term challenges in freight transport systems, even with the possibility of incorporating qualitative data from surveys or expertise transform to quantitative values [51]. They provide a unique capability to test various scenarios and policies before implementation, ensuring that decisions are grounded in a thorough understanding of the system's dynamics. This makes simulation models not only useful for academic research but also highly applicable in real-world transport policy and planning.

As a group, simulation models provide a powerful and adaptable approach to forecasting, particularly in environments characterized by uncertainty and change. They allow for the incorporation of new variables and changing conditions, offering a level of flexibility not typically found in more traditional models [16]. Moreover, simulation models can be employed even when data is scarce or incomplete, using assumptions to fill in gaps and explore potential outcomes. This makes them invaluable in fields like freight transport, where decision-making often requires balancing complex, interrelated factors over long time horizons.

4.3.1 System Dynamics Models

Method Description

System Dynamics (SD) is a modeling methodology designed to understand and simulate the behavior of complex systems over time. It has become a crucial tool for analyzing systems in various fields, including engineering, economics, environmental management, and transportation. It is particularly useful for long-term forecasting and policy analysis, where the system's behavior is influenced by multiple interconnected factors that evolve dynamically over time [51]. The fundamental principles of System Dynamics are based on systems thinking, a perspective that underlines the importance of understanding the relationships and feedback loops between different components of a system.

At its core, system dynamics operates on the concept of feedback loops, as shown in the causal loop diagram, Figure 4.2. Feedback is central to SD because it captures how changes in one part of a system can influence other parts, which, in turn, feed back to affect the original variable [51]. Feedback can be reinforcing (positive) or balancing (negative). Reinforcing feedback loops amplify changes, leading to exponential growth or decline, while balancing loops stabilize the system by counteracting changes.

For example, in a transport demand model, an increase in traffic congestion (a result of higher freight demand) might lead to longer delivery times, which could prompt firms to reduce the number of shipments, ultimately reducing congestion—a balancing loop. Conversely, economic growth could lead to increased freight demand, prompting further investment in infrastructure, which spurs more growth, illustrating a reinforcing loop. The presence of these feedback mechanisms makes SD particularly adept at modeling systems where cause and effect are not immediately obvious or linear, being a valuable

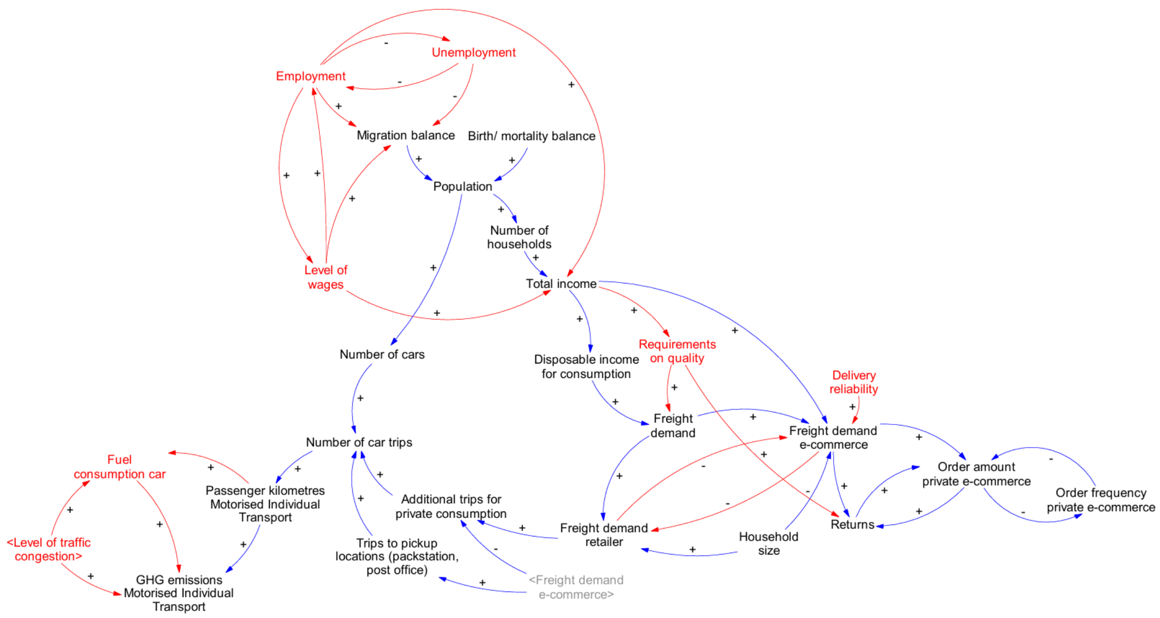

Figure 4.2: Causal loop diagram of socio-demographic and socio-economic structure [51]

tool to model these non-linear and complex relationships in the freight transport system [16].

Another key principle of SD is the concept of stocks and flows, Figure 4.3. Stocks represent the accumulations of resources, goods, or other elements within a system at any given time. Flows, on the other hand, are the rates at which stocks change [52]. For instance, in a freight transport model, the total number of trucks on the road at any time could be a stock, while the number of trucks entering or leaving the road network per hour would represent flows. Stocks and flows help model how different elements of the system accumulate or deplete over time, providing insights into trends and future states of the system. By understanding these accumulations, SD can help forecast the long-term consequences of current decisions or actions.

Causal loop diagrams (CLDs) and stock-and-flow diagrams are the primary tools used in system dynamics to visualize and model systems. CLDs depict the feedback loops and relationships between variables in a system, providing a qualitative understanding of how different elements influence one another. Stock-and-flow diagrams, whose parameterisation method is detailed in [51], offer a more detailed, quantitative representation, allowing modelers to simulate the system's behavior over time and evaluate the impacts of different policies or strategies.

Additionally, system dynamics emphasizes the importance of delays. Many systems involve delays between an action and its consequences, which can obscure the cause-and-effect relationships. For example, the introduction of new transport policies might take time before their effects are felt in terms of reduced emissions or congestion. SD models incorporate these time delays to more accurately reflect real-world systems, where imme-

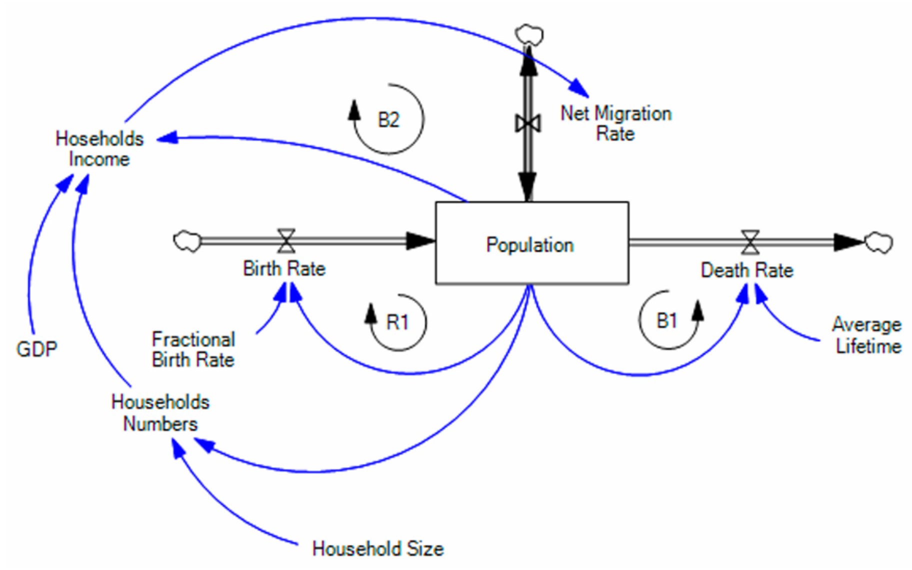

Figure 4.3: Stock-flow diagram of socioeconomic structure & consumption behaviour [52]

diate feedback is rare, and decisions made today might only manifest their full impact years down the line. This makes SD a essential tool to understand the system behaviour in complex networks such as the freight transport system, which in real-world is affected by non-linear relationships and side-effects.

Forecasting Capabilities

One of the primary strengths of system dynamics lies in its capacity to model complex systems and their behaviors over time. This is particularly relevant in freight transport demand forecasting, where interactions between multiple variables, such as economic growth, infrastructure capacity, and regulatory policies, create a dynamic and evolving system. SD excels at capturing feedback loops, both reinforcing and balancing, which helps in simulating how these variables interact with one another. Within the framework of this thesis, where long-term forecasting is key, the ability to incorporate time delays and future states makes SD a powerful tool since it enables a deeper understanding of how current policy decisions might influence future transport demand or GHG emissions [53][55].

Another strength of SD is its holistic approach, which allows it to integrate both qualitative and quantitative data. By modeling not only physical infrastructure but also policy interventions, public behavior and economic variables, SD provides a comprehensive view of how transport systems evolve. This is valuable when comparing forecasting techniques because it demonstrates how changes in one aspect of the system (e.g., economic policies) can evolve through and affect other parts of the system such as demand patterns or emissions.

Moreover, the SD model's capacity to incorporate intangible variables, such as stakeholder behavior or environmental goals, offers a unique advantage. In freight transport forecasting, these variables often play a critical role in long-term decision-making but are difficult to quantify using traditional statistical methods. Its ability to simulate these variables over time makes it a strong candidate for capturing the broader impacts of policy decisions

However, system dynamics is not without limitations. One notable constraint is its dependence on accurate and comprehensive data to construct meaningful models. Since SD operates by simulating the relationships between variables over time, not only the quality of the data used to establish these relationships is crucial, but also the expertise to validate feedback loops. Moreover, in freight transport demand forecasting, where data on future technological advancements or policy impacts may be sparse or uncertain, this reliance on data can limit the model's precision, basing this prediction mainly in the subjective opinion of experts.

Another limitation lies in the abstraction necessary to create SD models. By focusing on the system as a whole and simulating large-scale interactions, SD can sometimes oversimplify the micro-level details, overlooking the individual actors' behaviours. So, while SD excels in simulating long-term trends, it is less effective at providing short-term, highly granular forecasts, which might be better captured by econometric, time-series or agent-based models. Being a model used for the overall understanding of the dynamics of a complex system in the long-term.

Therefore, as it has been seen, system dynamics has several valuable uses. It is particularly valuable for scenario analysis, allowing researchers to simulate the impact of different policies, technological changes or economic conditions on future transport demand. For instance, SD can model the effects of increased rail transport, changes in vehicle emissions standards, or shifts in consumer behaviour on freight demand, providing insights into how these factors might evolve over time. This makes it a useful tool for policymakers seeking to understand the long-term implications of their decisions.

Additionally, SD can be applied to evaluate the sustainability of different freight transport systems. By modeling not only the economic factors driving demand but also environmental and social factors, providing additional essential functionality to policymakers, helping them to build better strategies. For instance, it could be used to forecast the environmental impacts of different freight transport modes under various policy scenarios, helping to compare methods based on sustainability criteria.

Furthermore, system dynamics can be effectively integrated with other modeling techniques to address its limitations and provide a more comprehensive view of freight transport demand forecasting. One common approach is integrating SD with Input-Output (I-O) models [56]. These models are economic models that describe the interdependencies between different sectors of an economy. They capture how the output of one sector (e.g., manufacturing) is used as an input by another sector (e.g., logistics or transport services), providing a detailed view of the economic flows and how changes in one part of the economy affect others.

So, while SD models the dynamic behavior of systems over time, I-O models provide a snapshot of the economic flows between sectors at a given point in time. For instance, an I-O model might be used to calculate the demand for freight services based on changes in production and consumption patterns in various economic sectors, while SD can simulate how this demand evolves over time, taking into account factors like infrastructure development and policy changes. This integration provides a richer, more detailed forecast by combining the temporal strengths of SD with the detailed economic linkages of I-O models.

Moreover, SD can also be combined with Agent-Based Models (ABM) to provide a more granular view of how individual actors (such as logistics companies or consumers) behave within the larger system. ABM focuses on the decision-making processes and interactions of individual agents, offering micro-level insights that complement SD's macro-level focus. Regarding the goal of this framework, this combination could allow for having a comprehensive model at both the micro and macro levels robust enough for long-term forecasting.

Multi-criteria Systematic Comparison

Table 4.10: Systematic evaluation of system dynamics

Accuracy ★★★★☆	+	Ability to capture feedback loops, delays, and accumulations in complex systems, making them well-suited for long-term forecasting. They can provide high accuracy in stable systems.
	-	However, their accuracy depends heavily on the assumptions made regarding system behavior, potential structural changes and relationships between variables. While they can provide high accuracy in stable systems, accuracy may degrade when applied to highly volatile systems with unpredictable external shocks.
Data Requirements ★★½☆☆	+	These models typically rely on aggregate data and can function with less granular data than some other methods
	-	SD models require data to parameterize the relationships between different parts of the system, such as transport demand, infrastructure capacity, and economic activity. Accurate calibration of the relationships between variables is critical for reliability.

Scalability ★★★★☆	+	System dynamics models are highly scalable and can be applied at multiple levels (local, national, or international) and across different time horizons.
	-	As the scale of the system increases, the complexity of the feedback mechanisms and the number of variables also grow, which can make large-scale SD models more challenging to manage and to understand.
Complexity ★★★☆☆	+	Conceptual casual loop diagrams give them transparency to understand the internal mechanisms of the model.
	-	Designing and calibrating a system dynamics model requires a deep understanding of the system and its components, which increases the level of difficulty in both development and interpretation. They are inherently complex due to their focus on capturing dynamic interdependencies, feedback loops, and non-linear behaviors within a system.
Cost-effective ★★★☆☆	+	Moderate operational costs once the model is established if the size is not excesive. Cost-effective for running multiple scenarios and analyses.
	-	Developing and maintaining SD models can be costly due to their complexity and the time required for proper calibration and validation. The data needs for calibration and the computational requirements for simulating large, dynamic systems can drive up costs
Timeliness ★★★☆☆	+	Capable of providing long-term forecasts and evaluating policy impacts over extended periods. If it is designed correctly, it doesn't need too much calibration due to its adaptability and long-term forecasting.
	-	SD models tend to be slower to develop and run due to their complexity. Calibration, scenario testing, and simulation runs can take significant time, especially when modeling large systems with numerous feedback loops and interactions.
Robustness ★★★★⯨	+	SD models are highly robust in their ability to handle complex, dynamic systems with multiple feedback mechanisms. They are well-suited for scenario analysis and uncertainty assessment, enabling planners to explore how the system behaves under various conditions (e.g., economic shocks, policy changes, technological innovations).
	-	Their performance heavily depends on the accuracy of the assumptions and relationships built into the model, so it relays mainly in the expertise of implementers.
Interpretability ★★★⯨☆	+	SD models often come with powerful visualization tools (e.g., stock and flow diagrams, causal loop diagrams), which can help in understanding the overall system behavior.
	-	System dynamics models can be difficult to interpret for non-experts due to the complexity of the feedback loops and system interactions.

Integration ★★★★☆	+	They integrate well with other models such as econometric models or agent-based models. Their ability to model dynamic systems makes them ideal for integration with models focused on specific components, providing more detailed modelling at micro-level, allowing for a more comprehensive view of system behavior.
	-	Its main limitation is its complexity, but if careful design is applied, it is able to cope with it.
Functionality ★★★★☆	+	System dynamics models provide highly detailed insights into the structure and behavior of complex systems over time, making them functional for capturing a wide range of factors (e.g., economic, environmental, and policy impacts). Multiple and valuable tools for planners (scenario analysis, uncertainty, long-term, system behaviour, system changes, etc.)
	-	They may lack detailed outputs at the granular level (disaggregate data) such as specific routes or modes for freight.

System dynamics offers a powerful framework for understanding and forecasting freight transport demand, particularly in long-term, complex systems where interactions between variables are dynamic and non-linear. Its strengths in handling feedback loops, scenario analysis and structural changes make it an excellent tool. However, its limitations, especially in terms of abstraction and lack of data granularity, suggest that integrating SD with other models like input-output or agent-based Models can provide a more robust forecasting framework. By combining these methods, it is possible to leverage the strengths of each to create a comprehensive and flexible model that addresses both the macro-level trends and micro-level behaviors influencing freight transport demand.

4.3.2 Agent-Based Models

Method Description

Agent-Based Models (ABM) are a type of simulation model that focuses on the actions and interactions of autonomous agents—individual entities such as people, firms, or organizations—within a defined system. In the context of the complex freight transport systems, ABM offers a valuable approach for capturing the behavior of various stakeholders in the sector, including shippers, carriers, regulators and consumers. Unlike traditional aggregate econometric models that focus on system-wide trends, ABM provides a bottom-up perspective, modeling how individual decisions and interactions collectively shape the behavior of the entire system.

At its core, ABM operates by simulating the behavior of individual agents, each governed by a set of predefined rules or decision-making processes. In freight transport, agents might represent logistics companies deciding how to route shipments, consumers determining how and when to place orders or regulators adjusting policies to manage traffic congestion [54]. These agents interact with each other and with their environment, giving place to emergent events, patterns of behaviour that result from the collective actions of individuals. This capacity to model emergent behaviour is a key strength of ABM, particularly in systems like freight transport, where the actions of a single agent can significantly influence the overall system such as a peak in demand causing congestion or supply chain delays.

ABM has such a value for understanding complex, adaptive systems where heterogeneity among agents and localized decision-making are important, being an essential tool to represent real-world logistic dynamics. The ability to simulate how individual stakeholders respond to changes in infrastructure, regulations or market conditions makes these models robust and suitable for long-term prediction. For example, ABM could model how different logistics firms adjust their behavior in response to new environmental regulations such as emissions caps or congestion charges, providing insights into how such policies might impact overall freight demand, allowing for a comprehensive scenario analysis.

Many Agent-based models are develop within MATSim, which is an open-source framework for large-scale agent-based transport simulations [57]. This toolkit operates by simulating the daily activities and transport choices of individual agents, each of which represents an entity like a driver, vehicle or firm. These agents make decisions based on a set of predefined rules, which are influenced by factors such as travel time, cost and preferences. MATSim's ability to simulate large-scale transport systems, involving thousands or even millions of agents, provides a detailed picture of how individual decisions accumulate to affect overall transport demand, congestion and network performance.

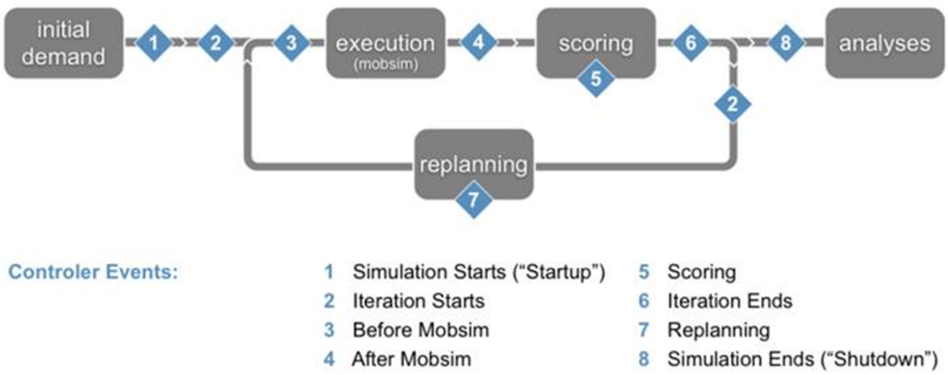

Figure 4.4: Main structure of the MATSim Controler [58][54]

One of the key strengths of MATSim is its iterative learning process [58]. In each iteration, agents evaluate their previous travel choices and make adjustments to optimize their objectives (e.g., minimizing travel time or cost), as shown in Figure 4.4. This process of trial and error allows MATSim to simulate how agents adapt to changes in the transport network such as the introduction of new infrastructure, changes in policy or fluctuations in demand. This adaptability is particularly valuable in long-term forecasting, where transport systems are expected to evolve due to technological advancements, economic shifts or regulatory changes. Additionally, MATSim follows a modular approach, providing a flexible structure for further integration of other modules or models to enhance the forecasting accuracy or increase the number of features.

One of ABM's key features is its use of an activity-based approach (which is the case for most agent-based models), where each agent's behaviour is modeled based on their daily activity schedules rather than just trips [59]. This allows the simulation to incorporate a more detailed and realistic representation of travel demand, including the temporal and spatial aspects of freight movement. In freight transport forecasting, this approach enables models to simulate how logistics firms adjust their operations, such as route planning and scheduling, based on various factors like traffic congestion, fuel costs or delivery windows.

Furthermore, Dynamic Traffic Assignment (DTA) models is an important complement too since they model the evolution of traffic flows over time, allowing for a more realistic simulation of how traffic congestion, travel times and route choices change dynamically as agents make decisions in response to evolving conditions on the road network [59]. When combined with ABM, it can significantly enhance the model's ability to simulate real-world transport systems, especially for freight transport in urban environments.

In the context of freight transport forecasting, these models have historically been used for the urban environment [60], due to the fact that these are complex and highly dynamic networks that are affected by the decisions of thousands or millions of agents, and also due to the current inability to take this modelling approach to a national or international scale due to its detailed micro-modelling [61].

Forecasting Capabilities

The strength of ABM lies in its ability to model heterogeneity and micro-level behaviors. In freight transport demand forecasting, agents are not homogenous, having varying preferences, capacities and constraints. These models allow practitioners to model these differences and simulate how they affect the system, being a more accurate and realistic approach. For instance, different logistics companies might have varying fleet sizes, cost structures, and environmental priorities, all of which influence their decision-making processes. Therefore, ABM can provide a more granular view of how specific actors contribute to larger trends in freight demand, making it a useful complement to more aggregate models like system dynamics, which focuses on system-wide behaviors.

Another key advantage of ABM is its flexibility in adapting to new conditions and integrating different types of data. In freight transport, changes in infrastructure, economic conditions or technology can all influence agent behavior. ABM is well-suited to incorporate these changes, as it allows for the modification of agent rules and behaviors based on new inputs. This adaptability makes ABM particularly useful in long-term forecasting, where the ability to model how individual actors might respond to uncertain future scenarios is crucial. Moreover, this capability to adapt allows policymakers to perform all kind of analysis, scenario analysis, risk analysis, uncertainty analysis to build the optimal strategies, aligning with the ultimate goal of this thesis.

As discrete choice models, they are able to quantify behavioural factors to better model the agent, by using qualitative methods as the SP/RP surveys. This provide a quite realistic approach to the micro-modelling since it is hard to determine those subjective variables from standard data sets.

It must be also mentioned the diverse range of features that ABMs can offer [59][60][54]. Due to its micro-modelling and disaggregate approach, ABMs is able to simulate plenty kind of decisions such as mode choice, vehicle choice, route selection, learning ability, etc. In addition, models can be upgrade to offer different KPIs such as external cost (health impact, congestion, accidents), environmental impact, operational features, etc. Therefore, ABM becomes an essential tool that can support policymakers and private companies to perform all kind of analysis (scenario analysis, risk analysis or policy impact assessment), including friendly user face to improve the interpretability of outcomes for the non-technical stakeholders, Figure 4.5. Therefore, ABMs, with such a great and diverse functionality, offer a robust tool to evaluate and compare different strategies.

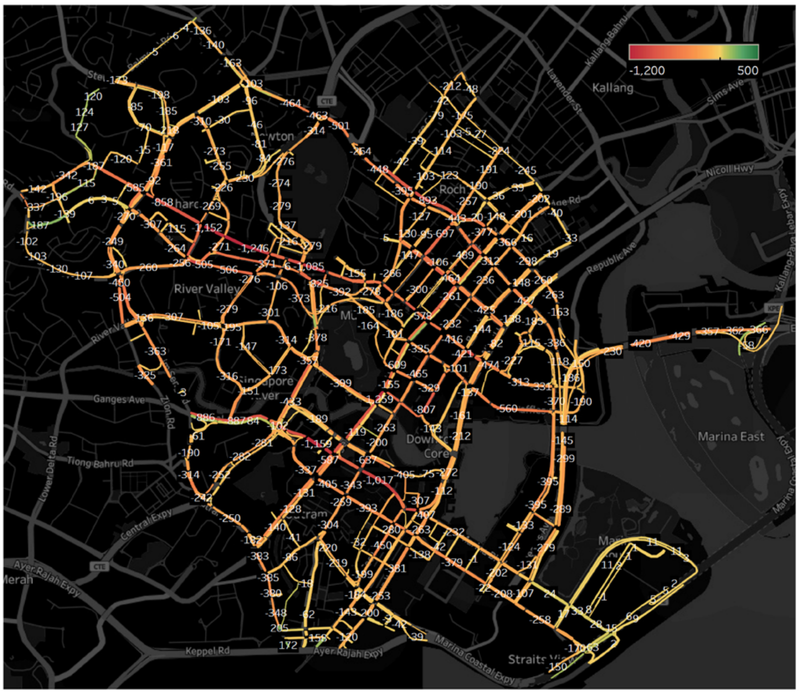

Figure 4.5: Visualisation of vehicles in SimMobility [60]

However, ABM is not without limitations. One challenge is the computational complexity involved in simulating large numbers of agents, especially in systems as complex as European freight transport networks. The detailed nature of ABM can make it resource-intensive, particularly when modeling interactions between thousands or millions of agents, reducing its current feasibility to urban scale or regional scale applying some simplifications or aggregations [54]. To deal with these limitations, research is focus on optimisation strategies to reduce the computation load without compromising the accuracy of the model [62].

Moreover, while ABM excels at capturing micro-level behavior, it can sometimes struggle to accurately predict system-wide trends without the support of complementary models that provide macro-level insights, being commonly combined with SD and others econometric system-wide approaches like I-O models.

ABM are also commonly combined with other econometrics methods such as, the previously mentioned, Dynamic Traffic Assignment which is an equilibrium model that helps to model the evolution of traffic flows. Furthermore, discrete choice models can be also used to improve the behavioural accuracy of the agents [63].

Multi-criteria Systematic Comparison

Table 4.11: Systematic evaluation of agent-based models

Accuracy ★★★★☆	+	ABMs can provide high accuracy in capturing the complex interactions between individual agents (e.g., shippers, carriers, consumers) and their environments. They are excellent for modeling heterogeneous behaviors and can provide very accurate forecasts in the short- to medium- term.
	-	Accuracy may suffer for long-term predictions due to the unpredictability of individual behaviors over time. It should be combined with system-wide approaches like SD to improve its macro-modelling and then its long-term forecasting.
Data Requirements ★★★★★	+	SP/RP helps to model behavioural preferences of the agents.
	-	ABMs require highly detailed data about individual agents and their decision-making processes. This can include socioeconomic data, behavioural patterns, and interaction rules, which are often hard to collect and validate. Data requirements can be immense, depending on the complexity of the system.
Scalability ★★⯪☆☆	+	Technically is scalable to systems of any size in geographic and temporal dimensions.
	-	Their computational complexity increases exponentially as the number of agents and interactions increases, increasing significantly its computation and data requirements. For large-scale applications, such as long-term European freight forecasting, scalability becomes a major issue unless simplifications or aggregations are applied [54][61]. Not feasible to scale up, limitation to urban level.

Complexity ★★★★⯪	+	This complexity and disaggregation allows for a accurate behavioural modelling.
	-	Complex models due to their ability to simulate interactions between multiple agents, each with potentially unique behaviors. Designing, calibrating, and running these models can be very challenging and require a high level of expertise. The complexity grows with the number of agents and the rules governing their interactions.
Cost-effective ★⯪☆☆☆	+	ABMs offer a powerful tool to optimise strategies for both publich and private sectors.
	-	The development and maintenance costs of ABMs can be high because of the detailed data and complex computational requirements. Significant cost in data collection, development and computational power. Additionally, significant resources may be needed for ongoing model refinement and recalibration, particularly when used for large-scale freight systems.
Timeliness ★★☆☆☆	+	Research in optimisation technique to reduce computational requirements and speed up its forecast.
	-	Due to the complexity and detailed simulation of interactions, ABMs can be slow to run, especially when simulating large systems over long periods. Updates and recalibrations can also be time-consuming, limiting the ability to quickly generate new forecasts.
Robustness ★★★★⯪	+	ABMs are highly robust in modeling complex, adaptive systems and can handle significant variability in agent behaviors. They are well-suited for scenario analysis, allowing users to test how the system behaves under different economic, social or policy conditions. Its long-term robustness can be improved by integrating system-wide models such as SD.
	-	Their robustness is dependent on the accuracy of the input data and the rules governing agent behavior.
Interpretability ★★★⯪☆	+	With good visualization tools, the simulation results can be made more accessible.
	-	The results of ABMs can be challenging to interpret, especially for non-experts, due to the complexity of interactions and the potentially large amount of output data. Understanding the underlying mechanisms may require significant expertise.
Integration ★★★★☆	+	ABMs can integrate with other models, such as econometric models, SD or optimization techniques, to enhance overall functionality. Modular structure can facilitate further integrations.
	-	Integrating them can be challenging due to the differences in methodologies and data requirements, maintaining data consistency.

Functionality ★★★★★	+	ABMs excel in functionality, providing detailed insights into individual-level interactions, including behavioral dynamics, decision-making processes, and adaptive responses to system changes. They allow for a high degree of granularity, including spatial and temporal disaggregation. They offer a diverse range of features and tools that support the decision-making of planners.
	-	Their complexity can limit the practical use for large-scale, long-term freight forecasts, having to do simplifications or aggregation in bigger scales.

In conclusion, Agent-Based Models (ABM) offer a powerful and flexible framework for simulating the complex dynamics of freight transport systems by capturing the individual decisions of diverse agents such as logistics firms, transport operators and regulators. The ability of ABM to incorporate key features like external costs, routing, mode choice, environmental impact and adaptive decision-making makes it highly valuable for forecasting and policy analysis. With its focus on scenario analysis, ABM allows policymakers to evaluate the outcomes of various interventions—such as regulatory measures, infrastructure investments and sustainability initiatives—in a dynamic and detailed manner. This comprehensive approach provides critical insights into how individual behaviors aggregate to impact overall system efficiency, sustainability and equity, making ABM an essential tool for designing informed, adaptive, and effective transport policies.

However, while ABM would be the ideal method due to its versatility and capacity to model complex systems, it has significant limitations in terms of scalability. As the size and complexity of the system increase, the computational and data demands grow exponentially, making large-scale simulations challenging without advanced technological infrastructure or important simplifications.

4.4 AI-Machine Learning Models

To conclude the comparison of models, moving on to the last group, the one that has been found to be increasingly gaining importance in research recently. Artificial Intelligence (AI) techniques have emerged as powerful tools for addressing complex forecasting challenges, particularly in dynamic fields like freight transport demand forecasting. AI techniques allow for the analysis of large datasets and the modeling of complex relationships between multiple variables, providing more accurate and adaptive forecasts compared to traditional statistical methods.

These methods, which include a range of machine learning algorithms and optimization techniques, are increasingly being integrated into transport planning and decision-making processes. By using AI it is possible to capture non-linear patterns, account for uncertainty and improve predictions through continuous learning, all of which are essential for long-term forecasting and scenario analysis in freight transport systems.

At the core of AI techniques is the ability to learn from data with the aim of identifying patterns, trends and relationships that may not be immediately visible through traditional analysis. Unlike conventional models, which are typically predefined and static, AI models can adapt and improve as they are exposed to new data. This makes them well-suited for environments characterized by variability and uncertainty, such as the evolving freight transport system. With the increasing availability of data from sensors, economic indicators and infrastructure, AI techniques offer a sophisticated means to make more informed and reliable forecasts.

In addition to prediction capabilities, AI techniques also incorporate powerful optimization methods to enhance decision-making processes. Genetic Algorithms (GA) are one such optimization technique, inspired by the principles of natural selection and evolution. In GA, solutions to a problem are treated like individuals in a population, and through the processes of selection, crossover, and mutation, better solutions are evolved over time. The algorithm evaluates the fitness of each solution based on predefined criteria and iteratively improves the population until an optimal or satisfactory solution is found. In the context of freight transport, GAs can be used to optimize routing, fleet management, or resource allocation, helping to improve operational efficiency and reduce costs.

In addition to prediction capabilities, AI techniques also incorporate powerful optimization methods to enhance decision-making processes. Genetic Algorithms (GA) are one such optimization technique, inspired by the principles of natural selection and evolution. In GA, solutions to a problem are treated like individuals in a population, and through the processes of selection, crossover, and mutation, better solutions are evolved over time [64]. The algorithm evaluates the performance of each initial solution to select the best ones based on predefined criteria, then it cross the solutions and randomly modify them, iteratively improves the population until an optimal or satisfactory solution is founnd. In the context of freight transport, GAs can be used to optimise routing, fleet management or resource allocation, helping to improve operational efficiency and reduce costs or to optimise calibration process of another method [65].

Another essential component of AI in forecasting is the use of Bayesian methods, which provide a probabilistic framework for decision-making under uncertainty. Bayesian methods rely on Bayes' theorem, which updates the probability of a hypothesis as more evidence or data becomes available.

The theorem is mathematically expressed as:

$$P(H|E) = \frac{P(E|H) \cdot P(H)}{P(E)} \tag{4.20}$$

where:

- $P(H|E)$: The **posterior probability**, the probability of the hypothesis H given the evidence E.
- $P(E|H)$: The **likelihood**, the probability of observing the evidence E given that the hypothesis H is true.
- $P(H)$: The **prior probability**, representing the initial belief about the hypothesis H before observing the evidence.
- $P(E)$: The **marginal likelihood**, the total probability of the evidence E, considering all possible hypotheses.

This approach is particularly valuable in scenarios where the information is incomplete or uncertain, as it allows models to incorporate both prior knowledge (beliefs) and new evidence dynamically. In transport forecasting, Bayesian methods are useful for continuously adjusting predictions as new data such as changes in infrastructure, economic conditions or traffic patterns becomes available. This flexibility is crucial for long-term forecasting, where evolving conditions often demand adaptive models that can respond to emerging trends, and it also allows for risk analysis [66][67].

Of the multiple emerging techniques in the field of AI, those considered most important for the context of freight transport demand forecasting in this thesis will be analysed, being the following 3 subgroups:

- **Artificial Neural Network (ANN):** Ideal for modeling complex, non-linear relationships and time-dependent data.
- **Support Vector Machine (SVM):** Strong in scenarios where it is necessary to classify or predict freight demand under conditions of non-linearity and high-dimensionality.
- **Random Forests (RF):** It provides robustness and interpretability by reducing the variance and overfitting problems common in complex forecasting models.

By studying these three techniques within the AI techniques group, it is possible to offer a comprehensive analysis of how different AI methods can be applied to the challenges of freight transport demand forecasting.

4.4.1 Artificial Neural Networks

Method Description

Artificial Neural Networks (ANN) are a subset of machine learning algorithms designed to simulate the way the human brain processes information. ANNs consist of interconnected layers of artificial neurons (or nodes) that are used to recognize patterns, make predictions and learn from data [11]. Their ability to model complex, non-linear relationships between inputs and outputs makes them highly effective for a wide range of applications, including freight transport demand forecasting.

ANNs are very valuable because they can adapt to the complexity of real-world data, learning to map intricate patterns through a process called training, where they adjust internal parameters (weights) to minimize the difference between predicted and actual outcomes [11]. While many types of ANNs exist, this thesis will focus on the most commonly used architectures, they are used for different purposes and are widely applicable in the domain of time-series forecasting, pattern recognition and transport modeling.

- **Feedforward Neural Networks (FNN)**

  The Feedforward Neural Network (FNN) is the most basic form of an ANN. In an FNN, the information moves in one direction, from the input layer through one or more hidden layers to the output layer, meaning each input influences the output in a straightforward [68]. FNNs are typically used for tasks such as regression or classification, where the goal is to map a fixed set of inputs to a corresponding output.

  FNNs are easy to implement and interpret, making them a popular choice for tasks where the relationships between variables are relatively simple. However, FNNs are limited in their ability to handle sequential or time-dependent data, as they do not maintain any memory of previous inputs.

- **Recurrent Neural Networks (RNN)**

  They are designed to address the limitations of FNNs by introducing loops in the network, allowing it to maintain a memory of previous inputs. This is especially useful for sequential data such as time-series data, where the current output may depend on past inputs. In an RNN, information is passed not only forward through the layers but also back into previous layers, enabling the network to learn temporal dependencies [69].

  RNNs are commonly used in tasks like time-series forecasting, where sequences of data are essential. However, standard RNNs struggle with long-term dependencies, as the information from earlier inputs can get lost or diminished over time, a problem known as the vanishing gradient problem.

- **Long Short-Term Memory (LSTM)**

  To overcome the limitations of standard RNNs, Long Short-Term Memory networks were developed. LSTMs are a specialized type of RNN that can capture long-term dependencies by using a memory cell mechanism that allows the network to remember or forget information over longer sequences of data [70]. This makes LSTM well-suited for tasks that require modeling of long-term temporal dependencies such as freight transport demand forecasting, where past data points can have an influence on future predictions over extended periods.

LSTM networks are utilised time-series forecasting due to their ability to effectively manage the flow of information across long sequences of data. In freight transport demand forecasting, LSTMs can model complex patterns in historical data, making them ideal for predicting long-term trends and seasonal fluctuations [71].

- **Convolutional Neural Networks (CNN)**

  While convolutional neural networks are most famously associated with image processing, they have found increasing use in applications involving spatial or temporal data, being useful for detecting spatial-temporal patterns in transport data [72].

  In the context of freight transport, they can help in predicting traffic flows, analyzing route optimization or understanding how geographic regions impact freight demand. CNNs' ability to capture local features makes them highly effective for tasks where understanding spatial patterns is key.

ANNs are a versatile and powerful toolset within AI, capable of modeling complex patterns and relationships in data. Among these types, FNN and LSTM networks are the most widely used in transport demand forecasting, however, each type of ANN has its strengths and applications. FNNs are straightforward and effective for static data, while RNNs and LSTMs excel in handling sequential, time-dependent data. CNNs, although traditionally used in image processing, are increasingly useful for spatial-temporal data analysis. Together, these ANN architectures provide the flexibility and power needed to tackle complex forecasting problems, such as freight transport demand in dynamic environments.

Forecasting Capabilities

ANN has significant potential for improving freight transport demand forecasting due to their ability to model complex, non-linear relationships and process large, multi-dimensional datasets. One of the main strengths of ANNs is their adaptability as they can learn directly from data, identifying hidden patterns and trends, which makes them particularly useful in dynamic environments. Unlike traditional models, ANNs can account for various factors that influence demand such as economic indicators, infrastructure changes and market dynamics. This ability to process diverse inputs and uncover complex relationships enhances the accuracy of long-term freight demand forecasting. Furthermore, ANNs are flexible across different forecasting tasks, from short-term demand predictions to long-term strategic analyses.

However, ANNs come with notable limitations. They require large amounts of high-quality data to perform optimally, which can be a barrier in the freight transport sector, where data collection and consistency are often limited. Another significant drawback is the "black box" nature of ANN models [68]. While they can produce highly accurate forecasts, they offer limited transparency in terms of explaining how individual inputs influence the final output. This lack of interpretability can be problematic for stakeholders who need clear, understandable insights from forecasting models [73].

Additionally, ANNs are computationally demanding when dealing with deep networks like LSTMs or CNNs. This computational intensity can be a barrier for organizations that lack the necessary infrastructure to support such models [68]. Overfitting is another risk, especially when training on small datasets, which can lead to models that perform well on historical data but poorly on new or unseen data.

In terms of their practical application, ANNs are commonly used in time-series forecasting where they can analyze historical freight demand data to predict future trends. LSTMs are particularly effective in this domain due to their ability to handle sequential data and model long-term dependencies[72]. ANNs are also useful for multi-modal freight forecasting, where they can account for the demand across different transport modes such as road, rail, or air. Moreover, they can be employed in scenario analysis, allowing stakeholders to simulate the effects of various policy changes or infrastructure investments on future freight demand.

ANNs can also be integrated with other models to enhance their performance. For instance, Genetic Algorithms (GA) can be used in conjunction with ANNs to optimise parameters such as weights and learning rates, improving the overall performance of the model. Bayesian methods can also be applied to optimise the ANN's parameters, ensuring that the model generalizes well to new data and mitigates the risk of overfitting.

Additionally, ANNs can be combined with Dynamic Traffic Assignment (DTA) models to optimize freight routing and scheduling decisions, where ANN predicts demand and DTA allocates resources in real time [74]. Another common possibility is to integrate with traditional ARIMA time series, where ARIMA captures linear relationships and LSTM models the non-linear, long-term dependencies in freight demand data [69].

In terms of current implementation, ANNs are increasingly being applied in research and pilot projects focused on freight transport demand forecasting. However, in practical, everyday applications, their adoption remains somewhat limited. While large logistics companies and government agencies are beginning to explore the use of ANN models, traditional methods such econometric models are still more commonly used due to their simplicity and transparency. The barriers to broader adoption of ANN models include the high data and computational requirements, as well as concerns over interpretability. Many organizations are hesitant to rely on models that function as a "black box," even if they offer higher predictive accuracy compared to more traditional methods.

Despite these challenges, as data infrastructures improve and computational resources become more accessible, the practical implementation of ANN models in freight transport demand forecasting is expected to increase. The ability of ANNs to handle complex, non-linear data and adapt to changing conditions positions them as a powerful tool for forecasting in dynamic environments, adapting perfectly to the current requirements. As these models become more interpretable and user-friendly, they will likely see wider adoption in both research and industry applications, offering significant benefits for long-term freight transport planning and decision-making.

Multi-criteria Systematic Comparison

Table 4.12: Systematic evaluation of artificial neural networks

Accuracy ★★★★⯪	+	ANNs are known for their high accuracy, especially when large datasets are available. They are highly effective in identifying non-linear patterns and relationships, which makes them well-suited for complex systems like freight transport.
	-	However, the accuracy depends on the quality and quantity of the training data and can degrade if the model overfits or encounters unseen conditions.
Data Requirements ★★★★☆	+	High quality data enhance accuracy.
	-	ANNs require large amounts of high-quality, labeled data for training. They require detailed data and may struggle or provide inaccurate forecasts if the data is incomplete or noisy. Data preprocessing (cleaning, normalization) is essential for good performance.
Scalability ★★★★☆	+	ANNs are highly scalable and can be applied to large datasets and complex systems. They can be trained for local, regional or global-scale forecasts and they perform well across different temporal horizons.
	-	As the model and data scale increase, so do the computational requirements, which can be a limiting factor.
Complexity ★★★★⯪	+	
	-	ANNs are inherently complex and often seen as "black box" models, meaning that their internal decision-making processes are difficult to interpret. Designing, training and tuning ANNs (e.g., selecting the appropriate architecture, number of layers, neurons, activation functions) requires significant expertise. This complexity can be a barrier for both implementation and understanding.

Cost-effective ★★☆☆☆	+	Once trained, ANNs can be efficient to run, making them more cost-effective for ongoing use.
	-	The development and training of ANNs can be expensive due to the high computational costs, especially for large-scale models. Expertise is required. Hardware requirements add to the overall cost.
Timeliness ★★★☆☆	+	Once trained, ANNs can generate forecasts quickly, which makes them suitable for real-time applications. The timeliness of updates (e.g., re-training) depends on the availability of new data and computational resources.
	-	Training the model can be time-consuming, especially for large models with complex architectures.
Robustness ★★★★☆	+	ANNs are highly robust in capturing non-linear relationships and handling large, complex datasets. Compatible to scenario analysis and handling of uncertainty.
	-	They are sensitive to the quality of training data and can struggle with unexpected changes or out-of-sample conditions if not trained on a diverse dataset. ANNs can tend to overfitting if not properly regularized, which reduces their robustness.
Interpretability ★★☆☆☆	+	Tools like SHAP (SHapley Additive exPlanations) can help explain model outputs.
	-	One of the main weaknesses is their low interpretability, being key for stakeholders to make decisions. The complexity of the model architecture, especially in deep learning variants, makes it difficult for users to understand how the model arrived at a particular prediction. ANNs are considered ”black box” models.
Integration ★★★★☆	+	ANNs can be integrated with other models or frameworks such as econometric models or time series. ANNs can be used as part of a hybrid approach, providing a strong predictive component while other models handle system-level dynamics or feedback (SD, I-O).
	-	The differences in methodologies may complicate integration.
Functionality ★★★½☆	+	They can model complex systems with many inputs and provide detailed predictions. Ability to handle a large number of variables and non-linear relationships.
	-	The output may lack intuitive interpretations, and specific features like temporal disaggregation or scenario-based outputs may require additional work.

In conclusion, Artificial Neural Networks (ANN) provide a powerful and flexible framework for addressing the complexities of freight transport demand forecasting. Their ability to model non-linear relationships, process large datasets, and adapt to changing conditions makes them highly effective in forecasting scenarios where multiple factors influence demand. Techniques like LSTMs networks are specially useful for time-series forecasting, allowing for accurate predictions based on historical trends. While ANNs excel in predictive performance, their lack of interpretability and high computational requirements remain significant challenges, limiting their widespread adoption in practical, industry-wide applications.

Despite these limitations, the integration of ANNs with other models can enhance their utility. As data infrastructures improve and computational barriers decrease, ANNs are expected to play a more prominent role in the freight transport sector, providing more accurate and adaptive forecasting models. With further advancements in model interpretability and user-friendliness, ANNs have the potential to become a core in long-term transport planning and decision-making processes.

4.4.2 Support Vector Machine Models

Method Description

Support Vector Machines (SVM) are a widely used machine learning technique which are well-suited for both classification and regression tasks. In the context of freight transport demand forecasting, SVM offers a robust method for analyzing complex and high-dimensional data, which is typical in transport systems where multiple factors such as economic indicators, infrastructure changes and policy interventions affect demand [75]. SVM is valued for its ability to handle non-linear relationships and for performing well even when there is limited data available, making it a versatile tool in predictive modeling.

SVM operates by finding the optimal hyperplane that separates data points from different classes in classification tasks or fits a regression line that minimizes prediction errors in regression tasks. It does so by transforming data into a higher-dimensional space using kernel functions, enabling the model to solve problems where data may not be linearly separable in its original space [75]. This transformation allows SVM to capture complex relationships between input variables (e.g., traffic patterns, economic trends) and the target variable (e.g., freight demand).

At the core of SVM lies the concept of maximising the margin, which refers to the distance between the data points closest to the hyperplane (called support vectors) and the hyperplane itself [76]. By maximizing this margin, SVM ensures that the model is more generalisable and less susceptible to overfitting, making it robust in situations where data is noisy or sparse. In freight demand forecasting, this robustness is crucial when dealing with incomplete or imperfect data, which is common in transport systems where data sources may be fragmented [16].

SVM models work through the use of kernel functions, which enable the algorithm to handle non-linear data by mapping it into a higher-dimensional space where a linear separation (or regression) is possible. The most commonly used kernels are the linear kernel, polynomial kernel, and the radial basis function (RBF) kernel[77]. In freight forecasting, the ability of SVM to apply these kernels means it can model non-linear relationships between factors like fuel prices, economic growth and traffic congestion, providing accurate demand predictions even when the relationships are complex and non-intuitive.

For regression tasks, SVM uses a variation called Support Vector Regression (SVR) [76]. In SVR, instead of finding a hyperplane that perfectly separates the data, the model finds a hyperplane that best fits the data while minimising the prediction error within a certain tolerance. This makes SVR particularly useful for predicting continuous outcomes such as freight volumes or demand levels, where exact classifications are less important than minimising forecasting errors [78].

Forecasting Capabilites

One of the primary strengths of SVM is its ability to handle non-linear relationships between variables, which is useful in freight transport forecasting since freight demand is influenced by various interconnected factors, such as infrastructure capacity, economic trends, fuel prices and traffic patterns, and SVM excels in modeling these complex, non-linear interactions. Through the use of kernel functions, SVM can map data into higher dimensions, allowing it to separate or model relationships that are not linearly separable in the original input space [79]. This makes it effective in identifying complex patterns in the data that simpler models might miss.

SVM also performs well in situations where data is limited or noisy, which is often the case in freight transport systems, especially when dealing with fragmented or inconsistent datasets [79]. Unlike models that may overfit by trying to model every detail in the data, SVM focuses on finding the optimal margin that separates different outcomes (or minimises regression errors), making it less susceptible to overfitting [77]. This generalisation capability ensures that SVM can provide reliable forecasts even in uncertain environments. Additionally, SVM is particularly suited for high-dimensional datasets, where the number of input variables is large, a frequent scenario in freight forecasting when multiple factors, including weather, traffic and economic indicators, must be considered.

Nevertheless, SVM's complexity, especially when dealing with large datasets, remains as weakness. Training an SVM model can be computationally intensive, as the algorithm must evaluate all support vectors to find the optimal hyperplane. This can become a challenge when applying SVM to large-scale freight transport systems with extensive data.

Another limitation is the difficulty in interpreting SVM models. While SVMs can produce highly accurate results, their decision-making process is not always easy to interpret.

This can be a disadvantage when forecasting models need to provide transparency or explainability for policymakers, who require clear, interpretable insights to support their decisions. SVMs are also sensitive to the choice of kernel function and parameters, which means they often require careful tuning to achieve optimal performance. If these parameters are not appropriately selected, the model may either overfit or underfit the data.

Therefore, SVM can be applied to time-series forecasting, especially in situations where demand patterns are complex and influenced by many variables. The Support Vector Regression (SVR) variant of SVM is particularly well-suited for predicting continuous outcomes such as freight volumes or future demand levels [77]. SVR minimises prediction errors while maintaining flexibility in how it fits the data, making it effective for forecasting freight demand over time, considering fluctuating factors like traffic, fuel prices or economic growth.

SVM is also effective in classification tasks within the transport sector, where the goal might be to classify different demand scenarios based on a variety of input factors [76]. For example, SVM can help classify high-demand and low-demand periods for freight transport based on variables like seasonal patterns, economic indicators or infrastructure availability.

Regarding its compatibility with other models. SVM can be integrated with other machine learning techniques and optimisation algorithms to improve forecasting accuracy and efficiency. For example, SVM and Genetic Algorithms (GA) can be combined, where GA is used to optimize the selection of SVM hyperparameters. This integration improves model performance by fine-tuning SVM for specific freight demand forecasting scenarios.

It can be also integrated with traditional forecasting models to enhance its performance and make it more adaptable to different forecasting needs. Once such integration is between SVM and ARIMA models, which is particularly useful for time-series forecasting since they are often combined to capture both linear and non-linear patterns in data set [80].

Moreover, SVM can work alongside Dynamic Traffic Assignment (DTA) models to predict demand levels that influence real-time traffic routing and scheduling decisions. In such an integration, SVM predicts demand based on external factors (like economic data or seasonal trends), while the DTA model simulates how this demand affects the transport network, optimising routes and resource allocation in real-time.

As ANNs, the implementation of SVM in practical freight transport demand forecasting is still in the early stages but is gaining traction, particularly in academic research and specialised pilot projects. Its main limitations are its complexity and computational demands. However, as more organizations adopt AI techniques and gain access to better data and computational resources, SVM is starting to be recognised for its robustness in handling non-linear data and avoiding overfitting.

Multi-criteria Systematic Comparison

Table 4.13: Systematic evaluation of support vector machine

Accuracy ★★★★☆	+	Strong performance in classification and regression tasks, especially in cases where the relationship between variables is non-linear. They are highly accurate when the right kernel functions are used and when there is a clear margin of separation between classes (or regression outcomes).
	-	Their performance may degrade if the data is noisy or if the correct hyperparameters are not selected.
Data Requirements ★★★½☆	+	SVMs can perform well with relatively small datasets compared to other machine learning methods like ANNs.
	-	They require clean, well-prepared data, as they are sensitive to noise and outliers. Data preprocessing, such as normalization or standardization, is essential for achieving good results.
Scalability ★★★☆☆	+	Effective for short- to medium- term and they could be used for long-term as a part of a hybrid model.
	-	SVMs are less scalable than some other methods, particularly for large datasets. The computational complexity of SVM increases with the size of the dataset, as it involves quadratic programming. This makes SVMs less suitable for large-scale forecasting or when working with very large datasets, such as nationwide freight transport systems. They are used for static tasks and without extense data sets, therefore, not very suitable for long-term forecasting.
Complexity ★★★½☆	+	SVM models are relatively complex to implement compared to simpler models like linear regression but are easier to use than ANNs.
	-	The complexity lies in selecting the appropriate kernel function (linear, polynomial, radial basis function, etc.) and tuning hyperparameters. Specialised expertise is required.
Cost-effective ★★★☆☆	+	SVM models are relatively cost-effective, especially when working with smaller datasets. They are cost-effective for small to medium-sized datasets.
	-	For larger datasets, the computational cost increases significantly due to the quadratic optimization required during the training process. They become expensive for larger applications.
Timeliness ★★★☆☆	+	Once trained, they are efficient in generating predictions. The overall timeliness of SVMs depends on the size of the dataset and the complexity of the kernel used.
	-	Training SVMs can be time-consuming, especially for large datasets or when using non-linear kernels.

Robustness ★★★★☆	+	SVMs are quite robust, especially in high-dimensional spaces, and are effective in cases where the data is not linearly separable due to their ability to handle non-linear relationships through kernel functions.
	-	SVMs can be sensitive to outliers, which may impact their robustness if the data is noisy or not well-preprocessed.
Interpretability ★★★☆☆	+	SVM models, mainly with linear kernels, can be interpreted relatively easily as they provide insights into which variables are most influential in the classification or regression task.
	-	SVM models using non-linear kernels are harder to interpret, especially when working with higher-dimensional data.
Integration ★★★★☆	+	SVMs can integrate well with other models or techniques, such as being used as part of an ensemble method
	-	Integration with more complex models may be challenging due to differences in methodologies, especially when dealing with non-linear kernels.
Functionality ★★★☆☆	+	SVMs provide strong functionality in terms of their ability to handle non-linear relationships and multi-dimensional data. They work well for both regression and classification tasks and can be adapted to many forecasting scenarios.
	-	SVMs may not be as flexible as other methods like ANNs in handling very complex or evolving systems.

Support vector machines present a strong and adaptable option for freight transport demand forecasting within the context of this thesis. Their ability to handle complex, non-linear relationships and robustness against overfitting makes them a valuable tool for scenarios where data is limited or highly dimensional. Although SVMs are computationally intensive and less interpretable than simpler models, they offer significant advantages in terms of accuracy and generalisation.

As freight forecasting continues to evolve, integrating SVM with other models and optimization techniques will likely enhance their applicability, especially in real-time transport systems and large-scale decision-making processes. The degree of implementation in practical applications is increasing and with improvements in data infrastructure, SVM could become a more mainstream choice for forecasting in the freight sector.

4.4.3 Random Forests

Method Description

Random Forests (RF) is an ensemble machine learning technique that builds multiple decision trees during training and merges their outputs to improve predictive accuracy and control overfitting. In the context of this thesis, Random Forests stand out for their robustness, ability to handle high-dimensional data and it is particularly well-suited for complex forecasting tasks where multiple factors interact, as is the case in freight transport systems, where economic indicators, infrastructure developments, traffic patterns and environmental policies all influence demand.

Before further description of RF, the decision tree concept must be introduced. A decision tree is a supervised machine learning model used for both classification and regression tasks. It works by successively splitting the dataset into subsets based on the values of input features, creating a tree-like structure. Each internal node in the tree represents a decision based on a feature and each leaf node represents a final outcome or prediction.

At each node, the algorithm chooses the best feature to split the data by maximizing a certain criterion, such as information gain (for classification) or variance reduction (for regression). The process continues until the tree reaches a stopping condition such as a maximum depth or a minimum number of data points in a leaf node.

While decision trees are easy to interpret and flexible, they can be prone to overfitting, especially when trained on small datasets. Therefore, RFs are designed to address some of the key limitations of individual decision trees. They overcomes this issue by creating a large number of decision trees (hence the "forest") and combining their predictions. This ensemble approach reduces variance and improves the model's generalization, making RF more robust in predicting outcomes even in scenarios with noisy or incomplete data, which is common in real-world freight transport systems.

The fundamental principle behind Random Forests is bootstrap aggregation (or bagging). In this process, the algorithm creates multiple decision trees by training each tree on a randomly selected subset of the training data (with replacement). By training on different subsets of the data, each tree in the forest learns slightly different patterns. When making predictions, each tree outputs a prediction and the final result is obtained by averaging the predictions for regression tasks or taking a majority vote for classification tasks. This method reduces the risk of overfitting by ensuring that no single tree dominates the model's predictions.

In addition to randomly selecting data subsets, random forests introduce randomness by selecting a random subset of features for each split in the decision trees. This ensures that the trees are decorrelated from each other, avoiding problems of collinearity [81]. In freight transport forecasting, where many factors such as road conditions, fuel prices and seasonal demand fluctuations interact in complex ways, this approach allows RF to capture a wide variety of relationships between variables while maintaining robustness.

Forecasting Capabilities

One of the major strengths of Random Forests is their ability to handle high-dimensional data. Freight transport demand forecasting involves numerous variables, from economic indicators and infrastructure data to external factors like fuel prices and weather. RF excels at processing datasets with a large number of input variables and can model the interactions between them without overfitting [82]. This is critical in freight forecasting, where different factors often influence demand in non-linear ways.

RF also provides interpretability through its feature importance scores. The model can rank variables by their contribution to the final prediction, offering valuable insights into which factors most influence freight demand, being useful in understanding the relative importance of variables.

As the other machine learning techniques, one notable limitation is its computational cost when dealing with very large datasets or when a large number of trees are required to achieve high accuracy. While RF is faster than more complex modles like ANNs, its resource requirements can be significant.

Another limitation is that, while RF models provide feature importance rankings, they are generally considered less interpretable than simpler models like linear regression or ARIMA. Although the model can indicate which variables are important, it does not easily provide insights into how individual variables interact or the specific relationship between inputs and outputs. Furthermore, RF may struggle with highly imbalanced datasets, where certain outcomes (e.g., high or low freight demand) are much more common than others.

Taking into account the forecasting capabilities of RFs, they can be used in time-series forecasting, predicting transport demand based on historical data, economic conditions and infrastructure trends. They are well-suited for scenarios involving multiple factors that interact in complex ways. For example, RF can be used to predict freight volumes for different transport modes (road, rail, air) based on a wide range of inputs, including traffic data, fuel costs and regulatory changes.

Another use of RF is in scenario analysis since its ability to simulate the effects of various policy changes, infrastructure developments or economic shifts on future demand. Moreover, RF's ability to process multi-dimensional data makes it valuable in multi-modal freight transport systems, where demand forecasting requires consideration of various transport modes and the interplay between them.

Regarding the integration with other models, one common integration is with ARIMA models, where ARIMA captures the linear components of time-series data and RF is used to model non-linear residuals that ARIMA cannot handle. They can also be combined with genetic algorithms to optimize RF's parameters, such as the number of trees or the depth of individual trees. This optimization can improve the accuracy and efficiency of RF models, especially when dealing with large datasets typical in freight demand forecasting.

In terms of practical implementation, random forests are also increasingly being adopted, though they are not yet as widespread as traditional models. Many pilot projects and academic studies have explored RF's application in transport demand forecasting and large logistics firms and transport agencies are starting to recognise its value for long-term planning and operational decision-making.

Multi-criteria Systematic Comparison

Table 4.14: Systematic evaluation of random forests

Accuracy ★★★★☆	+	Highly accurate for both regression and classification tasks, thanks to their ensemble learning approach. RF excels in non-linear relationships and datasets with multiple variables, performing well for short- to medium-term predictions.
	-	It is not really suitable for long-term forecasting, requiring frequent re-training as underlying relationships in the transport system evolve.
Data Requirements ★★★⯪☆	+	RF models can handle both small and large datasets, and they perform well with minimal data preprocessing, such as normalization or handling missing values. They can work with a variety of data types.
	-	They typically require a large amount of data to fully exploit their potential, especially when working with high-dimensional datasets.
Scalability ★★★☆☆	+	Random forests scale well with large datasets and are efficient at managing large numbers of features, making them suitable for large-scale applications such as freight transport across a country or region. Highly scalable geographically and operationally.
	-	The computational demands increase significantly as the scale of the dataset grows, which can be a limiting factor for large-scale long-term forecasts in freight systems with high data complexity.
Complexity ★★★☆☆	+	RF is less complex to implement than ANNs.
	-	While decision trees are simple to understand, the ensemble nature of RF makes it harder for non-experts to interpret the model's predictions and internal mechanisms.
Cost-effective ★★★⯪☆	+	Once the model is established, RF is cost-effective in terms of operational costs, especially in comparison to more complex AI models.
	-	Computational resources required for training RF models on large datasets can be expensive, particularly for high-dimensional and large-scale freight demand forecasting.
Timeliness ★★★☆☆	+	RF provides relatively quick results once trained. Its timeliness for real-time updates and recalibrations is moderate, being potentially a valuable tool for real-time operation **tra**
	-	The training process can be time-consuming, especially for large datasets and increasing number of trees.

Robustness ★★★⯪☆	+	By averaging multiple decision trees, they reduce the risk of overfitting. They can handle noisy data well and are less affected by outliers compared to individual decision trees. They are also flexible in dealing with non-linear relationships.
	-	While random forests are robust in capturing non-linear relationships and avoiding overfitting, their performance in long-term forecasting can be limited without proper adjustments. For robust long-term forecasts, RF should be used in conjunction with other models (such as time-series models like ARIMA or LSTM [83] or require frequent retraining to adapt to evolving trends.
Interpretability ★★★☆☆	+	Tools for visualizing RF outputs can help improve interpretability to some degree. Feature importance can show what are the key drivers.
	-	RF ranks relatively low in interpretability because it is more challenging to explain than traditional models like decision trees or regression models.
Integration ★★★★☆	+	Random forests can integrate well with other machine learning models or methodologies. Their flexibility allows them to work well in ensemble methods or alongside other algorithms.
	-	The lack of temporal dynamics are one the challenges for further integration with other techniques as well as the computation complexity and data preprocessing.
Functionality ★★★★☆	+	They provide highly functional models for both regression and classification tasks since they can handle a wide variety of data types, manage missing data, and work well for large-scale datasets.
	-	They don't have additional key features that might be valuable for stakeholders such as external cost calculation, environmental measures, etc.

Random forests offer a robust and flexible method for freight transport demand forecasting, particularly in scenarios involving high-dimensional datasets. Their strengths in handling complex, non-linear relationships and their resistance to overfitting make them well-suited for dynamic environments like freight transport. While RF has limitations related to computational costs and interpretability, its integration with other models can enhance its utility in real-world forecasting tasks. As data infrastructure improves, RF is expected to see broader implementation in practical freight transport demand forecasting applications, offering valuable insights for both operational and strategic decision-making.

Chapter 5

Discussion of Results

5.1 Overview of the Comparison

After evaluating each forecasting model individually, the general conclusions of the systematic comparison are now exposed to assess the suitability of time-series models, econometric models, simulation models and AI techniques as well as overall insight of current freight transport demand modelling for long-term forecasting in Europe. This discussion highlights the strengths and limitations of each model regarding their applicability in addressing the complexities of the European freight system. These conclusions are framed within the broader goals of managing future demands of freight transport while meeting the decarbonisation objectives set by the European Union for 2050.

Time Series

Time-series models have been extensively reviewed due to their historical effectiveness in short-term forecasting. In this review, it has been proven ARIMA's ability to capture trends, seasonality and cyclical components, making it a feasible tool for immediate forecasting needs in the European freight transport sector for transport companies or association with less resources or expertise in this field. However, due to its reliance on past patterns, ARIMA and other time-series techniques, are not viable as standalone solutions for long-term forecasting. The freight transport landscape in Europe is dynamic, influenced by economic shifts, trade policies and technological changes. As a result, ARIMA should only be considered as a complementary tool within a broader forecasting framework or as part of a hybrid approach. The model's ability to integrate into larger systems makes it useful, but its limitations in capturing long-term structural changes underscore the need for its inclusion as a support tool rather than the primary forecasting technique. As it has been remarked, it is still a valuable method that can greatly help in short- to medium term operational management for companies.

Econometric Models

Regarding the following group, econometric models have traditionally been the fundamental of freight transport demand forecasting. These models were developed to understand how socio-economic factors influence systems, offering an adaptable and structured approach by incorporating macro-variables like GDP, trade volumes and fuel costs and their relationship with transport demand. Despite the limitation of this traditional approach, mainly characterised by the 4-step method (which was created originally for passenger transport demand), they are still the most common techniques used at practical level since its reliability and suitability for long-term forecasting due to its ability to understand how shifts in economical performance can lead to changes in the overall transport behaviour.

However, it must be reminded that their limitations are also quite significant as many of their techniques have an static nature, not being able to be a long-term tool in a environment with the rapid technological, structural and policy changes as it is expected to be in Europe for the following decades. Additionally, in spite of being the most adequate methods due to the current capabilities, they have also high requirements as they need extensive datasets (which may not be fully or easily available due to the fragmented nature of data in logistic sector and privacy issues) and careful calibration, being sensitive to the assumptions made in the model (regarding the stability of the relationship between variables). These are the reason why econometrics are not seen as the final method in the field of freight transport demand forecasting, they could be described as the current step which will be substituted by further development in more advanced and complete techniques.

Within econometric models, several techniques were examined, but special attention is given to discrete choice models. These models are crucial for their ability to capture individual behavior and preferences, offering a disaggregate approach that is essential for understanding decision-making processes within the freight transport system. In Europe, where freight transport decisions are shaped by a wide range of actors—shippers, carriers, regulators—discrete choice models provide unique insights into the behavioral aspects of these stakeholders. Their detailed, micro-level analysis, behavioural modelling and possible stochastic approach make them one of the most promising techniques for further development, particularly in the context of long-term forecasting, being able to be combined with other promising techniques such as agent based models. Furthermore, cointegration and error correction models must be underlined too since their valuable insights for long-term relationships whit the incorporation of volatility and short-term variability, being able to deal with some uncertainty which makes them valuable for this field.

Simulation Models

On the other hand, simulation models could be considered as the current second most dominant technique, they are recognized as a very promising approach for long-term freight demand forecasting and have already found practical applications in various transport planning contexts. These models are highly valued for their ability to simulate complex systems and interactions, offering a wide range of functionalities that are particularly useful for stakeholders involved in decision-making processes. A particularly notable feature of simulation models, comparing to the traditional econometric models, is their ability to handle non-linear relationships and complex networks, which are inherent in the freight transport system. Agent-based models in particular, offer a micro-level approach, providing detailed insights into the behavior of individual agents, such as shippers, carriers and regulators.

This micro-approach allows ABMs to capture the internal dynamics of decision-making at the individual level, which is often missed by more aggregate models apart from discrete choice models. This granularity also offers a wide range of functionalities such as time dimensional of transport, multimodality, type of vehicles, type of commodities, environmental impact, external costs, etc. Therefore, this excellent functionality allow policy-makers and planners to have an extensive alternatives of analysis using different scenarios, cases or assumptions since they are able to deal with structural changes, technological innovations of shifts in political frameworks, which are crucial for long-term forecasting.

However, simulation models are not only focus on the micro-approach. System dynamics models are another powerful tool that are valuable for understanding and analysing the broad, aggregate behaviors of large-scale systems over time. As reviewed, their ability to capture the non-linear relationships and feedback loops between different components of the freight transport system, makes them effective for examining long-term trends and system-wide interactions as they show how changes in one part of the system (e.g., an increase in fuel prices or a new regulation) can ripple through the entire system and affect overall freight demand. Therefore, simulation models constitute currently a very valuable tool since they offer innovative approach in both macro- and micro-way, that even offer a more comprehensive framework for long-term forecasting when they are both combined, which is perfectly feasible.

Despite their many advantages, there are some reasons that explain why econometric model are still in use instead of simulation ones. One of the main challenges is their complexity, which requires significant computational resources and expertise to implement and maintain. Also, setting up a simulation model involves gathering high-quality and detailed input data and calibrating the model to accurately reflect real-world conditions, which not only are time-consuming and expensive, but also may not always be available or easy to collect, especially in an international context. These limitations in data availability and computational demands are the main reasons that have restricted the widespread use of simulation models, specially agent-based models, which its detailed and complex structure is still not viable for bigger scales as required by the EU goals.

These constraints are specially for ABMs, reducing their applicability for urban-level forecasting, where there is a need of capturing detailed and localised interaction in a complex but not that big environment. When scaling up to international freight transport forecasting, more traditional econometric models ted to dominate. However, since SD has more flexible data and computational requirements due to its macro-approach, they are way more suitable for long-scale models and they have been already used in international scale ones as in the ASTRA model [9]. Ideally, it would be a very dominant tool if ABM could be applied for greater scales since its valuable insights and detailed outcomes. This step is still not close, but there are current efforts in developing optimisation techniques to reduce the computational cost as in developing new data collection process to address the input requirements, that will make possible to improve step by step the scalability of ABMs as some advances in these fields are achieved.

AI Models

The last and most recent group of AI techniques has received significant attention in recent years, both in academic research and practical applications. This shift was clearly identified during the literature review and further confirmed by the VOSviewer analysis, which highlighted an increasing focus on AI methods for transport demand forecasting. Researchers and practitioners are increasingly exploring the potential of AI to revolutionise the way transport demand is predicted, particularly due to AI's ability to process large datasets, uncover hidden patterns and adapt to rapidly changing environments. This innovative new approach with these fresh advantages matches perfectly with the growing complexity of transport systems and the need for more advanced tools that can handle the vast amounts of data generated by modern technologies, such as IoT devices, GPS, and real-time tracking systems.

The development of AI techniques, including artificial neural networks, support vector machines and random forests, has opened up new possibilities for transport demand forecasting. ANN, for instance, is known for its powerful ability to recognize patterns in large datasets, making it highly suitable for capturing the intricate non-linear relationships between various factors that influence freight demand, that previous groups of techniques may miss. Similarly, SVM and RF are valued for their robustness in handling classification tasks and managing diverse data inputs, which are common in the highly dynamic transport environment.

Therefore, this last group of technique has shown the potential to outperform the traditional techniques, and if not at least cover certain shortcomings or gaps of those techniques. Furthermore, AI techniques are really well-suited for real-time data processing, offering a level of adaptability that traditional models cannot match, making AI them especially relevant for long-term forecasting, where the ability to incorporate new data and adjust predictions is crucial.

However, as it has been point out through this thesis, despite of the promising future of AI techniques, they have been reached the final step of development yet since they are still part of pilot programs or used in specific cases to prove their applicability. Thus, as this development keeps going and data infrastructure improves, especially with advancements in IoT, GPS tracking and other real-time data collection technologies (More reliable and comprehensive datasets will enhance the accuracy of AI-driven forecasts, allowing these models to provide deeper insights into future trends and shifting market conditions), the application of AI techniques will become more common at practice level and even more effective.

Another key limitation to overcome, in order to be able to apply these techniques, is their already mentioned "black box" nature. This lack of transparency is a significant barrier to the widespread adoption of AI techniques in transport demand forecasting, where clear and explainable results are essential for informed decision-making by stakeholder as they need to justify their actions, policies or strategies based on understandable basis. Therefore, to be able to use AI techniques in applicable forecasting models, not only must be improved the previously explained issues but also there must be developed interpretation tools or strategies to become more accessible and trusted by decision-makers.

According to the state and trend in research in the field of freight transport demand forecasting and the potential advantages that could offer an AI model, these limitations that AI techniques are facing will eventually be solved and these techniques will play a major role in the field of transport demand forecasting. Even though this promising future, if the goal is to start building a model for the long-term forecasting in Europe scale, it is yet not viable to use these techniques either now or in the very coming years, unless their participation in the model is very reduced or complementary.

Hybrid Models

Given the evaluation of these specific techniques, it is clear that no single model is perfect or sufficient on its own, at least not in the current state. Each technique provides valuable insights into different facets of freight demand forecasting, but they are most effective when used in combination. These models should be viewed as complementary tools, much like different pieces of a puzzle, where their integration can result in more comprehensive and reliable forecasts. Briefly explained, time-series models like ARIMA should be used to capture short-term trends, econometric models are critical for understanding behavior and economic drivers, AI techniques can process large-scale real-time data, and simulation models offer the capacity to explore the micro- and macro-dynamics of a system. By combining these methods, hybrid models offer the most appropriate solution for addressing the complexities and uncertainties of long-term freight forecasting in Europe.

Hybrid models provide the flexibility to integrate the strengths of each technique, making them the most effective option for long-term forecasting. Combining the behavioral insights from discrete choice models with the adaptability of AI techniques and the scenario-planning power of agent-based and system dynamics models allows for a more holistic understanding of future freight demand. This hybrid approach not only improves the accuracy of forecasts but also provides the robustness needed to handle unpredictable factors like economic downturns, policy shifts and technological advancements. Hybrid models are not just a combination of techniques but represent a strategic approach that acknowledges the complexity of the transport system and the need for diverse tools to meet Europe's long-term decarbonisation and economic goals. Therefore, none other than hybrid models should be considered as the actual state-of-the-art model and research should keep enhancing the compatibility between models in order to develop the ultimate model.

General Findings

After conducting a systematic comparison of the current forecasting methods, it becomes clear that, despite the promising advances made in recent years, these tools are still not capable of producing highly accurate and robust long-term forecasts at the European scale without facing limitations or uncertainty that compromise at certain extent the accuracy and reliability of the forecast. The recent developments have provided important progress, but they remain insufficient for fully addressing the complex challenges that were outlined at the beginning of this work. The nature of long-term freight transport forecasting in Europe is highly dynamic, influenced by technological, political, structural changes and several stakeholders along the supply chain, and no current model has yet proven capable of overcoming these complexities without making certain assumptions that introduce uncertainty into the forecasts.

One of the key issues that continues to affect the performance and reliability of all forecasting models, to a greater or lesser degree, is the availability and quality of data. This remains a significant challenge across Europe and limits the accuracy of both traditional and advanced forecasting methods. Fragmented data sources, inconsistent reporting standards across countries and the absence of comprehensive, high-quality datasets create barriers to generating reliable long-term forecasts. Without robust data, even the most sophisticated models are unable to produce fully accurate outcomes. For this reason, improving data collection processes and infrastructure is essential for enhancing the capabilities of forecasting tools, and if not well addressed the forecasting techniques will be always underperforming compare to their actual potential. There needs to be a concerted effort to establish more cohesive data frameworks across European countries, allowing for the integration of fragmented datasets, especially within the logistics and freight transport systems.

Policies aimed at opening access to data will be critical in this process. By promoting greater transparency and data sharing across different sectors and regions, it will become easier to compile the necessary data inputs that fuel forecasting models. The logistics system, in particular, would benefit from a more open and integrated data ecosystem, where information from various stakeholders ranging from transport operators to regulatory agencies is made available in a standardized format. This would not only improve the accuracy of current forecasting methods but also help reduce the uncertainty inherent in long-term predictions. However, this degree of data sharing is not looking very probable to happen as private companies will always oppose measures that force them to share sensitive information that could compromise their market advantage, especially in the highly competitive and global market that both the logistics and industrial sectors are.

As already mentioned, the investment in data infrastructure not only will improve the accessibility to quality data of freight flows and patterns but also will enhance the applicability of most advanced techniques. Another important tool, identified in this work, in addressing data gaps is the use of revealed preference (RP) surveys that collects information on actual shipment activities from businesses which reflects their real-world logistics choices, in contrast to stated preference (SP) surveys, where respondents are asked to make hypothetical choices. RPs have proven to be valuable in capturing actual transport and logistics behavior in countries like Sweden and France with their respective CFS [36] and ECHO [84] surveys. They offer detailed insights into freight movements and logistics behaviors, providing key data for modeling efforts, serving as strong examples of how structured data collection efforts can significantly enhance the quality of data available for freight forecasting. Expanding similar surveys across more European countries would be a major step toward overcoming the current data challenges, contributing to more accurate and reliable forecasts at European scale.

Apart from data availability, other issues as the decision-making modelling are still underdeveloped. While behaviour modelling has shown significant upgrades in recent years by being incorporated in modes thanks to discrete choice models and agent-based models, their development is still not advanced enough to fully capture the complexities of decision-making within logistics systems. In many cases, the decision-making process is oversimplified or modeled predominantly from the perspective of shippers, without considering the broader range of actors involved in the logistics chain, such as carriers, logistics service providers and governmental agencies. In other cases, multiples agents are modelled using a via contract approach to simulate the behaviour between the different agents, however, this approach is not the most common one and it is underdeveloped due to its more complex nature [54].

In addition to the technical capabilities of forecasting models, the importance of interpretability must also be underscored. While this aspect was not initially emphasised as a key challenge in the early stages of the thesis, it has become evident that interpretability plays a crucial role in the practical application of these models. The ability for stakeholders, especially policymakers, to understand how a model generates its forecasts is essential for building trust and ensuring informed decision-making.

Figure 5.1: SimMobility visualisation tool [85]

Complex models like AI and ABM can often operate as "black boxes", therefore, focusing research efforts on improving the interpretability of these models is vital for enhancing their utility, having internal dynamics explanations or visualisation tools that play a significant role in this regard, as they allow for clearer representation of model outputs, as seen in Figure 5.1 .By providing intuitive, visual insights into how forecasts are derived, visualization tools help bridge the gap between complex data-driven models and their real-world application. They can illustrate key trends, scenarios and decision pathways in a way that is accessible to non-technical stakeholders, making the models more actionable and effective in shaping policy and strategy.

Although the ideal state of forecasting modelling is not yet close as it has been pointed out, promising and constant improvements for the different challenges presented, have been found along this work. It is also important to note that freight transport models historically lagged behind passenger transport models, particularly at the beginning of the century. Freight forecasting often relied on passenger transport models, adapting them for freight purposes, which led to limitations in capturing the unique characteristics of freight movement. However, in recent years, a major effort has been made to close this gap and develop specific models for freight forecasting. Commodity-specific models have been introduced, which focus on the unique attributes of different goods being transported. These developments aim to provide a more accurate representation of freight flows, matching or even exceeding the performance of traditional passenger models. This shift represents a significant advancement in the ability of forecasting models to address the specific demands of freight transport, offering more precise tools for long-term planning.

Moreover, it is important to acknowledge that freight forecasting models are increasingly being enhanced with new features and functionalities, allowing for more comprehensive assessments that extend beyond simple demand forecasting. These improvements make it possible to use models for scenario analysis, policy assessment, environmental impact evaluation and risk analysis, being the ABMs the ultimate example of functionality since they offer from micro-features modelling the behaviour of individual agents to macro-features that show how the aggregation of individual agents affect the network in terms of bottlenecks, delays, environmental cost, etc.

This expansion of functionalities provides stakeholders with valuable tools for evaluating the broader implications of different strategies, making models more applicable to real-world challenges. For instance, using models for environmental impact assessments allows policymakers to estimate the long-term effects of various transport policies on carbon emissions and sustainability. Similarly, the ability to conduct risk analysis and policy assessment strengthens the strategic planning process, enabling stakeholders to identify potential vulnerabilities and evaluate the effectiveness of different regulatory frameworks or infrastructure investment. These added capabilities make models not just forecasting tools but versatile instruments for comprehensive decision support in the complex logistics and transport sectors.

In conclusion, while the forecasting models reviewed in this work show great potential, they are not yet capable of delivering high-accuracy, robust long-term forecasts for freight transport at the European scale without making certain assumptions that introduce uncertainty. Data availability remains a crucial challenge that impacts the performance of all types of models. To improve forecasting accuracy, it will be necessary to address data collection processes, enhance infrastructure for data sharing, and adopt policies that promote open data initiatives to integrate the fragmented logistics system. Additionally, expanding the use of commodity flow surveys, like those in Sweden and France, will provide the critical data needed to improve the robustness of future forecasting models. Moreover, further advancements in behavior modeling are essential to better represent the complexities of decision-making in logistics, ensuring that future models capture the full range of factors influencing transport demand. As models continue to evolve, their increasing ability to conduct scenario analysis, policy assessments, environmental impact evaluations, risk analysis and increased interpretability will further enhance their utility, making them indispensable tools for stakeholders navigating the complexities of long-term freight transport forecasting.

5.2 State-of-the-Practice Models

In this section, the focus shifts to exploring the state-of-the-art models currently applied in freight demand forecasting. By examining models implemented from urban to international scales, the aim is to identify the techniques being utilized across different contexts and realise of their degree of implementation in real application models.

Urban Models

In this section, it will be explored three prominent urban-scale freight models: Polaris, SimMobility Freight and Mass-GT. Each of these models offers unique approaches to forecasting freight demand within urban environments to address the complexities of logistics in dynamic and densely populated areas.

Polaris is a comprehensive agent-based model designed to simulate the interactions between various actors in urban freight systems. It is particularly valuable for analyzing the dynamic nature of urban logistics and decision-making at the micro-level. Polaris uses a combination of discrete choice models to capture individual decisions of agents, such as route selection, vehicle choice, and delivery schedules, providing detailed insights into freight flow within urban environments. The model integrates real-time data inputs, making it highly adaptive to changes in urban conditions such as traffic or policy interventions. Polaris also leverages optimization techniques to improve freight transport efficiency, allowing users to explore various scenarios, such as the impact of new infrastructure or regulations on freight movement [86][87].

SimMobility Freight, part of the larger SimMobility framework, focuses specifically on urban freight distribution. This model incorporates both agent-based modeling and discrete choice models to simulate the decision-making processes of various stakeholders, including shippers, carriers and logistics service providers. The model is designed to forecast both short- and medium-term freight demand and provides valuable insights into how urban logistics systems respond to policy changes or infrastructural developments. One of the notable features of SimMobility Freight is its ability to model multiple scales, from individual deliveries to broader logistics networks, making it particularly useful for assessing the impact of urban policies on freight flows. The model also emphasizes behavioral realism by including a range of decision-making processes, such as the choice of vehicle types and delivery routes [88].

For MASS-GT Netherlands' model, the model employs a combination of econometric models and simulation-based techniques. One key econometric approach used is the tour formation model, which is a discrete choice model that simulates the tactical decisions made by freight carriers such as which shipments to add to a tour. This model takes into account several variables, including transportation costs, vehicle capacity and constraints like maximum tour duration. The model is estimated based on observed tour patterns, providing a robust framework for analyzing different types of logistical operations. On the simulation side, MASS-GT employs a multi-agent framework that explicitly represents producers, consumers, and distribution channels. The network simulation component applies a static equilibrium model for route choice, based on generalized transportation costs and taking congestion into account. This allows the model to simulate how freight tours are distributed across urban networks, highlighting bottlenecks and identifying opportunities for efficiency improvements [89].

Regional Models

For the regional models, two different approach are shown with Florida's FreightSim and the Flemish SVRM.

For FreightSim, the model integrates both econometric and simulation approaches to forecast regional freight flows. FreightSim relies on a tour-based modeling framework, where the flow of goods is broken down into individual tours performed by trucks. It employs discrete choice models to simulate key logistical decisions, such as vehicle type selection, route choice and delivery scheduling. The model also incorporates activity-based simulation techniques to capture how changes in policies, economic factors, and infrastructure might impact freight flows at a regional scale. FreightSim's flexibility allows for detailed scenario analysis, providing valuable insights into how regional freight demand will evolve under different conditions [90].

The SVRM has a classical four-step structure including detailed network models for road, rail, and inland waterways, with several additions such as a time-period choice model. This time period model can be used to simulate the impact of changes in the level of congestion on the roads. One of the primary econometric approaches used is the multinomial logit model as well as equilibrium model. The equilibrium framework ensures that freight flows are assigned in a way that minimises transportation costs while considering congestion and other network conditions [91].

National Models

The SAMGODS model, which is the national freight transport model for Sweden, the model utilizes a variety of econometric techniques. A key component of SAMGODS is its use of multinomial logit models, which are applied to model the decisions related to shipment size, transport mode and transport chain choices. These choices are influenced by factors such as transport costs, time and value density. The SAMGODS model also incorporates disaggregate stochastic models, providing a more granular and probabilistic approach to freight demand forecasting, using the national (RP) CFS survey. This disaggregation allows for more realistic representations of shipper behavior, as it accounts for the variation in individual shipment decisions rather than relying on aggregate data alone.

The model employs an aggregate-disaggregate-aggregate (ADA) framework, where aggregate flows are first determined between production and consumption zones. Then, in a disaggregate step, these flows are broken down into shipments between individual firms and their logistics decisions, such as mode choice and shipment size, are modelled. Finally, the model aggregates these disaggregated flows for network assignment, enabling it to simulate how freight moves through Sweden's transport infrastructure [92].

On the other hand, TRABAM which is applied in Belgium, the model is built on an agent-based approach specifically designed to simulate freight transport decisions at the national scale. This model integrates different cargo types (liquid bulk, solid bulk, containers, pallets and mobile units) into its decision-making process regarding vehicle and mode choice. By using regression-based methods to generate shipments based on economic and demographic data, TRABAM is able to simulate realistic freight movements between thousands of traffic zones in Belgium [54].

The agents in the model, representing logistics service providers, optimise their transport operations by choosing the most efficient route, vehicle and mode of transport based on costs, congestion and time. This approach allows for detailed simulation of multimodal transport, taking into account real-world logistics constraints such as vehicle capacity and depot locations. It uses the framework of MATSim for the agent-based model development. This model show real application for both external cost calculation and scenario cases.

International Models

Regarding the international scale models, more models will be reviewed since it adjust to the final goal of improving the current long-term forecasting for the European scale.

Firstly, the ASTRA model operates using a system dynamics approach to simulate freight transport at a European level. The ASTRA model is designed to evaluate transport policies and their long-term effects on freight and passenger demand. It integrates several subsystems, such as the economy, trade, transport and environment, into one overarching framework. This system dynamics methodology does not rely on equilibrium based modeling but instead models cause-and-effect relationships, where variables change dynamically over time through feedback loops.

ASTRA's freight transport module generates and distributes freight demand across different transportation modes. It incorporates factors such as cost, infrastructure capacity and environmental impact, making it a comprehensive tool for assessing how freight demand evolves in response to economic growth and policy changes by combining SD with input-output modeling [9].

For the TRIMODE model, which operates at an international scale across Europe, the model employs an integrated system dynamics approach to link transport, energy, and economic models. It uses a four-stage transport model for both passenger and freight movements. It also incorporates a two-layer general equilibrium model that operates at both regional and national levels to represent economic activities and their impact on transport demand [93].

TRIMODE's econometric techniques include modeling the growth of freight demand based on economic variables and trade flows between production and consumption zones. It uses discrete choice models for mode choice and shipment size decisions, capturing the trade-offs logistics operators face based on transport costs, travel times, and environmental impacts.

Another remarkable model is the PASTA model, developed by the International Transport Forum (ITF). This forecasting method uses a four-step approach to estimate freight transport demand across various modes such as road, rail, and maritime. It employs generalized linear models (GLM) to estimate freight production and consumption, using socio-economic variables like population, trade and GDP. The model then applies distance bin split models (with similar principles of a gravity model) to assign freight flows across different distances, commodities, and vehicle types. PASTA is particularly designed for scenario analysis, including assessing the impacts of decarbonisation policies and CO2 emissions reduction strategies on freight transport [94].

In addition, the model uses mode choice models to simulate how freight operators choose between different transportation modes based on factors like cost, time and capacity. By integrating these forecasting techniques, PASTA enables a detailed examination of long-term trends and the potential effects of policy interventions on both national and international freight movements. The model's ability to incorporate feedback loops and dynamic adjustments also makes it well-suited for evaluating how changes in policy such as carbon pricing or fuel regulations, impact freight flows and emissions.

And last but not least Transtools 3, the model is designed for forecasting both freight and passenger transport across Europe. It applies a disaggregate freight transport chain choice model which focuses on simulating the selection of transport chains, including road, rail, inland waterways and maritime modes. One of the primary econometric techniques used is the nested logit model, which captures the decision-making processes of shippers in terms of choosing between different transport modes and routes. This model structure allows for the representation of substitution effects between different transport chains, reflecting the influence of costs, time and logistics factors on freight decisions.

Transtools 3 also integrates non-linear cost functions, which account for the varying sensitivities of freight operators to changes in transport costs and time. The model's ability to use disaggregate data from sources like the Swedish Commodity Flow Survey and the French ECHO survey allows it to estimate decisions at the shipment level, providing a more granular and accurate forecasting tool. In addition, the model incorporates an aggregate-disaggregate-aggregate (ADA) approach, where aggregate freight flows are disaggregated into individual shipment decisions and then re-aggregated for network assignment purposes [91].

Summary of Models Review

The review of current models offers key insights into the application of forecasting techniques across different scales. ABMs while highly effective at the urban, become less feasible as the scale increases due to computational constraints. The largest ABM model identified is TRABAM, which, despite being large-scale, simplifies many aspects of the agent-based framework to maintain computational feasibility when using it at full scale. As the scale expands, models tend to shift towards more aggregate methods like System Dynamics (SD), which are better suited for international forecasting. SD models, such as those used in ASTRA, capture broader system dynamics and long-term trends but lose the granularity that ABM offers in localised contexts.

Across all scales, econometric models remain the most dominant approach, reflecting their long-standing role in freight transport forecasting. At the urban level, discrete choice models are commonly used to capture the behavior of logistics operators, such as vehicle and route choices. As we move to larger, national and international scales, traditional four-stage models become more prevalent. These models are particularly effective at handling large datasets and simulating broad economic and trade flows but often lack the detailed behavioral insights that ABM provides.

The review of current freight forecasting models reveals that most use a combined approach of simulation and econometric models, effectively merging the strengths of both methods. Econometric models, particularly discrete choice models and four-stage models, dominate across different scales, from urban to international contexts. Simulation models complement these econometric methods by providing dynamic system modeling.

Interestingly, no time-series models are employed in any of the models reviewed, due to their limited applicability, as previously highlighted, especially for long-term forecasting in complex freight systems.

A notable finding in this review is the absence of AI techniques in the state-of-practice models, even though they have been increasingly emphasised in recent research. This highlights a gap between the state-of-the-art developments seen in academic literature and the state-of-practice models currently in use. The fact that no AI techniques have been adopted in the reviewed models reaffirms that these technologies are still in the developmental phase for transport demand forecasting.

To conclude, some valuable insights are the integration of freight transport models with passenger transport models, the consideration of tour formation, detailed emission calculation and micro-simulation at the level of shipments. Furthermore, modularity of models is a key characteristic since not only facilitates its integration with other model but also allow to run models more efficiently, for instance, a short-term module can estimate the tour formation each day, while a long-term module recalculates structural changes each simulation year. Therefore, this enables to reduce significantly the computational requirements since all modules don't have to be run in every iteration.

5.3 Future Trends

The future of freight transport forecasting will play a crucial role in supporting the transitions that are essential for achieving sustainability goals. Forecasting models must serve as reliable tools for guiding changes such as the fuel transition to low-carbon energy sources, infrastructure investments and the implementation of sustainability policies. These models provide the critical insights needed for stakeholders to trust in these transitions, helping to anticipate and navigate the uncertainties associated with evolving logistics systems and regulatory frameworks. By forecasting the impacts of these changes, models will help policymakers and businesses make informed decisions that align with decarbonisation efforts.

A significant trend is the further integration of freight and passenger models, as both systems share modes of transport, particularly in urban environments. This integration can optimise shared infrastructure, reduce congestion and enhance overall system efficiency. As such, it can be expected to see more comprehensive models that encompass both freight and passenger flows, providing a more holistic view of transportation demand.

The twin forces of digitalization and sustainability are becoming the clear drivers of freight transport demand in the coming years. Digital technologies such as IoT, AI, and blockchain are transforming logistics by enhancing real-time tracking, route optimization and predictive analytics. At the same time, the shift towards sustainable logistics, such as zero-emission vehicles and renewable energy use in transport, will continue to shape the way freight demand evolves.

Many models are also beginning to incorporate e-commerce modules, particularly focused on last-mile delivery. This reflects the growing importance of urban logistics, as e-commerce demand reshapes supply chains and requires more granular models that can simulate the complexities of last-mile operations. The urban scale is becoming the main focus of these developments, as cities face increasing pressure to manage freight flows while reducing emissions and congestion.

Furthermore, the noticeable shift away from traditional four-stage models toward more disaggregated econometric and simulation models, is a trend that is expected to continue. These models offer greater flexibility in capturing the behavior of individual agents and provide more detailed insights into freight movements. The move toward more disaggregate approaches allows for a more comprehensive understanding of logistics operations and better adaptation to evolving transport trends. This shift is driven by the need for more accurate, adaptable forecasting tools that can handle non-linear relationships, behavioural modelling, the complexities of modern and data-rich logistics systems.

Finally, AI techniques are expected to keep developing, offering powerful new tools for forecasting freight demand. As data infrastructure improves and the availability of real-time, high-quality data increases, AI will become more effective at processing complex datasets, identifying patterns and providing accurate, adaptable forecasts. Though not yet widely implemented in current models, AI techniques have the potential to transform freight forecasting in the future, enabling more intelligent, responsive and efficient logistics systems, without forgetting the need for more interpretability. Additionally, this data infrastructure improvement not only will help AI techniques, but also will enhances overall accuracy of the rest of the models, specially agent-based models. These model will experienced further optimisation techniques to improve their feasibility at bigger scales as they will keep developing following their valuable modularity nature, that enhance their integration capabilities as well as enable possible optimisation strategies as currently in use in some of the models reviewed as SimMobility.

Chapter 6

Conclusions

The conclusion of this thesis highlights the critical role that freight transport demand forecasting plays in supporting the European Union's ambitious decarbonisation goals and the overall sustainability of its transport system. Through the systematic comparison of different forecasting techniques, this work has provided a detailed evaluation of the strengths and limitations of various approaches, including time-series models, econometric methods, simulation models and artificial intelligence techniques.

The methodology applied in this thesis involved a detailed review and comparison of various forecasting models. This approach enabled a rigorous assessment of the models' applicability across different scales and contexts, ensuring that the results are both robust and relevant to the challenges facing the European transport system. Chapter 4 plays a pivotal role in highlighting the performance of each forecasting method and outlining the suitability of each model, particularly in relation to their scalability and the accuracy of long-term forecasts, providing a clear framework for understanding the trade-offs inherent in different modeling approaches.

The analysis has demonstrated that while traditional models, such as econometric methods and four-stage models, remain prevalent, newer approaches like agent-based models (ABM) and system dynamics (SD) are gaining traction, especially for addressing complex, dynamic logistics systems. However, it has become clear that as the scale of forecasting increases, the feasibility of employing ABM decreases due to computational challenges. Models like TRABAM, which operate at a national scale, illustrate this trend through necessary simplifications to the agent-based framework. Meanwhile, system dynamics models, like those used in ASTRA, offer valuable insights at an international level, particularly for long-term forecasting and policy impact assessments.

A key takeaway from this work is the predominance of econometric models across all scales of freight forecasting, from discrete choice models in urban contexts to traditional four-stage models as the scale increases. These models, while effective, require rigorous calibration to remain accurate and reliable over time. Additionally, most models combine econometric techniques with simulation approaches, offering enhanced capabilities for scenario analysis and long-term planning.

Furthermore, the analysis has revealed that while academic research increasingly explores the potential of AI techniques, such as neural networks and machine learning, these approaches are still largely in the developmental phase and have yet to be widely adopted in practical freight forecasting models. This highlights the need for further research and development to bridge this gap and fully harness the power of AI in transport demand forecasting.

The trends identified in this thesis point to a continued shift from traditional four-stage models towards more disaggregate econometric and simulation models, as well as the growing importance of digitalisation and sustainability as the key drivers of change in freight transport. Forecasting must evolve to support these transformations, serving as a reliable tool for guiding shifts towards low-carbon fuels, infrastructure investments and sustainability policies. The integration of freight and passenger transport models is also expected to become increasingly important, particularly at the urban scale, where e-commerce and last-mile delivery are reshaping logistics systems.

In conclusion, while significant progress has been made in the development of freight transport forecasting models, there is still much work to be done to ensure these models can fully address the complex challenges posed by the evolving logistics landscape. This systematic comparison laid the foundation for this understanding by systematically comparing models and underlining the growing need for hybrid approaches. Future efforts should focus on further developing hybrid models that combine the strengths of econometric, simulation, and AI techniques, ensuring that forecasting remains a critical tool for achieving the EU's long-term decarbonisation goals and enhancing the efficiency and sustainability of the freight transport system.

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