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Vilniaus Gedimino
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Edvardas LIACHOVIČIUS

DATA-DRIVEN METHOD FOR INCREASING EFFICIENCY IN ROAD FREIGHT TRANSPORTATION

DOCTORAL DISSERTATION

TECHNOLOGICAL SCIENCES,
TRANSPORT ENGINEERING (T 003)

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Abstract

Large and medium-sized asset-based road transport companies have long-term growth strategies. The logistics business is cyclical, and companies, especially asset-based, must align their growth ambitions with market cycles. Growth during a cycle of decreasing demand for transportation services and declining prices can negatively impact businesses, leading to underutilisation of resources and significant financial losses. Conversely, when demand recovers, and transportation rates increase, there is often a delayed readiness – a shortage of human and other resources (e.g., to achieve the desired number of trucks). This situation can result in unused market potential, competitive losses, and the inability to achieve strategic goals on time.

Business digitalisation brings an opportunity to develop novel technological solutions that may increase efficiency in the transportation sector. Efficiency in transportation companies is analysed in this dissertation, focusing on developing a freight rate and demand a prognosis method. By taking different approaches, the research offers a comprehensive subject analysis. It helps bridge the literature gap on demand and freight rate prognosis in road freight transportation.

The study employs artificial intelligence-based and econometric models, including multivariate models, to comprehensively analyse the subject matter and address the problem. These models consider various factors influencing demand and pricing, such as economic indicators, accumulated practical experience and market trends.

The analysis results provide valuable insights into demand prognosis and pricing in the road freight transport industry during significant market fluctuations. It can serve as a valuable reference for companies in the sector.

Based on the investigation, a data-driven method for increased efficiency in road freight transportation has been developed, and the possibility of its integration into the company's IT system has been analysed.

The dissertation includes an introduction, three chapters, general conclusions and references.

The main results of the dissertation were published in four scientific publications: two in journals referenced by the *Web of Science* database with Impact Factor and two in Conference Proceedings. Research results were presented during the international conference *Transbaltica* plenary session (2019) and conference *Transport Problems* (2024).

Reziumė

Didelės ir vidutinio dydžio kelių transporto įmonės su nuosavu transporto priemonių parku turi ilgalaikes augimo strategijas. Logistikos verslas yra cikliškas, todėl įmonės, ypač turinčios nuosavą parką, privalo suderinti savo augimo ambicijas su rinkos ciklais. Augimas esant mažėjančiai paklausai transporto paslaugoms ir mažėjant tarifams gali neigiamai paveikti verslą – tai gali lemti nepakankamą resursų panaudojimą ir reikšmingas finansines nuostolių problemas. Priešingai, kai paklausa atsinaujina ir transportavimo tarifai kyla, dažnai atsiliekama su pasirengimu – trūksta žmogiškųjų ir kitų resursų (pavyzdžiui, norint pasiekti pageidaujamą sunkvežimių skaičių). Tai gali lemti neišnaudotą rinkos potencialą, konkurencijos praradimus ir nesugebėjimą laiku pasiekti strateginius tikslus.

Verslo skaitmenizacija suteikia galimybę kurti naujus technologinius sprendimus, kurie gali padidinti transporto sektoriaus efektyvumą. Šioje disertacijoje nagrinėjamas transportavimo efektyvumo didinimas, sutelkiant dėmesį į krovinių tarifų ir paklausos prognozavimo metodų kūrimą. Tyrimų metu pritaikius įvairius metodus pateikiama išsami temos analizė, užpildant literatūros spragą dėl paklausos ir krovinių tarifų prognozavimo kelių transporto sektoriuje.

Disertacijoje taikomi dirbtinio intelekto ir ekonometriniai modeliai, įskaitant daugiamatius modelius, siekiant išsamiai išanalizuoti temą ir spręsti problemą. Šie modeliai atsižvelgia į įvairius veiksnius, darančius įtaką paklausai ir kainodarai, tokius kaip ekonominiai rodikliai bei sukaupta praktinė patirtis ir rinkos tendencijos.

Atlikti tyrimai pabrėžia paklausos ir krovinių tarifų prognozavimo svarbą didinant kelių krovinių transporto pramonės efektyvumą. Pateikiamas metodas, kurį įmonės gali taikyti prognozavimui.

Remiantis tyrimu, buvo sukurtas duomenimis pagrįstas metodas efektyvumui kelių transporto srityje didinti ir išanalizuota jo integracijos į įmonės IT sistemą galimybė.

Pagrindiniai disertacijos rezultatai buvo paskelbti keturiuose moksliniuose leidiniuose: dviejuose žurnaluose, kuriuos indeksuoja *Web of Science* duomenų bazė su cituojamumo rodikliu, ir dviejuose konferencijų leidiniuose. Tyrimų rezultatai buvo pristatyti tarptautinės konferencijos *Transbaltica* plenarinėje sesijoje (2019 m.) ir konferencijoje *Transport Problems* (2024 m.).

Notations

Symbols

b – bias vector (liet. kompensavimo vektorius);

B – backshift (lag) operator (liet. vėlavimo operatorius);

$\hat{B}$ – maximum value of the likelihood function of the model (liet. didžiausia modelio tikimybės funkcijos reikšmė);

c – intercept (liet. kirtimas);

$C, accom\&allow_{ij}$ – average accommodation and allowance costs (liet. vidutinės apgyvendinimo ir pašalpų išlaidos);

$C, amort_{ik}$ – vehicle amortisation costs (liet. transporto priemonės amortizacijos išlaidos);

$C, dist_{ij}$ – distance-related costs (liet. su atstumu susijusios išlaidos);

C, fin_{ik} – vehicle financing costs (liet. transporto priemonių finansavimo išlaidos);

$C, fuel_{ij}$ – average fuel price per km (liet. vidutinė degalų kaina už km);

C, ind_{ik} – indirect costs, including operational expenses, administration costs, and other commercial costs (liet. netiesioginės išlaidos, kurios apima veiklos išlaidas, administravimo išlaidas ir kitas komercines išlaidas);

C, ins_{ik} – insurance costs (liet. draudimo išlaidos);

C, lab_{ik} – labour cost associated with driver salary per time taken to drive from the origin i to the origin k , including free kilometres (liet. darbo sąnaudos, susijusios su vairuotojo atlyginimu už laiką, kurį reikia nuvažiuoti iš taško i į tašką k , įskaitant neapmokamus kilometrus);

$C, rep\&mant_{ij}$ – average maintenance and repair costs of the vehicle, including tyre wear costs (liet. *vidutinės transporto priemonės priežiūros ir remonto išlaidos, įskaitant padangų nusidėvėjimo išlaidas*);
 C, tax_{ik} – taxes, including government, regional, provincial, and municipal (liet. *mokesčiai, įskaitant valstybinius, regioninius, provincijos ir savivaldybių mokesčius*);
 $C, time_{ij}$ – time-related costs between cargo pickup location i and final destination j (liet. *su laiku susijusios išlaidos tarp pakrovimo vietos i ir iškrovimo vietos j*);
 $C, toll_{ij}$ – average toll cost per km (liet. *vidutinė rinkliavos kaina už km*);
 d – the order of the differences of the data-integrating part $I(d)$ (liet. *integralinės dalies eilė*);
 d_{ij} – distance between origin and final destination (liet. *atstumas tarp pakrovimo ir iškrovimo vietos*);
 D – seasonal differencing term equal to 1 or 2 (liet. *sezoninio skirtumo parametras lygus 1 arba 2*);
 f – activation function (liet. *aktyvavimo funkcija*);
 k – number of estimated parameters (liet. *nustatytų parametrų skaičius*);
 n – sample size (liet. *imties dydis*);
 p – number of lag observations in the model, also known as the order of the $AR(p)$ model (liet. *$AR(p)$ modelio eilė*);
 q – size of the moving average window, also known as the order of $MA(q)$ model (liet. *$MA(p)$ modelio eilė*);
 t – time (liet. *laikas*); p
 t_{ij} – driving time from origin to the final destination (liet. *vairavimo laikas nuo pakrovimo iki iškrovimo vietos*);
 $TC_{i,j}$ – total cost between cargo pickup location i (origin) and final destination j (liet. *visos išlaidos tarp pakrovimo vietos i ir iškrovimo vietos j*);
 W – matrix of the learnable input connection weights (liet. *mokymo metu parenkamų įvesties ryšio svorių matrica*);
 x – input vector (liet. *įvesties vektorius*);
 $X_{i,t}$ – explanatory variable i at time moment t (liet. *kintamasis i laiko momentu t*);
 y – output vector (liet. *išvesties vektorius*);
 y_{min} – minimal value in the dataset (liet. *minimali reikšmė duomenų rinkinyje*);
 y_{max} – maximal value in the dataset (liet. *maksimali reikšmė duomenų rinkinyje*);
 y_t – current time-series value (liet. *maksimali reikšmė duomenų rinkinyje*);
 $y_{t-1}, y_{t-2} \dots y_{t-p}$ – past time-series values (liet. *praeities vertės*);
 $\bar{y}_t$ – mean value (liet. *vidutinė vertė*);
 $\hat{y}_t$ – mean value of the prognosed value (liet. *prognozuojamos vertės vidutinė reikšmė*);
 a_k – sum of the input and the weight parameters (liet. *įvesties ir svorio parametrų suma*);
 β_i – coefficient (liet. *koeficientas*);
 ε_t – model innovations (random error) (liet. *atsitiktinė klaida*);
 Θ_q – moving average polynomial (liet. *slankiojo vidurkio daugianaris*);
 $\Theta_q(B)$ – non-seasonal moving average polynomial (liet. *nesezoninio slankiojo vidurkio daugianaris*);

$\Theta_Q(B^S)$ – seasonal moving average polynomial (liet. *sezoninio slankiojo vidurkio daugianaris*);
 σ – nonlinear activation function (liet. *netiesinė aktyvavimo funkcija*);
 ϕ_i – auto-regressive model coefficient (liet. *autoregresijos modelio koeficientas*);
 $\Phi_p(B)$ – non-seasonal auto-regressive polynomial (liet. *nesezoninis autoregresijos daugianaris*);
 $\Phi_p(B^S)$ – seasonal auto-regressive polynomial (liet. *sezoninis autoregresijos daugianaris*).

Abbreviations

ADF – augmented Dickey-Fuller (liet. *augmentuotas Dickey-Fuller*);
 AI – artificial intelligence (liet. *dirbtinis intelektas*);
 AIC – Akaike information criterion (liet. *Akaike informacijos kriterijus*);
 AICc – Akaike information criterion corrected (liet. *koreguotas Akaike informacijos kriterijus*);
 ALI – average logistic index (liet. *vidutinis logistikos indeksas*);
 ANN – artificial neural network (liet. *dirbtinių neuronų tinklas*);
 AR – autoregressive (liet. *autoregresijos*);
 ARIMA – auto-regressive integrated moving average (liet. *autoregresijos integruotas slenkamasis vidurkis*);
 ARIMAX – ARIMA with exogenous variables (liet. *ARIMA su egzogeniniais kintamaisiais*);
 B2B – Business-to-Business (liet. *verslas verslui*);
 B2C – Business-to-Consumer (liet. *verslas vartotojui*);
 C2C – Consumer-to-Consumer (liet. *vartotojas vartotojui*);
 CNN – convolutional neural network (liet. *konvoliucinis neuronų tinklas*);
 COM – Commission regulation (liet. *Komisijos reglamentas*);
 DNN – deep neural networks (liet. *giliaji neuronų tinklai*);
 EBIT – earnings before interest and taxes (liet. *pelnas prieš palūkanas ir mokesčius*);
 FE – forecast error (liet. *prognozavimo klaida*);
 FI – freight intensity (liet. *krovinių vežimo intensyvumas*);
 GDP – gross domestic product (liet. *bendras vidaus produktas*);
 GHG – greenhouse gas emissions (liet. *šiltnamio efektą sukeliančių dujų emisijos*);
 GTC – generalised transport cost (liet. *apibendrinti transporto kaštai*);
 EU – European Union (liet. *Europos Sąjunga*);
 EC – European Commission (liet. *Europos Komisija*);
 EPS – earnings per share (liet. *pelnas vienai akcijai*);
 IT – information technology (liet. *informacinės technologijos*);
 KPI – key performance indicator (liet. *pagrindinis veiklos rodiklis*);
 LPI – logistics performance index (liet. *logistikos veiklos rodiklis*);
 LSTM – long short-term memory network (liet. *ilgalaiškės trumpalaikės atminties tinklas*);
 MA – moving average (liet. *slankusis vidurkis*);
 MAE – mean absolute error (liet. *vidutinė absoliuti paklaida*);

MAPE – mean absolute percentage error (liet. *vidutinė absoliuti procentinė paklaida*);

MCDA – multiple criteria decision analysis (liet. *daugiakriterinė sprendimų analizė*);

MCDM – multiple criteria decision-making methods (liet. *daugiakriteriniai sprendimų priėmimo metodai*);

MFE – mean forecast error (liet. *vidutinė prognozės paklaida*);

MLP – multilayer perceptron (liet. *daugiasluoksnis perceptronas*);

MSE – mean square error (liet. *vidutinė kvadratinė paklaida*);

NUTS – nomenclature of territorial units for statistics (liet. *teritorinių statistinių vienetų nomenklatūra*);

NYMEX – New York Mercantile Exchange (liet. *Niujorko prekių birža*);

OPI – organisational performance index (liet. *organizacijos veiklos rodiklis*);

PEI – performance external index (liet. *našumo išorinis indeksas*);

R&D – research and development (liet. *moksliniai tyrimai ir plėtra*);

RELU – rectified linear unit (liet. *ištaisytas tiesinis vienetas*);

RMSE – root mean squared error (liet. *šaknies vidutinė kvadratinė paklaida*);

RNN – recurrent neural network (liet. *rekurentinis neuronų tinklas*);

ROA – return on assets (liet. *turto grąža*);

ROIC – return on invested capital (liet. *investuoto kapitalo grąža*);

ROI – return on investment (liet. *investicijų grąža*);

SARIMA – seasonal auto-regressive integrated moving average (liet. *sezoninis auto-regresijos integruotas slenkamasis vidurkis*);

SARIMAX – SARIMA with exogenous variables (liet. *SARIMA su egzogeniniais kintamaisiais*);

SCOR – supply chain operations reference (liet. *tiekimo grandinės operacijų nuoroda*);

STEO – short-term energy outlook (liet. *trumpalaikės energetikos perspektyvos*);

SWOT – strengths, weaknesses, opportunities, and threats (liet. *stiprybės, silpnybės, galimybės, grėsmės*);

TC – transportation cost (liet. *transportavimo kaina*);

TRAN – Committee on Transport and Tourism (liet. *Transporto ir turizmo komitetas*);

UK – United Kingdom (liet. *Jungtinė Karalystė*);

US – United States (liet. *Jungtinės Valstijos*);

TKMs – tonne-kilometres (liet. *tonkilometrai*);

VAR – vector equilibrium correction (liet. *vektoriaus pusiausvyros korekcija*);

WTI – West Texas Intermediate (liet. *Vakarų Teksaso vidutinis lygis*);

ZIP – zone improvement plan, post code (liet. *pašto indeksas*).

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Introduction

Problem Formulation

Asset-based road freight transportation companies perform under constant market competition and changing regulatory basis. The sector's digitalisation and increased data availability have opened up new opportunities to implement data-driven models for improving technological processes and overall efficiency. The prognosis of demand and freight rates is a prevalent challenge in the global freight transportation industry due to the complexity and variability of the data.

The dissertation addresses this issue by exploring and utilising data-driven models and proposing technological IT-based solutions that increase the efficiency of road freight transportation.

Relevance of the Dissertation

An accurate prognosis of contract freight rates and demand helps the company make decisions on pricing, resource allocation, and capacity planning, leading to increased efficiency and profitability. Due to a lack of data, the scientific community has not studied this problem sufficiently, so it has been unclear whether applying certain methods would solve it. The dissertation provides new insights and

knowledge into applying data-driven methods for increased efficiency, advancing the field, and providing a basis for future research. By having a reliable approach, road freight transportation companies gain a competitive advantage.

Research Object

The research object is road freight transportation processes and methods of increasing their efficiency.

Aim of the Dissertation

The aim of the dissertation is to create a data-driven decision support method for increasing efficiency in road freight transportation and investigate its performance through empirical analysis using real-world data.

Tasks of the Dissertation

To achieve the aim of the dissertation, the following tasks are to be performed:

1. To undertake a literature analysis to identify the scientific gap and select appropriate models and methods for addressing the problem.
2. To develop econometric and ANN-based mathematical models for freight rates and demand prognosis.
3. To evaluate the efficiency and performance of the developed models using real-world data.
4. To create a method using developed mathematical models to improve the transportation process, targeting efficiency improvement in road freight transportation companies.

Research Methodology

A theoretical study focusing on analysis and synthesis was performed to enhance strategies for increasing efficiency in freight transportation. This research involved analysing scientific publications, applying prognostic models and methods, and identifying gaps in existing literature. The study selected state-of-the-art solution methods, utilising mathematical modelling techniques. Tools included econometric models such as autoregressive integrated moving averages (ARIMA), seasonal ARIMA (SARIMA), and evaluation metrics. The research

developed univariate and multivariate prognostic models leveraging ANN. The developed models were tested using real-world data, employing software such as Microsoft Office and MATLAB.

Scientific Novelty of the Dissertation

1. Novel statistical, econometric, and ANN-based models have been developed to prognose freight rates and demand.
2. Key external parameters have been identified for freight rate prognostic models and used in method development.
3. A novel method based on the use of real data has been developed to increase the efficiency of road freight transportation.

Practical Value of the Research Findings

The method developed in this dissertation has important implications for asset-based road freight transportation. It will be used as a key component in the contract freight rate and demand estimation process, helping companies improve the efficiency of transportation processes.

Defended Statements

1. Econometric and ANN-based models are effectively used to prognose freight rates and demand and increase the efficiency of freight transportation.
2. Implementing multivariate models considering economic parameters yields superior results compared to previously used models.
3. Contract freight rate follows spot freight rate trends with a delay of several months, and spot rates should be used for the prognosis of contract rates.

Approval of the Research Findings

The main outcomes of the dissertation were published in four scientific publications: two in journals referenced by the *Web of Science* database with an impact factor, one in the Conference Proceedings of the *Web of Science* database, and one

in Conference Proceedings. The author has made two presentations at international scientific conferences:

- *Transbaltica*, plenary session. Vilnius, Lithuania, Vilnius Gediminas Technical University, 2 May 2019.
- *Transport Problems*, Poland, Katowice, Silesian University of Technology, 19 June 2024.

Structure of the Dissertation

The dissertation begins with an introduction, followed by three chapters, conclusions, references and annexes.

The First Chapter presents the relevant scientific literature on road freight transportation processes, companies' efficiency, and prognosis techniques, ensuring the study is grounded in existing knowledge and research.

The Second Chapter analyses technological aspects of the freight transportation process, focusing on ways to increase efficiency, and develops a method for increasing efficiency based on prognostic models for freight rate and demand estimation.

The Third Chapter uses real-world data to test their accuracy and validity and to evaluate the effectiveness of the mathematical models created in the Second Chapter. This Chapter provides an in-depth analysis of the results and assesses the strengths and limitations of the models. It proposes an efficiency improvement method focusing on prognostic models based on the investigation. Also, the Chapter analyses the possibility of its implementation in asset-based freight transportation companies and presents the algorithm of the developed method.

In conclusion, the dissertation summarises the main findings and provides a comprehensive list of references. All the results presented throughout the dissertation highlight the study's significance and contribution to the increasing efficiency of the road freight transportation process. Conclusions state that the aim of the research work is achieved and the study tasks are completed.

The total scope of the dissertation is 108 pages and contains 31 equations, 26 figures, six tables and 105 bibliography sources.

State-of-the-art in Road Freight Transportation and Analysis of Efficiency Improvement

In this Chapter, an overview of the recent global changes in the business environment concerning technological processes leading to the digitalisation of the transportation process is provided. The analysis focuses on the road freight transportation sector and its processes, considering various economic, social, environmental, technological, political and legal factors influencing its development. Furthermore, the current state of efficiency improvement with a focus on prognosis tools in the transportation sector is examined, identifying gaps and formulating the tasks that need to be addressed to improve the accuracy and efficiency of technological solutions. The main research findings of this Chapter are published in the author's four publications (Liachovičius, Skrickij, Podvieszko, 2020; Liachovičius, Šabanovič, Skrickij, 2023; Liachovičius, Skrickij, 2020; Liachovičius, Kojis, Skrickij 2024).

1.1. Global Changes in the Transportation Business Environment

The business environment has changed significantly during the recent decades and has impacted the transportation sector. A global shift can be seen from hardware-based innovations to software-defined solutions. Conventional businesses and new business models are digitised worldwide. The fundamental change is the emergence of platforms that bring together producers and consumers in high-value exchanges (Zao et al., 2020; Harvard Business Review, 2016). Examples of platforms in supply chains are Amazon and Uber Freight. These companies act as intermediaries, developing and managing aggregation platforms for goods and services of the same type (Ruggieri et al., 2019). Their role is not to develop, manufacture, or (re)sell products and services but to connect different market sides (Zhao et al., 2019). Such platforms are often not physically involved in delivering the service to customers, have no formal obligations to supply-side users, and therefore enjoy beneficial taxation and regulation compared to incumbents (Täuscher and Kietzmann, 2017). At the same time, platforms attract large numbers of users, and it is essential to analyse their impact on conventional businesses.

The impact of these platforms on conventional businesses is noteworthy. Zervas et al. (2016) analysed the effects of Airbnb on the hotel industry in the U.S. and found that a 1% increase in Airbnb listings resulted in a 0.05% decrease in quarterly hotel revenues. The authors also analysed whether a hotel's occupancy rate had decreased since Airbnb entered the hospitality industry and found that a 10% increase in Airbnb supply generated a marginal decrease in the hotel's occupancy rate of about 0.0007%. Wallsten (2015) examined the impact of Uber on yellow taxis in New York and claimed that the number of yellow taxi trips decreased as Uber grew. Chang (2017) also empirically assessed the economic impact of Uber on taxi drivers' business performance in Taiwan and found that Uber reduced taxi revenues by approximately 12% in its initial year and 18% in the third year of its entry. Kim et al. (2018) analysed whether the number of yellow and green taxi trips and revenue per taxi driver changed since Uber's entrance and found no direct evidence that it affected them.

High expectations about platforms' future profitability are often based on two related characteristics: scalability and network effects (Täuscher and Kietzmann, 2017). These conditions are mandatory to achieve profitability, but they are not sufficient if not supported by additional factors. The business model should be considered the main element of the platform's success or failure. A business model is defined as the design or architecture of the value creation, delivery, and capture mechanisms employed (Teece, 2010). The value creation dimension refers to the mechanisms that describe "what the company does" by expressing the firm's essential resources, activities, and processes. For platforms, this includes

the central architectural technology (e.g., purely web-based or mobile app) and how the platform integrates supply-side participants. The value delivery dimension describes elements that define what, how, and to whom value is generated, including the type of customer segments that the marketplace primarily connects, e.g., C2C, B2C, B2B (Ušpalytė-Vitkūnienė et al., 2022). The value capture dimension describes how the firm transforms the created and delivered value into revenues and profits.

Before changing the existing business model of a transportation company, it is essential to understand how investors see the transportation sector, what they value, and how they make decisions during business valuation. Therefore, value drivers that investors use to prognose and discriminate the future performance of companies were defined.

It should be noted that platform-based businesses are highly valued by investors compared to classic businesses. For example, Booking.com, which operates in the hospitality industry, has no hotels. At the same time, the company is worth more than the Marriott hotel chain, which has more than 4,000 properties worldwide (Ruggieri et al., 2019). The Alibaba Group, a marketplace born in China that exports worldwide, is worth double McDonald's (Ruggieri et al., 2019). Such trends are surprising as some platforms are highly valued even if they do not generate profit and revenues are not high.

According to the performed literature review, there are different value drivers, while most researchers use only financial ones. Kiss (2015) provided an empirical analysis of value drivers in his investigation; eleven of them were considered: free cash flow to firm; earnings before interest and taxes; tax rate, reinvestment; invested capital; return on invested capital; net margin; cost of capital; market return on assets; and sales growth rate. They all were found to be important. Earnings before interest and taxes, reinvestment, invested capital, net margin, and the sales growth rate positively affect a firm's value; however, tax rate and market return on assets have a negative impact. Rappaport (1999) provided another approach, considering managers and investors. Rappaport (1999) identified the following value drivers that are also financial drivers: sales growth rate; operating profit margin; income tax rate; working capital investment; fixed capital investment; the cost of capital; and value growth duration. MacDiarmid et al. (2018) proposed a methodology for comparing and selecting financial drivers. The eight potential value drivers were analysed using a graphical comparison, followed by the numerical determination of the degree of correlation between the driver and enterprise value using the Pearson correlation coefficient. Hypothesis testing was finally done to investigate the strength of the relationships between the potential value drivers and enterprise values (MacDiarmid et al., 2018). The analysis of value drivers performed by Bistrova et al. (2014) revealed that sustainable shareholder value is based on long-term and stable economic performance,

accompanied by a properly implemented corporate governance system, high common reporting standards, rational capital budgeting politics, and high financial results accountability. It is possible to increase the investment attractiveness of a company for the existing and potential strategic and retail investors, the factors affecting shareholder wealth (Bistrova et al., 2014). Śledzik (2013) identified that in value-based management theory, the main focus all the time was on financial value drivers.

Still, there is a severe necessity for intangible valuation resources and identification. The authors used financial and non-financial drivers in the investigation. It was found that most of the existing methods of intellectual capital valuation are challenging to apply, require too much information, or are not thoroughly described (Śledzik, 2013). Some of the methods are not numerical; therefore, analysis becomes problematic. The main conclusion is that managers omitting non-financial drivers is a severe mistake in the shareholder value creation process.

Based on the literature review, no specific value drivers applicable in the road freight transport industry were found; an initial investigation has been performed to answer this question.

MCDM methods were implemented to select key value drivers for evaluating road freight transport companies. MCDM methods are popular for decision-making in various strategic fields, including economics, business, technology, and transportation (Brauers and Zavadskas, 2010; Podvezko and Sivilevičius, 2013; Sivilevičius and Maskeliūnaitė, 2019; Sivilevičius and Martišius, 2023; Maskeliūnaitė et al., 2023). Stojčić et al. (2019) provided a systematic review of the application of MCDM for sustainability; these methods were found to be widely used for decision-making in transport and logistics. Sevastjanov and Dymova (2009) proposed a new method for stock ranking based on MCDM and optimisation. Fuzzy MCDM methods for ranking various alternatives concerning their preference for a decision-maker were proposed by Mardani et al. (2015). Authors used financial drivers in their investigations: the market value of the firm to earnings before amortisation, interest and tax ratio, ROE, debt to equity ratio, current ratio (current assets to current liabilities), market value to net sales ratio, and price to earnings ratio. Drivers used by authors: earnings per share per cent change, revenue per cent change, change in pretax margin positive, change in return on investment, change in shares outstanding, EPS per cent change, depreciation of capital spending, market capitalisation, pretax margin, ROI, and revenue per cent change. Bilbao-Terol et al. (2012) developed proposals for constructing portfolios for investors considering ethical, social, and environmental criteria when making decisions. Escrig-Olmedo et al. (2017) continued developing investment feasibility studies that considered sustainable investments. Their work described four areas: social, environmental, economic, and corporate governance performance. The authors' approach extends the solution's applicability since the problem is

dealt with complexly, not just from a financial point of view. Often, scientists select which MCDM method to use intuitively. Cinellia et al. (2020) presented a comprehensive taxonomy to support applying MCDA. The authors distinguish three main phases: problem formulation, construction of the decision recommendation, and qualitative features and technical support. These phases include a subset of the characteristics that help the analyst implement the MCDA process. Such an approach allows for choosing the most appropriate methods for the problem under investigation and may be used to automate the decision-making process.

The weights of value drivers relevant to road freight transport companies were calculated during the initial investigation. The most important drivers were identified using a novel approach to problem-solving by implementing the MCDM methods. The identified key drivers are (1) business model, (2) the expertise of the people working in the company and management system, and (3) financial performance. During the investigation performed by the author, it was found that investors focus on the company's business model. The first conclusion could be based on the idea that digitalisation is changing business models worldwide. As a result, asset-based companies need to find a solution for further development, as companies that will only collaborate with platforms may not be exciting to investors, and the transition to platform-based business models is a likely scenario. Therefore, IT-related technologies in the transportation sector need to be developed.

1.2. Challenges and Opportunities for Road Freight Transportation

The current situation must be analysed before developing technological solutions to improve transportation processes effectively. The transportation sector of the 27 member countries of the EU was valued at more than EUR 1.3 trillion in 2020 (EU 27 turnover volume in the transportation sector by mode 2020). Germany accounted for 24% of the market value, France for 15%, and Italy 13% (turnover in Europe's transport and storage sector in 2020, by country). The total contribution of the first ten countries in the EU amounts to approximately 85% of the market.

Despite the dominance of road transport in EU freight transportation, significant challenges remain. Almost half of all freights in the EU are transported by heavy-duty vehicles (Research for the TRAN Committee 2018). This number is even higher in the U.S., where heavy-duty vehicles account for 63% of freight transportation (United States Department of Transportation, 2017). Although the railway occupies 18% of the transport share in the EU, efforts are underway to

increase this number. Inland water transport holds a modest share of a little over 6%, and not all EU countries have the infrastructure to support it.

To better understand the challenges and opportunities within the sector, reviewing the current situation in EU road freight transport is crucial, considering five factors: political and legal, technological, social, economic, and environmental.

Political factors include national and EU-level market interventions such as taxes, tariffs, trade barriers, market regulation, and public infrastructure issues (Analysis of the EU Logistics Sector, Final Report, 2015). Legal factors address consumer protection, social laws, health and safety regulations, and competition rules. Political and legal considerations are intertwined, especially with social aspects such as working time restrictions being regulated through political decisions. Political factors highly influence transportation industry regulation. Among the fundamental changes affecting freight transportation in the EU are those outlined in the White Paper (2011), the European Green Deal (2019), and the Global Gateway (2021). The Global Gateway initiative provides a framework for constructing resilient connections and cooperation worldwide, focusing on physical infrastructures like fibre optic cables, clean transport corridors, and power transmission lines, thereby strengthening digital, transport, and energy networks. EU transport infrastructure policy comprises the TEN-T core network, featuring nine significant corridors connecting various transport modes (Analysis of the EU Logistics Sector, Final Report, 2015). This policy also addresses cross-border corridors focusing on Asia, including China and India. Taxation in road freight transportation depends on two parameters: the country of carrier registration (VAT, income tax, charges related to vehicle registration, etc.) and the selected route (toll, parking fees, etc.). The tax burden and charges for road freight transportation vary significantly across the EU countries (Konečný et al., 2018).

The transportation sector is in the throes of immense technological change, presenting risks and opportunities (Išoraitė et al., 2022). For decades, logistics companies were not expected to invest significantly in R&D activities, yet doing so can now greatly enhance their competitiveness. Key areas of investigation include technology development and the implementation of innovations (Analysis of the EU Logistics Sector, Final Report, 2015). Digitalisation plays a pivotal role in transforming business models (Abu-AlSondos et al., 2024). Introducing green vehicles, such as electric and hydrogen-powered trucks, addresses environmental concerns, while vehicle automation can alleviate driver shortages and enhance safety by minimising human error. The evolution of automated logistics warehouses also promises to revolutionise the sector (Kumar et al., 2022), although the pace of automation is slower than ideal.

Regarding software solutions, trends include software-as-a-service (SaaS) models (Khalil and Winkler, 2023; Al-Madhagy Taufiq-Hail et al., 2021;

Cheung et al., 2021), where users pay only when the software is used, and data analytics involving big data. Quick decision-making based on big data analytics has become essential, significantly reducing time lags. Cybersecurity is also crucial as the sector increasingly relies on software (Khan et al., 2023; Mohsendokht et al., 2024), with technologies like blockchain offering promising safety improvements during digital transformations.

The Physical Internet concept presents another innovative technological approach. It envisions an open global logistics system based on physical, digital, and operational interconnectivity through encapsulation, interfaces, and protocols (Skrickij et al., 2023). This approach seeks to replace current logistical models, offering new efficiencies and opportunities.

Social factors encompass demographic growth and structure, cultural aspects, and societal consciousness regarding health and the environment. These factors also cover ecological elements such as climate change, transport externalities (noise emissions and air pollutants), and energy and environmental legislation. Following Brexit, the EU's population was projected to increase by 2.2% from 2013 to 2030 (from 507.2 million to 518.5 million inhabitants). However, the ageing population remains a critical concern. The share of the population aged 65 or above is forecasted to rise from 17.4% in 2010 to 23.6% by 2030 (Analysis of the EU Logistics Sector, Final Report, 2015). This demographic shift will influence social and consumer behaviour, though not as much as technological advancements. The increasing prominence of electronic business is changing consumption patterns, with more companies moving into the virtual space.

Another significant challenge is the global shortage of truck drivers. In 2017, the Truck Driver Shortage Analysis reported over 63,000 vacancies in the U.S., which has continued to rise. In Europe, there were 52,000 vacancies in the UK, 45,000 in Germany, and 20,000 in France (European Road Freight Transport, 2018). The COVID-19 pandemic exacerbated this situation. While automated trucks present a potential solution, advancements in this area have been slow, necessitating more immediate solutions.

Regarding GDP, the EU is the second-largest economy globally after the U.S. According to World Bank data, the GDP of the EU stands at USD 17,282 billion, behind the U.S. at USD 19,391 billion, with China in third place at USD 12,238 billion (European Road Freight Transport, 2018). Internal risks include the rise of populist governments in some member states. Despite these challenges, the wealth gap within EU countries is narrowing, and the economy is growing. This economic stability is expected to influence the freight transportation sector by shifting demand patterns for consumer goods and altering the spatial structure of production (Analysis of the EU Logistics Sector, Final Report, 2015).

Globalisation and increased trade volumes outside the EU will likely have a positive economic impact. By 2040, Europe's contribution to global growth is

forecasted to be 16.8%, with China leading at 31.8%, followed by the U.S. at 22.9%. India and Brazil are also expected to be significant contributors (Analysis of the EU Logistics Sector, Final Report, 2015). China's One Belt, One Road initiative will significantly impact road freight transport by enhancing rail connectivity between Europe and Asia, ultimately increasing the demand for road freight transportation.

Environmental challenges, such as raw material scarcity, particularly fossil fuels, are a growing concern. The anticipated scarcity will drive energy costs, necessitating innovative solutions to mitigate these risks and reduce transport-related emissions. Globally, efforts must be made to minimise the impacts of climate change.

The challenge of reducing GHG emissions presents both significant hurdles and substantial opportunities for the road freight transportation sector. According to the proposed strategies, GHG emissions should be reduced by at least 55% by 2030 compared to 1990 levels. This ambitious target is critical to the EU's broader environmental goals to combat climate change and enhance air quality.

The White Paper on Transport outlines a comprehensive plan to mitigate GHG emissions across the transport sector. However, specific EU regulations addressing CO₂ emissions from heavy-duty vehicles were only introduced in 2018. The legislative framework, codified in COM 284 (2018), mandates that the EU's fleet of new heavy-duty vehicles must achieve the following reductions in CO₂ emissions compared to reference levels:

I. By 15% from 1 January 2025 to 31 December 2029.

II. By at least 30% from 1 January 2030 onwards.

These regulations underscore the urgent need for road freight transportation to adopt more sustainable practices and technologies. One significant challenge is ensuring that freight shipments over short and medium distances – typically below 300 kilometres – remain feasible for trucks while meeting stringent emissions targets. Since trucks are likely to continue dominating these routes, innovative solutions are required to enhance their efficiency and reduce their environmental impact.

Overcoming these challenges also provides numerous opportunities for the road freight transportation industry. Investment in new technologies, such as electric and hydrogen-powered trucks, significantly diminishes GHG emissions (Zheng et al., 2024). These advancements contribute to environmental sustainability and offer long-term cost savings through improved energy efficiency and reduced dependence on fossil fuels.

Moreover, the shift towards greener practices enhances the industry's public image and meets the growing demand from consumers and businesses for more environmentally friendly transport solutions.

Companies that take proactive steps to reduce their carbon footprint will likely gain a competitive advantage as sustainability becomes an increasingly critical factor in business operations and decision-making.

Another opportunity lies in promoting freight multimodality, particularly for longer distances where road transport alone may not be the most economical or environmentally viable option. The sector optimises logistics, reduces emissions, and improves performance by integrating road transport with rail, maritime, and air transport. Multimodal transport solutions are particularly effective in reducing the carbon footprint of long-distance freight shipments, making them more attractive to shippers and helping meet regulatory requirements.

Road freight transportation in the EU faces numerous challenges and opportunities, especially in light of the imperative to reduce GHG. Political and legal frameworks, technological advancements, social dynamics, economic shifts, and environmental considerations all play crucial roles in shaping the sector's future. Embracing innovation and technological solutions will be vital to navigating these complexities and ensuring a resilient and efficient transport system. A SWOT analysis is performed in the next sub-chapter to identify how current challenges impact transportation companies.

1.3. Identification of Road Freight Transport Strategies and Trends from the Transportation Perspective

Road freight transport is undergoing significant transformations, presenting substantial challenges and exciting opportunities (Table 1.1). The recent favourable economic cycle in the EU has positively impacted the road freight transportation sector. The number of new vehicles in the EU fleet increased by almost 6%, reaching a total increase of up to 22%, according to Eurostat data (Eurostat, 2019). Concurrently, the number of vehicles aged two years and three years increased by approximately 2% each, while those aged four to seven saw a decrease. However, after 2022, the situation has changed, and the last few years have not been so favourable.

Although relatively young, the EU has seen significant growth, with the monetary union established only in 1999. Over the last 20 years, several candidate countries have joined as member states, significantly expanding the market size and population of the EU. This expansion has benefited transportation companies, providing opportunities to shift focus from domestic markets to international ones. Given the lower living standards in new member states, road transportation businesses in these regions have become highly competitive globally.

Table 1.1. SWOT analysis of road freight transport in the EU

Strengths	Weaknesses
<i>Economic activity/ GDP increase</i> <i>EU market enlargement</i> <i>EU population increase</i> <i>Low barrier to entering the market</i> <i>Highly fragmented European transportation market</i> <i>Relatively new vehicle fleet</i>	<i>Ageing society</i> <i>Shortage of drivers and wage pressure</i> <i>Lack of R&D innovations for the industry</i> <i>Infrastructure quality is uneven across the EU</i> <i>Transport-related emissions and climate change</i> <i>Fossil fuel scarcity</i>
Opportunities	Threats
<i>Autonomous vehicles</i> <i>Digitalisation</i> <i>The proliferation of digital businesses</i>	<i>Double standards in regulation</i> <i>Shift from road transport to rail</i> <i>Change of transportation paradigm</i>

As previously identified, over 90% of the EU's road freight businesses employ fewer than ten people. The dominance of SMEs in this sector is a strength, as it lowers barriers to entry and fosters competition.

There are two main types of companies in the logistics sector: asset-based companies and freight forwarding companies that organise cargo transportation without owning vehicles. The latter have minimal capital requirements, contributing to high competition in this segment. In contrast, asset-based companies require significant initial capital investment; a truck in the secondary market costs around 40,000 euros, plus additional costs. Small companies often face challenges working through intermediaries, as large customers prefer direct dealings with significant companies, eroding smaller players' profits. Additionally, vehicle maintenance costs are relatively high for small companies without direct access to vehicle manufacturers.

One of the weaknesses affecting road freight transportation is the ageing population in the EU, which poses economic challenges (Pais-Magalhães et al., 2020). Furthermore, the industry faces a severe shortage of drivers across member states, leading to increased wage pressures. The sector also lags in R&D innovations compared to other industries, highlighting a pressing need to promote these activities. The digitalisation of the transport sector offers an unparalleled opportunity to revolutionise transportation paradigms (Adnan, 2024). Big data analytics could provide a competitive edge by enabling quicker responses to challenges (Kashyap, 2019). Autonomous vehicles represent another promising technology, potentially reducing accidents by eliminating human error and addressing the shortage of drivers (Gheisari et al., 2024; Skrickij et al., 2020).

The widespread use of diesel engines in road freight transport contributes significantly to environmental pollution and climate change. With the impending

scarcity of fossil fuels exacerbated by the rapid growth of the Chinese economy, the environmental impact of transport is a critical concern. Regulatory measures have been implemented to address these issues. In 2018, the EC introduced its first regulation on GHG for road freight transport, underscoring the importance of such measures.

However, regulatory changes also pose threats. Some requirements presented in regulations can reduce competitiveness, particularly for Eastern European companies. For instance, Article 8b of Regulation COM 277 (2017) mandates that transport undertakings organise drivers' work schedules so drivers can return home for a weekly rest at least once every three consecutive weeks. This regulation does not significantly affect the drivers in Western Europe due to the high density of orders, but it can increase empty running rates for Eastern European companies. These companies may respond by establishing new offices in Western or Central Europe, allowing drivers to travel home without their trucks, but this would change the country of tax payment.

Additionally, the shift from road to rail transport introduces new threats. While it is ideal for cargo to be transported via road for distances up to 300 km and by rail for longer distances, this requires additional infrastructure. In countries where rail passenger transport is prioritised, cargo transport durations could increase due to passenger trains having precedence.

The maximum freight vehicle weight variation across EU member states presents another challenge. While most EU countries enforce a maximum weight limit of 40 tonnes, Finland allows vehicles with a maximum weight of 76 tonnes and nine axles, which reduces emissions and evenly distributes loads without damaging road pavements. Such alternative solutions, however, are not universally adopted by the EU.

The primary threat for individual companies remains technological advancements. As transport services evolve to achieve higher efficiency and sustainability, companies that fail to adapt risk losing their market share. A practical approach to understanding the sector's dynamics is considering how investors value the transportation sector, offering insights into potential growth areas and investment opportunities.

In conclusion, road freight transportation in the EU faces multifaceted challenges influenced by political, technological, social, economic, and environmental factors. However, these challenges also present numerous opportunities for innovation and growth. The sector can enhance its competitiveness and sustainability by embracing digitalisation, fostering R&D, and adapting to regulatory changes. Reducing GHG is critical, necessitating a concerted effort from all stakeholders to mitigate environmental impact and ensure a resilient future for road freight transport.

1.4. Improvement of Road Freight Transportation Process Efficiency

A critical review of the existing situation provides a basis for proposing technological solutions with the highest impact possible. The highest impact may be in the provision of software-based technological solutions. During the preparation of the dissertation, a suitable task was defined. This task is to increase the efficiency of the transportation process:

1. The performance of a supply chain is measured using different methodologies that fall into several categories: customer service (Wang et al., 2015), operational effectiveness (Qi et al., 2017), financial efficiency (Lee, 2021), and innovation and learning (Haq et al., 2020).
2. Customer service metrics include on-time delivery percentage, cargo travel time, consistent quality of the service, and others, which depend on the type of cargo defined by the customer.
3. Operational metrics involve the utilisation rates of warehouses and vehicles and the depreciation of empty kilometres. Measuring these components helps optimise logistics processes, reduce wastage, and improve the overall efficiency of supply chain operations.

Previously, profit was the overall objective of any logistics system (Dornier, 1998) and the key financial metric. With changes in business models, situations have evolved, and a few new metrics have emerged, including cost per unit, total supply chain cost, and company revenue. These metrics vary depending on the specific case under investigation, providing a more comprehensive view of financial health.

Innovation and learning metrics measure the rate of new product introductions or employee training levels (Haq et al., 2020). These metrics are crucial for fostering a culture of continuous improvement and adaptation to changing market conditions.

Different indexes are used for performance measurement. The LPI is one of the widely used KPIs proposed by the World Bank (The LPI Methodology). It is based on six indicators:

1. The efficiency of customs and border management clearance,
2. The quality of trade and transport infrastructure,
3. The ease of arranging competitively priced shipments,
4. The competence and quality of logistics services,
5. The ability to track and trace consignments,
6. The frequency with which shipments reach consignees within scheduled or expected delivery times.

The calculation of this index is based on surveys and is often criticised for its subjectiveness (Beysenbaev and Dus, 2020). There are proposals to improve the

calculation methodology by adding statistical data. Nevertheless, this index is used to compare countries, not companies.

The SCOR model recommends 12 supply chain metrics for performance evaluation (Huan et al., 2004; Pettersson, 2008):

1. Delivery performance,
2. Fill rate,
3. Order fulfilment lead time,
4. Perfect order fulfilment,
5. Supply chain responsiveness,
6. Production flexibility,
7. Total logistics management cost,
8. Value-added employee productivity,
9. Warranty cost,
10. Cash-to-cash cycle time,
11. Inventory days of supply,
12. Asset turns.

These metrics align with the five main groups described in this Chapter.

Another way to measure supply chain performance is through the ALI (Pettersson, 2008):

$$ALI = PEI(1 - SCCI), \quad (1.1)$$

where *PEI* is the performance external index, calculated by multiplying the delivery precision index, lead time index, and customer satisfaction index, and *SCCI* is the supply chain cost index, calculated by dividing the total supply chain cost by net sales. *ALI* should be higher, meaning closer to 1, or 100%, rather than zero. This means a company needs to have a low *SCCI* while maintaining a high *PEI*. *ALI* is calculated for all companies involved in the supply chain. In some cases, a company can charge for excellent customer service. A value of 0.4 for *ALI* in one company may be more successful than 0.6 in another (Pettersson, 2008).

It is essential to distinguish between performance and efficiency. According to the classification used for the calculation of the *OPI*, the overall performance of organisations is measured in four main domains:

- I. Effectiveness – the ability of a company to carry out programmes to a high standard and continuously improve its operation, following its vision, mission, objectives, and goals.
- II. Efficiency – the ability of an organisation to plan and budget for its interventions with technical and financial efficiency analyses.
- III. Relevance – the ability of an organisation to respond to its beneficiaries' actual and current needs and to remain alert to any changes that might influence this capacity.

IV. Sustainability – the ability of an organisation to ensure that its programmes and services are supported by a diverse group of allies and networks, along with its capacity to guarantee, maintain, and manage diverse, own, local, and international sources of funding and resources (cash and/or in-kind), achieving long term results.

This dissertation's main focus is developing technological solutions for efficiency improvement in road freight transportation. Generally, efficiency is described as minimising costs and maximising output (Cowie and Ison, 2017). Beaumont (1999) defined efficiency by measuring how well resources are utilised. Companies can proactively manage their resources and investments by employing models for demand and freight rate prognosis to navigate market fluctuations and gain a competitive edge.

In summary, increasing efficiency in road freight transportation is multifaceted, involving numerous metrics ranging from customer service and operational efficiency to financial health, innovation, and learning. Focusing on efficiency, broadly defined as minimising costs while maximising output, allows organisations to enhance their supply chain performance, effectively respond to market dynamics, and maintain competitiveness in a challenging logistics environment. Employing advanced prognostic models further aids in resource optimisation, ensuring long-term sustainability and success in road freight transportation.

1.5. Prognosis Techniques in Road Freight Transportation

Technological solutions for an accurate freight transportation prognosis are the dissertation's main research object.

Prognosis in road freight transportation combines historical data with economic insights – freight rate, demand, technological solutions, budget planning or expanding to new markets. Different methods and models need to be tested to develop such a method.

Figure 1.1 presents a detailed taxonomy of available prognosis methods and models: qualitative, quantitative and hybrid. Qualitative methods combine two groups of methods. The first subgroup is univariate methods, which a single person can perform. These scenario-building methods are defined as a story with plausible cause-and-effect links that connect a future condition with the present while illustrating key decisions, events, and consequences (Glenn, 2009; Retek, 2021).

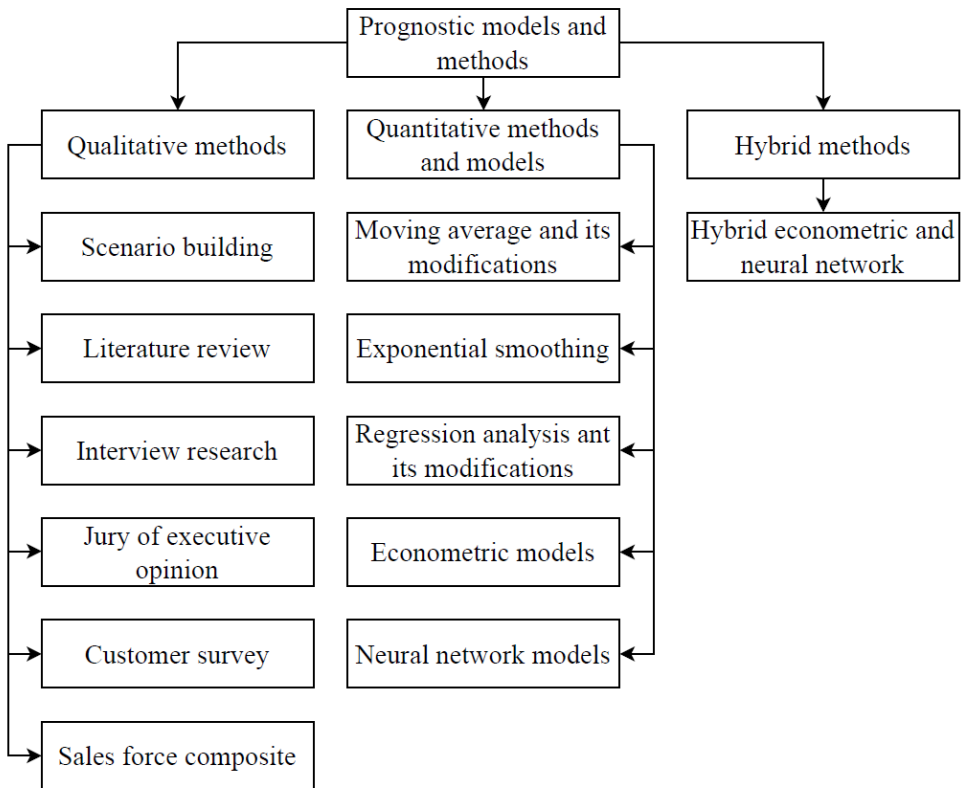


Fig. 1.1. Prognostic models and methods (compiled by the author)

A literature review can provide different parameters based on available data. The interview research method could be used to interview experts and ask specific questions. As a collective prognosis, the Delphi method can be used. Delphi's method is based on the multi-round survey; respondents can comment on questionnaires. After analysis, the results are shown to respondents, and they can modify their answers. Some convergence is observed after a few rounds (Kauko and Palmroos, 2014).

The sales force composite method is when the sales agents forecast the sales in their respective territories, consolidated at the branch/region/area level. All these factors are consolidated to develop an overall company sales prognosis (Sales Force Composite Method). It can be adapted for different areas where the initial prognosis is performed on a low level. After that, data are aggregated, adopting results at a high level.

Quantitative methods are widespread in prognosis. The MA and its modifications, such as daily MA, normalised MA, and other commonly called MA-type indicators of past prices, are widely used for prognosis in various areas, starting from the stock market and finishing with commodities (Wen et al., 2022; Srivastava et al., 2022; Luzia et al., 2023). Simple exponential smoothing is designed for situations with no seasonal pattern and no trend, so only the level of demand has to be found (Dekker et al., 2004; Kumar et al., 2024; Sapnken et al., 2024). Regression analysis-based methods could also be used for prognosis. However, the most widespread are econometric models. The econometric models are used for stationary and seasonal data. One of the classical and widespread algorithms is the ARIMA model, which includes AR, integrated (I), and MA parts (Dey et al., 2023; Amini et al., 2016; Babai, 2013). SARIMA models are used for seasonal data if prognosis data depends on a few parameters; multivariate models such as ARIMAX or SARIMAX could be used (Huang et al., 2024; Kumari and Muthulakshmi, 2024).

ANN usage has become a hot topic in prognosis; in many cases, such methods perform better than conventional models (Falatouri et al., 2022; Zhu et al., 2024). In recent years, the implementation of hybrid methods that combine econometric models, Kalman filtering, and ANN-based methods has increased (Shukur et al., 2015). Kalman filtering is a model-based approach that requires a mathematical model; at the same time, ANN is a data-driven approach; it can be developed for different processes without developing the mathematical model. This is the main advantage of ANN models; however, they require data, and data are not available for all processes. A hybrid method based on combining the conventional econometric and ANN models can perform better than either of the models used separately (Ruiz-Aguilar et al., 2014). Simultaneously, the complexity of such solutions increases, and their practical application becomes more complex.

Vilutiene et al. (2014) provided that prognostic models must meet the following conditions:

1. Models must be sufficiently simple to apply practically. The obtained results could be easily perceived and considered.
2. The observed phenomenon's tendencies in the future must remain the same as they were in the observation period.
3. The possibility of upgrading the models with new data.
4. The model must be multivariate; univariate models can only accidentally reflect the possible process development.
5. The models must evaluate the stochastic nature of initial data.
6. The experience and intuition of the professionals are significant in evaluating the estimations. The last point could be adopted only for some of the qualitative methods.

Prognosis of freight rates and demand are tasks of vital importance in logistics. The digitisation of the sector and the appearance of databases open up new opportunities in this area. Road freight transportation is separated into less-than-truck-load versus truckload. In this dissertation, only truckload was analysed.

There are two types of orders in freight transportation. First are spot rates and short-term freight pricing that reflect the truckload market's real-time supply and demand balance. The second group is contract rates, which are long-term truckload pricing for consistent freight volumes. According to Jason et al. (2021), if the aggregate spot freight rates increase by 20%, then the aggregate contract freight rates should be expected to increase by approximately 4% over the next few months, assuming the conditions remain unchanged. Similar results are achieved by Coyote Logistics (Coyote Truckload Market Guide, 2022), which continuously provides a truckload market prognosis (Fig. 1.2).

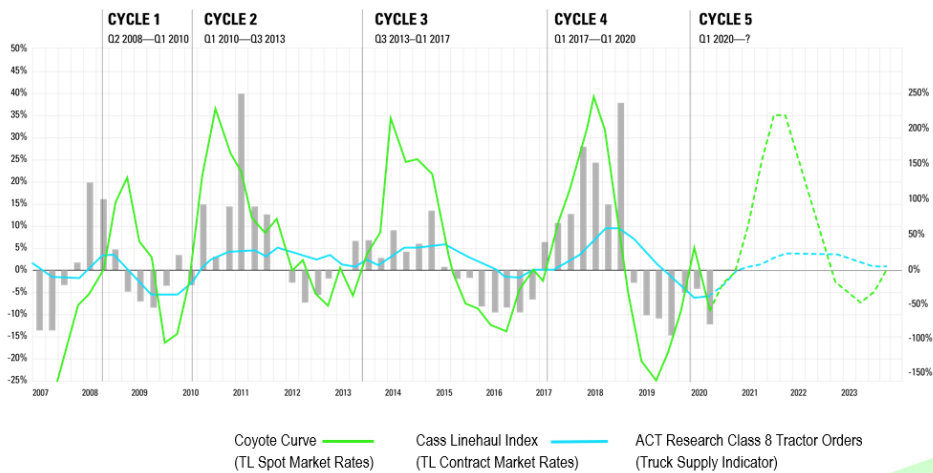


Fig. 1.2. Truckload market prognosis (Coyote Logistics contract and spot rates, 2022)

Coyote Logistics prognosis uses critical indicators for driving truckload rates: truckload volume, industrial production, imports, consumer spending, and sales-to-inventory ratio. It should be mentioned that Coyote Logistics makes a prognosis for the U.S. market only; there is no data aggregator in the EU for spots or contract freight rates. Separate companies collect information; however, their market share is relatively small, so data are not representative. Solutions must be developed for road freight transportation companies operating in the European market.

1.6. Conclusions of the First Chapter and Formulation of the Tasks for the Dissertation

The conclusion of the literature review highlights the following key points:

1. The road transportation sector is undergoing significant changes due to digitalisation, which offers opportunities to develop new tools to support decision-making in road freight transportation companies, increasing their efficiency. These tools can help companies make more informed and accurate decisions, improving their competitiveness in the market and increasing their profits.
2. A lack of prognosis tools for road freight transportation companies has been identified through the literature review. A performed literature review has shown that econometric and ANN-based mathematical models have great potential to solve tasks related to demand and freight rate prognoses.
3. Real-world data are required to evaluate the efficiency and performance of the econometric and ANN-based models.
4. A technological solution – a prognosis method – using developed mathematical models needs to be created that can be easily scaled for different regions and adapted for companies with various business models.

According to the conclusions of the First Chapter, the following tasks of the dissertation are formulated:

1. To perform a literature review, identify the scientific gap and select appropriate models for addressing the problem.
2. To develop econometric and ANN-based mathematical models for demand and freight rate prognoses.
3. To evaluate the efficiency and performance of the developed models using real-world data.
4. To create a method using developed mathematical models based on performed investigations that impact the transportation process and target increasing efficiency in road freight transportation companies.

Methodology of Long-Term Freight Rate and Demand Prognosis

In this Chapter, the theoretical framework of the dissertation is thoroughly presented. The importance of increasing efficiency in the road freight transportation process is analysed. A comprehensive description of the methodology and mathematical models used for the research, including various parameters that influence freight rates and demand prognoses, is presented. The contract pricing techniques are discussed in detail, including different types of data utilised for prognosis purposes, along with their sources, which are analysed. The econometric and ANN models are explained, and the metrics are presented for evaluating the proposed solutions. Finally, a developed technological solution is presented. The main research findings of this Chapter are published in two of the author's publications (Liachovičius, Skrickij, Podviezko, 2020; Liachovičius, Šabanovič, Skrickij, 2023).

2.1. Method for Increasing the Efficiency of Transportation Processes

Large and medium-sized asset-based road transport companies typically develop long-term growth strategies to sustain their business and expand their market presence. When preparing growth plans for the upcoming year, the numerical values of key metrics are usually derived from the previous year's results and aligned with the company's growth strategies. However, the logistics sector highly depends on the economic situation in the specific region where the activities are conducted. Consequently, the logistics business is cyclical, and companies, particularly asset-based ones, must align their growth ambitions with market cycles.

Relying solely on straightforward methods can have a detrimental impact on the efficiency of the companies. Specifically, such methods might impair the capability of the organisation to plan and budget its interventions effectively. When not strategically aligned, technical and financial efficiency analyses may not yield the desired outcomes. For instance, if a company pursues growth during a cycle marked by decreasing demand for transportation services and declining prices, this can have severe negative repercussions. It may lead to the underutilisation of resources, operations running below actual cost, and significant financial losses.

Conversely, when demand recovers and transportation rates increase, companies often face a delayed readiness to respond. This can result in a shortage of crucial resources, such as sufficient trucks or skilled personnel, thereby missing potential market opportunities. The inability to quickly adjust to increased demand can lead to competitive disadvantages and failure to achieve strategic goals within the desired timeframe.

Due to the transportation sector's digitalisation, different technological solutions, mainly based on IT, can be developed to control transportation processes effectively. Therefore, implementing a transportation demand and freight rate prognostic model gives companies a competitive advantage. Such a model enables proactive management of resources and investments, allowing companies to align their operations with anticipated demand and rate fluctuations. Possessing this foresight, even four to six months before market changes occur, allows crucial management decisions to be made or adjusted. For example, decisions regarding purchasing new trucks, hiring additional employees, or adjusting rates for new contracts are made with greater confidence and precision.

Developing a data-driven method for prognosis enhances a company's efficiency. By relying on accurate prognoses of market trends and demand fluctuations, companies allocate their resources better, optimise their operations, and improve their financial performance. This method ensures that growth strategies are based on historical data and forward-looking, incorporating market intelligence and economic prognosis.

2.1.1. Application of the Method for Increasing Efficiency in Road Freight Transportation

For asset-based freight transportation companies, evaluating efficiency involves using various metrics, as highlighted in Figure 2.1. In typical cases, the following metrics are calculated for a specified month:

- I. The *number of available trucks* refers to the operational fleet size and readiness for dispatch during the given month. It is a fundamental starting point as it sets the baseline for further calculations and profitability assessments.
- II. The *number of kilometres travelled per truck* captures the average distance each truck covers within the month. It reflects both the utilisation rate and operational reach, highlighting deployment efficiency.
- III. *Empty kilometres per truck* represents the percentage of total kilometres travelled by trucks without carrying freight. High percentages indicate inefficiencies in route planning and load management.
- IV. *Revenue per kilometre per truck* is a critical financial metric which calculates the income generated for every kilometre travelled by each truck, helping to assess the profitability of operations on a per-distance basis.
- V. The *number of shipments per truck* measures the total number of distinct shipments handled by each truck in the given month, providing insights into the asset utilisation and demand response.
- VI. The *average daily margin per truck* defines the average profit margin earned by each truck daily. It is crucial to evaluate the overall economic viability of the fleet operations.
- VII. *Operating profit* represents the net financial performance of the trucking operations after accounting for all revenues and expenses. It offers a comprehensive view of the company's profitability.

A correct prognosis of demand is essential for recalculating metrics, such as the *number of kilometres travelled per truck* and the *number of shipments per truck*. An accurate demand prognosis ensures that resources are optimally allocated and trucks are utilised to their full potential, thereby minimising empty runs and maximising shipment handling.

Freight rate prognosis is crucial in calculating metric *revenue per kilometre per truck*.

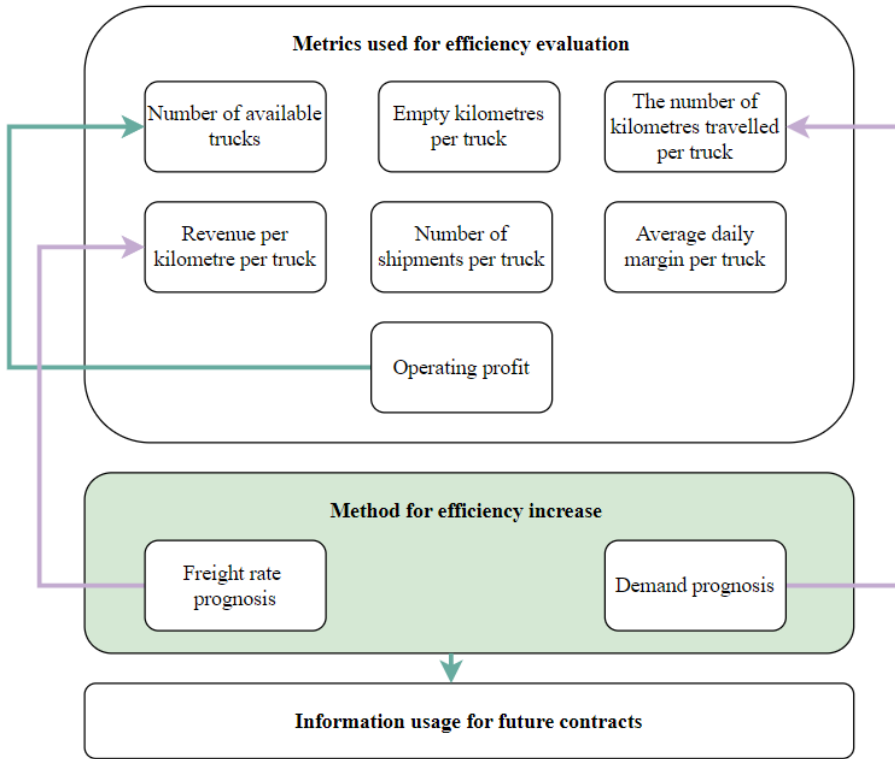


Fig. 2.1. Implication of method for increasing efficiency (compiled by the author)

The *average daily margin per truck* is calculated using these prognosed data points. This involves combining the revenue per kilometre with the distance travelled and the number of shipments to derive a daily profit margin, which is crucial for informed decision-making.

Operating profit is then estimated based on the aggregated revenue and expenses associated with the fleet's operations. Companies can foresee financial outcomes with greater precision by ensuring that these calculations are based on accurate demand and rate prognosis.

If the achieved results do not align with the default or expected values, a reassessment is conducted concerning the number of available trucks. This reassessment encompasses operational adjustments, such as redistributing trucks to busier routes, leasing additional trucks, or even reducing the fleet size to better match the demand and optimise profitability.

A technological solution is required to develop the functionality described above based on available data, mathematical models, and algorithms used during different market cycles.

Such a technological solution provides an exceptional opportunity for the company's proactive management. This method empowers decision-makers to enhance efficiency, minimise costs, and maximise profitability by facilitating the real-time monitoring of essential metrics and enabling swift operational adjustments. It leverages prognosis analytics to stay ahead of market fluctuations, thus allowing companies to maintain a competitive edge.

Beyond the monthly assessment, the method serves as a strategic asset. Integrating historical data and continuously refining prognostic models enhances long-term planning and resource allocation. Fleet managers can pre-emptively address potential inefficiencies, ensuring that the available trucks are deployed in the most economically beneficial manner. This method fosters an environment of continuous improvement. By regularly analysing and revisiting the critical performance metrics, areas for improvement are identified, and best practices are established across the fleet. This iterative process guarantees that the company meets and exceeds its operational and financial goals.

The proposed analytical framework transforms asset-based freight transportation companies' operations. The data-driven method enables companies to navigate the cyclical nature of the logistics industry, make informed decisions, and maintain a competitive edge. Through meticulous demand and rate prognosis, companies optimise their fleet utilisation and maintain robust financial health. This bolsters current performance and paves the way for sustained growth and operational excellence in the highly competitive logistics industry.

2.2. Task Formulation and Assumptions

Before presenting mathematical models, which are used for method creation, it is essential to describe how the transportation process is organised.

The road freight transportation industry typically operates using two main types of contracts: spot contracts for single shipments and long-term contracts for multiple shipments over an extended period. Long-term contracts, which generally span 12 months, are the primary focus of this dissertation and are referred to simply as "contracts".

As highlighted by CPRG (2020), the freight transportation industry has two principal pricing mechanisms: cost-based and market-based pricing. Cost-based pricing is divided into several methods:

- 1.1. mark-up pricing,
- 1.2. margins on direct cost,

1.3. rate-of-return pricing.

On the other hand, market-based pricing includes various methods:

2.1. profit-maximisation pricing,

2.2. market share pricing,

2.3. market skimming,

2.4. current revenue pricing,

2.5. promotional pricing,

2.6. demand differential pricing,

2.7. market competition pricing.

In the transportation sector, companies often employ a combination of market-based pricing methods while using cost-based pricing to monitor internal costs closely.

One helpful approach for cost-based pricing is the GTC model (JRC114409). The GTC is divided into two main components: distance-related costs and time-related costs. Distance-related costs encompass fuel, toll, vehicle maintenance, and wear and tear, including tyre replacement. These costs vary across the different EU countries due to variations in fuel prices and taxes. Time-related costs include driver salaries, vehicle financing and amortisation, insurance, and indirect costs such as manager salaries and utility expenses. These time-related costs are typically allocated across all vehicles within a company. According to EU averages of GTC costs, drivers' wages account for 42.1% of the total costs; fuel costs contribute 21.1%; ownership taxes comprise 0.6%; vignettes and tolls add up to 5.9%; other time-related costs are 5.9%, and other distance-related costs constitute 13.3%. The variability of these costs across different countries is significant; for instance, in France, driver costs are 39.1%, while in Slovakia, they are 29.6% (European Road Freight Transport, 2018). Such detailed cost information is crucial for accurately calculating overall expenses. Practically, GTC is evaluated for different regions. In 2019, the JRC presented a technical report (JRC114409), which estimated road transport costs between EU regions. Figures 2.2 and 2.3 graphically illustrate these costs. It is essential to note that the following data are speculative and not based on actual numbers. The cost of shipping by truck generally rises with increasing distance from France or Germany. This increment is due to the extended transportation times and mandatory rest periods required for farther regions, which elevate the GTC despite lower salary levels in these peripheral areas (JRC114409).

Nonetheless, this assumption might not apply to companies situated outside the key European regions. The average GTC for each region is calculated by considering bilateral trade flows and available trade data to address these regional discrepancies. This estimation provides a more accurate reflection of costs in various areas, and the information is depicted graphically in Figure 2.2. This detailed analysis helps understand the logistics and economic factors influencing road

freight TCs across different European regions, providing valuable insights for industry stakeholders and policymakers.

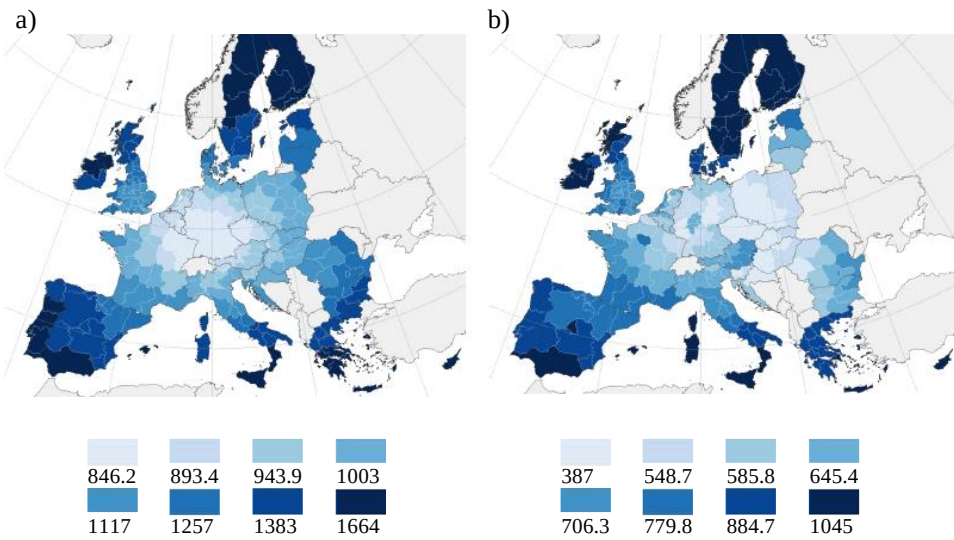


Fig. 2.2. Distance and time-related costs of GTC (JRC114409):
(a) distance-related costs; (b) time-related costs

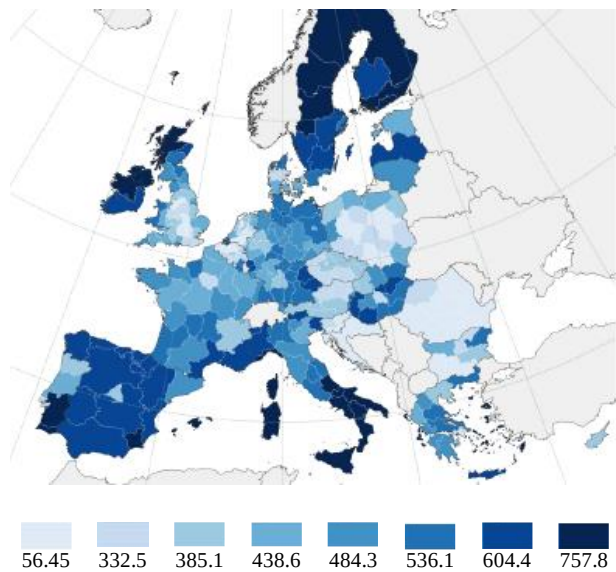


Fig. 2.3. Average GTC weighted by trade flows for each NUTS 2 region (JRC114409)

The data representation in Figure 2.3 is more accurate and reflects the TCs of each region. When determining contract pricing, it is crucial to consider the starting region, final destination, and cargo pickup location. Regions with higher economic development provide better opportunities for finding new cargo after delivery, as the travel time and distance to the new cargo will be shorter.

The above data should not be used as a reference, as it constantly changes, and companies typically collect and update this information internally. Additionally, the author in JRC114409 used the nomenclature of territorial units for statistics (NUTS2) regions to present the data, while road freight transportation companies typically divide regions based on the first two digits of the ZIP code. Such representation is presented in Figure 2.4.

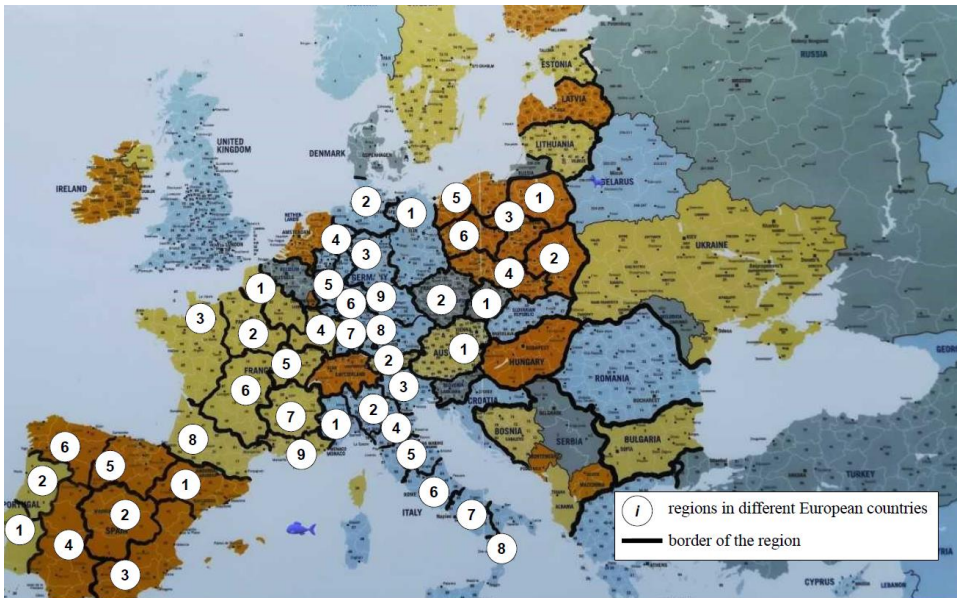


Fig. 2.4. Region separation companies commonly use based on the first two digits of the ZIP code (compiled by the author)

It is a multifaceted situation, primarily because the data required for multivariate prognostic models, sourced from the NUTS2 level, fundamentally differ from the internal data collected from various regions at the ZIP code level. This discrepancy arises because the granularity and scope of data at these two levels of aggregation are not aligned. However, this issue is currently not critical given that the statistical data often comes with a delay of up to ten months, rendering it impractical for immediate use in dynamic prognostic models. Moreover, irrespective of a company's size, it is challenging to obtain a sufficient number of journeys

covering all potential routes, exceeding 2000 possible directions to acquire reliable data on freight rates and demand patterns.

In contrast to the European scenario, the US transportation sector benefits from a broader scope of freight rate prognosis, which encompasses the entire country. Such a comprehensive approach allows for more reliable and expansive data analytics. However, this dissertation has developed a tailored tool to prognose freight rates, specifically between European countries. The uniqueness of the proposed method lies in its ability to provide targeted prognoses on a regional basis rather than a continent-wide perspective. The empirical results presented herein focus on the freight route using directions from the Netherlands to Italy, offering a case study highlighting the tool's precision and applicability within this specific corridor. However, the model can be scalable to all European directions. To elaborate further, the multivariate prognostic models necessitate a variety of data points at the NUTS2 level, such as economic indicators, demographic information, and transportation infrastructure specifics. This data significantly enhances prognostic models' accuracy and reliability when available on time. However, the lag in obtaining up-to-date statistical data remains a substantial hindrance. This delay affects the agility with which companies can respond to emerging trends and demands.

Additionally, the diversity and volume of data required for comprehensive analysis are often unattainable for smaller companies, or large logistics firms without extensive networks. Gathering sufficient data across more than 2000 possible freight directions to establish reliable historical trends and prognosis analytics is an enormous task. This limitation necessitates high-level aggregation and sometimes estimation, which can introduce inaccuracies. In contrast, the freight forecasting method used in the US provides a comprehensive dataset that covers the entire country. This holistic dataset allows for a more consistent and reliable prognosis. However, the method developed in this study is designed to address the fragmented nature of European data. They focus on specific cross-border routes, leveraging available data to provide accurate and valuable prognoses despite the regional complexity and data restrictions.

The detailed analysis included in this dissertation underscores the practical application and benefits of the developed prognosis method. These prognoses are crucial for logistics planning, cost management, and strategic decisions within the supply chain. In conclusion, while data availability and granularity challenges are non-trivial, developing region-specific prognosis tools provides a viable solution. By tailoring prognostic models to fit the unique characteristics of European routes, this dissertation offers a valuable contribution to transportation technologies, particularly in enhancing the precision and reliability of freight rate prognosis for specific international routes.

2.3. Impact of Environmentally Friendly Technologies on the Transportation Process

As highlighted in the first Chapter, many challenges may impact freight rates and demand. One of the most essential factors is reducing GHG emissions, shifting from road to rail transportation, and technological breakthroughs that may affect demand and freight rates. This sub-chapter presents assumptions regarding what this dissertation considered during the model development and what did not.

The calculation methodology of TC, which allows the evaluation of these aspects, is provided to address GHG reduction, the shift from road transportation to rail transportation, and technological breakthroughs. The author developed this methodology using JRC114409 as a background.

TC is calculated as follows:

$$TC_{ij} = C, dist_{ij} + C, time_{ij}; \quad (2.1)$$

where TC_{ij} is TC between cargo pickup location i (origin) and final destination j ; $C, dist_{ij}$ – distance-related costs; $C, time_{ij}$ – time-related costs between cargo pickup location i and final destination j .

Costs related to distance are:

$$C, dist_{ij} = (C, fuel_{ij} + C, toll_{ij} + C, accom\&allow_{ij} + C, rep\&mant_{ij})d_{ij}; \quad (2.2)$$

where: $C, fuel_{ij}$ – average fuel price per km; $C, toll_{ij}$ – average toll cost per km (EUR/km); $C, accom\&allow_{ij}$ – average accommodation and allowance costs (EUR/km); $C, rep\&mant_{ij}$ – average maintenance and repair costs of the vehicle, including tyre wear costs (EUR/km); d_{ij} – distance between origin and final destination (km). Dimension of $C, dist_{ij}$ is EUR. Costs related to distance are calculated twice, for the first time as already discussed, and for the second time considering free mileage (from destination point j to next origin k).

Costs related to time are:

$$C, time_{ik} = C, lab_{ik} + C, amort_{ik} + C, fin_{ik} + C, ins_{ik} + C, tax_{ik} + C, ind_{ik})t_{ik}; \quad (2.3)$$

where: C, lab_{ik} – labour cost associated with driver salary per time which takes to drive from origin i to origin k , including free kilometres (EUR/day); $C, amort_{ik}$ – vehicle amortisation costs; C, fin_{ik} – vehicle financing costs; C, ins_{ik} – insurance costs; C, tax_{ik} – taxes including government, regional, provincial and municipal; C, ind_{ik} – indirect costs include operational expenses, administration costs and other commercial costs; t_{ij} – driving time from the origin to the final destination.

Different cases are considered using this calculation methodology. GHG particle emissions can be reduced in trucks when the conventional transmission is changed to an environmentally friendly.

An example of *TC* (recalculated in percentage) is shown in Table 2.1, where two types of trucks are compared. Values for trucks with internal combustion engines are indicative and will vary over time, including vehicle registration place, destination vehicle travelling, etc. Some parameters are calculated using assumptions for electric vehicles, as factual values are unknown.

Table 2.1. Total cost for trucks with diesel engines vs electric

Cost distribution, %	Typical distribution for trucks with diesel engine	Possible distribution for electric truck	Comments
Fuel	29.04	17.4	80kWh consumption per 100 km was taken for calculation.
Accommodation & allowance	10.87	10.87	
Maintenance & repair	9.16	14.08	Indicative value is calculated from the price of the truck.
Toll	1.41	1.4	
Labour	22.09	35.56	Indicative value is calculated from the average speed, which is reduced for electric vehicles, with a possible travel distance of 300 km/h after charging 2.3 h.
Amortisation	10.96	52.94	Indicative value calculated from the price of the truck at its first generation, possible rapid price devaluation.
Financing	2.2	10.63	These values increase as the average speed decreases significantly.
Insurance	5.24	8.44	
Taxes	0.73	1.17	
Indirect	8.3	13.36	
TC, %	100	165.85	

Based on Table 2.1, TCs for electric vehicles will increase about 1.65 times (using current vehicle prices) compared to conventional. First, such a difference appears as the cost of electric vehicles is about three times higher compared to conventional vehicles. A second important point is increased expenses related to

time, as the average velocity of electric vehicles is much lower than conventional. This happens due to the limited travelling distance with one charge and the time needed to charge the batteries. Another possible solution is hydrogen trucks, which use fuel cell technology. The advantage of such a vehicle could be fast charging time; the main problem is the price, which is about six times higher than that of conventional vehicles.

In any case, the transition from conventional combustion engines to environmentally friendly ones is expected after some time and may take more than a decade. This work developed a method for increasing the efficiency of a forecasting horizon of up to 12 months, and vehicle technology change is not considered, as it may not make sense.

However, with the development of technologies, the price of “green vehicles” is expected to be reduced, and their widespread use will solve the problem of shifting from road to rail. Currently, in Western Europe, railroads are occupied by passenger trains during the daytime, and cargo is transported chiefly at night. A further shift to rail may negatively impact the traffic. The construction of new railroads requires significant investment in infrastructure. Trucks equipped with innovative powertrains will address the environmental issues associated with current road transport, eliminating the need to shift to rail.

The expected following technology is an autonomous vehicle, which can eliminate the need for a driver. This may eliminate labour costs and minimise TC in a range from 20% to 35%. However, these vehicles will need additional sensors for perception and vehicle-to-everything communication. It is still too early to determine how this will change the price of the vehicle.

2.4. Definition of External Indicators for Freight Rate and Demand Prognosis

As noted in prior research by Ruiz-Aguilar et al. (2014) and Miller et al. (2021), multivariate prognostic models are a prevalent method for undertaking prognosis tasks. They are adopted in the transportation sector. This research has carefully selected key indicators for determining truckload rates and demand, drawing insights from the literature, resources such as the Coyote Logistics website (Coyote contract and spot rates, 2022), and the experience of experts in road freight transportation. The primary indicators identified for analysis include TKMs, industrial production, imports, consumer spending, and fuel prices, all of which substantially impact TCs. Specific numerical values of these indicators for the selected corridor are detailed in Annex A.

It is essential to highlight that the EU lacks a centralised data aggregator for spot or contract freight rates. Instead, relevant data must be pieced together from

various sources, including Eurostat, and repositories such as Trading Economics and Statista. This fragmented data environment poses challenges for comprehensive analysis but underscores the importance of curating reliable indicators from multiple repositories.

Fuel prices, a critical factor influencing TCs, are sourced from the official European data portal (<https://data.europa.eu/data/datasets/eu-oil-bulletin?locale=en>). For instance, Figure 2.5 illustrates a comparison between the normalised fuel prices and the actual fuel prices paid by the investigated company. A strong correlation of 0.96 is found between the historical fuel price data that are publicly accessible and the actual fuel prices paid by the investigated company. Consequently, companies and researchers developing similar prognosis tools can effectively utilise the publicly available fuel price data for prognosis but lack sufficient internal data. This correlation provides a robust foundation in prognosis fuel costs, an essential component of transportation pricing models.

The European data portal on fuel prices is valuable as it provides detailed and updated information on fuel cost trends across the EU. Comparing the normalised fuel prices to the actual prices paid by the transportation company identifies discrepancies and regional cost variations essential for adjusting pricing models to reflect actual operational costs.

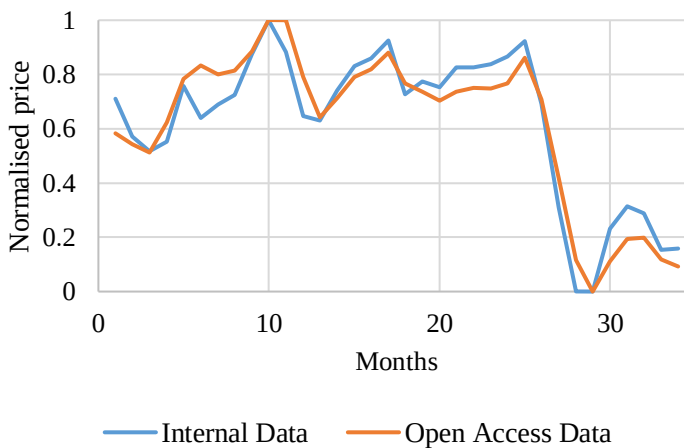


Fig. 2.5. Normalised fuel price

Multivariate models require the incorporation of selected indicators to provide a robust framework for truckload rates and demand prognosis. The chosen indicators, derived from established studies and real-world data, offer a comprehensive view of the variables affecting transportation economics. TKMs, as a

measure of freight volume over distance, combined with industrial production data, reflect the demand for freight services relative to economic activity. Import data, indicative of trade volumes, alongside consumer spending, which signals overall financial health, further enriches the model's prognosis power. Fuel prices are a direct cost component, affecting operational expenses and pricing strategies.

Moreover, the lack of a centralised freight rate data repository in the EU adds a layer of complexity to the research. Analysts must navigate through multiple data sources, each with its coverage and frequency of updates, to assemble a coherent dataset for analysis. Eurostat provides extensive statistical data on various economic indicators, while Trading Economics and Statista offer valuable insights and real-time data on global economic trends, including transportation metrics.

For practical application, combining these indicators into a multivariate model allows businesses to prognose truckload rates and demand more accurately. Understanding the interplay between these variables helps logistics companies optimise their pricing strategies, manage operational costs, and improve their service offerings.

Moreover, data related to TKM is also available through the European data portal, although it tends to be provided with some delay. Despite this lag, TKM is utilised by leveraging the FI parameter. FI is defined as the ratio between TKM (for inland modes) and GDP. This indicator was initially indexed in 1995. The unit of measurement, TKM, represents the movement of one tonne over a distance of one kilometre and encompasses transport by road, rail, and inland waterways. It is worth noting that rail and inland waterways transport are based on movements within national territories, regardless of the nationality of the vehicle or vessel. In contrast, road transport calculations are based on the movements of vehicles registered in the reporting country.

For this research, the FI for road freight transport was calculated. As the third Chapter details, linear regression was applied to generate a trendline and prognosis of the FI. With the values of FI and GDP, the TKM is accurately calculated.

It is important to note that FI exhibits a decreasing trend in both countries considered in this study, primarily influenced by two factors. First, there is the economic factor: Europe is experiencing a shift from an industrial-based economy to a service-oriented one, leading to a scenario where GDP growth outpaces the need for goods transportation. Second, there is the environmental factor: political decisions to reduce GHG emissions have shifted from road transport to rail and other environmentally friendly modes, resulting in an increased volume of goods transported by non-road methods.

The strong correlation between publicly accessible historical fuel prices and the company's actual fuel expenditures allows businesses and researchers to apply this data confidently in their prognostic models. This becomes especially relevant for those developing similar prognosis tools without extensive internal datasets.

Utilising publicly available fuel price data ensures a more comprehensive and inclusive method for freight rate prognosis, making it accessible to a broader array of entities within the logistics and transportation sector. Additionally, while TKM data from the European data portal are delayed, FI is a vital parameter for understanding and anticipating trends in logistics needs and informing strategic planning.

Commonly, the data used for prognosis are delayed by about three months. Data-related issues are problematic in Europe compared with the US, where all these data are available at the ATA Truck Tonnage Index, Federal Reserve Board, U.S. Bureau of Labor Statistics, U.S. Bureau of Economic Analysis, and U.S. Census Bureau. These data are presented with a very low delay (less than a month).

2.5. Econometric Models for Demand and Freight Rate Prognosis

The econometric models used for the prognosis of freight rates and demand are analysed in this sub-chapter. The first approach involves testing prognosis tools based on historical data of the same parameter. The main advantage of this approach is that it does not require external data (sub-chapter 2.2), which is often available only with significant delays and would also need to be prognosed.

For instance, historical data on freight rates are analysed to prognose future rates, considering factors such as seasonal variations, economic cycles, and demand fluctuations. Similarly, historical demand data helps to prognose future demand by identifying patterns and trends over time. This approach ensures that the models are tightly aligned with the specific transportation company's actual operational dynamics, enhancing the precision and relevance of the prognosis.

ARIMA models are a type of econometric model frequently used to prognose time series. Such types of models are simple and easy to apply. ARIMA models apply to static data. Data stationarity is checked using the method described in 2.5.1. If the stationarity conditions are not met, data differentiation is used.

Generalised equations of p order AR model (Kumar et al., 2021):

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t, \quad (2.4)$$

where y_t is the current time-series value; $y_{t-1}, y_{t-2} \dots y_{t-p}$ are past values; t denotes the time; p denotes the order of the autoregressive part of the $AR(p)$ model; c is the intercept; ε_t is model innovations (random error); ϕ_i is an auto-regressive model.

Generalised equations of q order MA model:

$$y_t = c + \varepsilon_t + \Theta_1 \varepsilon_{t-1} + \Theta_2 \varepsilon_{t-2} + \dots + \Theta_q \varepsilon_{t-q}, \quad (2.5)$$

where q denotes the order of the moving average $MA(q)$ model, Θ_q is the moving average polynomial.

The non-seasonal time series data $ARIMA(p, d, q)$ model is described using the formula (Markevičiūtė et al., 2022):

$$y_t = c + \phi_1 y_{t-1} + \dots + \phi_p y_{t-p} + \varepsilon_t + \Theta_1 \varepsilon_{t-1} + \dots + \Theta_q \varepsilon_{t-q}. \quad (2.6)$$

Also, $ARIMA(p, d, q)$ is presented in the form:

$$\phi_p(B)(1-B)^d y_t = c + \Theta_q(B)\varepsilon_t, \quad (2.7)$$

where d – order of the differences of the data integrating part $I(d)$; y_t – observations that are differentiated d times, usually $d = 0, 1, 2$; $\phi_p(B)$ is non-seasonal auto-regressive polynomial; and $\Theta_q(B)$ – non-seasonal moving average polynomial B – defined as the backshift operator, sometimes lag operator:

$$B^k y_t = y_{t-k}, \quad (2.8)$$

where k – the number of estimated parameters.

Non-seasonal AR polynomial:

$$\phi_p(B) = 1 - \phi_1(B) - \phi_2(B^2) - \dots - \phi_p(B^p). \quad (2.9)$$

Non-seasonal MA polynomial:

$$\Theta_q(B) = 1 + \Theta_1(B) + \Theta_2(B^2) + \dots + \Theta_q(B^q). \quad (2.10)$$

In logistics, seasonality is often observed; such time series are analysed by incorporating seasonal fluctuations in classical ARIMA models in the form of parameters $(P, D, Q)^S$ describing seasonal lags. Seasonal Auto-Regressive Integrated Moving Average model expressed in a form (Kumar et al., 2021):

$$\Phi_P(B^S)\phi_p(B)(1-B^S)^D(1-B)^d y_t = \Theta_Q(B^S)\Theta_q(B)\varepsilon_t, \quad (2.11)$$

where $\Phi_P(B^S)$ is a seasonal auto-regressive polynomial, and $\Theta_Q(B^S)$ is a seasonal moving average polynomial, D is a seasonal differencing term equal to 1 or 2; s – seasonal period.

Seasonal terms for seasonal AR:

$$\Phi_P(B^S) = 1 - \Phi_1(B^S) - \Phi_2(B^{2S}) - \dots - \Phi_P(B^{PS}). \quad (2.12)$$

Seasonal terms for seasonal MA:

$$\Theta_Q(B^S) = 1 + \Theta_1(B^S) + \Theta_2(B^{2S}) + \dots + \Theta_Q(B^{QS}). \quad (2.13)$$

Using ARIMA model with explanatory variables (ARIMAX) model presented in (4) is modified as follows:

$$\phi_p(B)(1-B)^d y_t = c + \Theta_q(B)\varepsilon_t + \sum_{i=1}^n X_{i,t}\beta_i, \quad (2.14)$$

where $X_{i,t}$ – explanatory variable i at time moment t ; β_i – coefficient.

The SARIMAX model is presented as follows:

$$\Phi_p(B^S)\phi_p(B)(1-B^S)^D(1-B)^d y_t = \Theta_Q(B^S)\Theta_q(B)\varepsilon_t + \sum_{i=1}^n X_{i,t}\beta_i. \quad (2.15)$$

Both the ARIMAX and SARIMAX models require input data. In this case, the data included tonne-kilometres, industrial production, imports, consumer spending, and fuel prices.

2.5.1. Data Stationarity, Normalisation and Econometric Model Performance Evaluation

The econometric models presented above need to be tested for the model performance's accuracy in explaining the relationships between the variables (Kumar et al., 2021). In this work it is done using the Bayesian Information Criterion (BIC):

$$BIC = k \ln(n) - 2 \ln(\hat{B}), \quad (2.16)$$

where $\ln(\hat{B})$ represents the likelihood function; k is the total number of model parameters (estimated parameters); n is the number of observations (sample size). Another model selection criterion is the Akaike information criterion (AIC):

$$AIC = 2k - 2 \ln(\hat{B}). \quad (2.17)$$

Due to the specific task under investigation, small datasets are available. The Akaike information criterion modified for the small samples (AICs) is used to estimate the econometric model for such datasets (Markevičiūtė et al., 2022):

$$AIC_c = AIC + \frac{2k^2 + 2k}{n - k - 1} = 2k - 2 \ln(\hat{B}) + \frac{2k^2 + 2k}{n - k - 1}, \quad (2.18)$$

where $\hat{B}$ the maximum value of the likelihood function of the model; n the sample size, and k the number of estimated parameters.

Time-series data are tested for stationarity before using the econometric methods described above. If the data are not stationary, data integration (single or double) solves an issue in most practical cases. The Augmented Dickey-Fuller (ADF) test is commonly used in applied statistics and econometrics to analyse time series for stationarity. ADF tests the null hypothesis (H_0) that a unit root is present in a time series sample.

If $p \leq 0.05$, the null hypothesis (H_0) is rejected, the data are stationary and do not have a unit root. If $p > 0.05$, the null hypothesis (H_0) fails to be rejected, the data have a unit root and are non-stationary (Brownlee, 2021).

Commonly, data are normalised before training the ANN or using econometric models. Normalised data generally speed up learning and lead to faster convergence. The procedure is expressed as follows:

$$y'_t = \frac{y_t - y_{\min}}{y_{\max} - y_{\min}}, \quad (2.19)$$

where y_t is the observed value at the time moment t ; $y_{\min}$ – minimal value in the dataset; $y_{\max}$ – maximal value in the dataset.

However, such an approach gives a minimum value of 0 and a maximum value of 1; for freight rate and demand, it is not the best option, as the freight rate could not be 0. So, another approach was used:

$$y'_t = \frac{y_t - y_{\text{ave}}}{y_{\max} - y_{\min}}, \quad (2.20)$$

where y_{ave} – average value in the dataset; in this case, normalised values change around an average value.

Such normalisation technique is used for ANN, as described in sub-chapter 2.6.

2.6. Artificial Neural Network-Based Models

This sub-chapter analyses the application of ANN for solving prognosis tasks and increasing efficiency in road freight transportation. Inspired by the human brain's structure and function, ANN has proven to be a powerful tool for the prognosis of complex patterns in various industries. Their utility in road freight transportation is no exception.

At the core of an ANN lies the artificial neuron, which is the fundamental building block of this sophisticated computational system. An artificial neuron, as illustrated schematically in Figure 2.6, is designed to mimic the behaviour of a biological neuron. It is a mathematical model that processes input data, performs computations, and produces output. The resemblance to biological neurons lies in their ability to learn from data and improve performance over time, a process modelled after the learning mechanisms of the human brain. McCulloch and Pitts (1943) proposed this approach for the first time.

For artificial neurons k , there are $m + 1$ inputs, input parameters $x_0, x_1, \dots, x_m$ and weights $w_{k0}, w_{k1}, \dots, w_{km}$. The x_0 input is assigned the value +1, which makes it a biased input $b_k = w_{k0}$.

As a result, the neuron has only m actual inputs ($x_1, x_2, \dots, x_m$).

The sum of the input and the weight parameters is calculated:

$$a_k = \sum_{j=0}^m x_j w_{kj}. \quad (2.16)$$

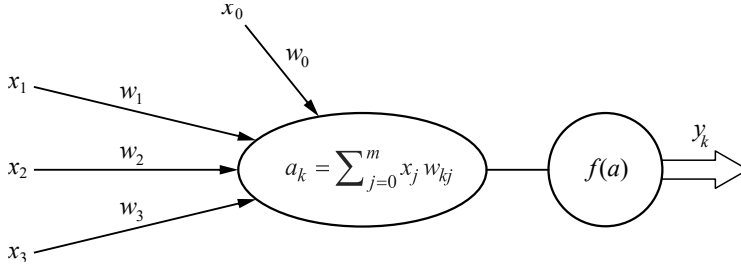


Fig. 2.6. Artificial neuron (created by the author)

The output of the neuron k is:

$$y_k = f\left(\sum_{j=0}^m x_j w_{kj}\right), \quad (2.17)$$

where f is the activation function. There are different activation functions; the simplest one is the Binary step, which is expressed as:

$$f(a_k) = \begin{cases} 1, & \text{if } a_k \geq w_{k0} \\ 0, & \text{if } a_k < w_{k0} \end{cases}. \quad (2.18)$$

Depending on the task, Sigmoid, Hyperbolic tangent, Rectified Linear unit (RELU), and others are used.

Connecting artificial neurons can create various types of ANNs. The simplest form is a one-layer feedforward ANN; the number of neurons (k) is equivalent to the number of outputs. However, in most cases, feedforward ANN consists of an input layer, one or multiple hidden layers, and an output layer. When ANN includes numerous hidden layers, it is called a DNN. DNNs are categorised into several types, each suited to specific applications. The two primary categories of DNNs are:

1. RNN – a type of ANN architecture with feedback loops that model sequential dependencies in the input, such as in time series, sensor, and text data (Li, 2024). The most commonly used RNN is an LSTM (Kojis et al., 2022).
2. CNN – DNN architecture, widely applied in image processing and characterised by convolutional layers that shift windows across the input, with nodes that share weights, abstracting the input (typically an image) to feature maps (Šabanović et al., 2020; Šabanović et al., 2024).

It should be noted that the variety of ANNs is much broader than what is described here.

The learning of various ANN types is supervised, semi-supervised, or unsupervised.

MLP and LSTM were used during an initial investigation. MLP provided reliable results, so it was the final ANN used in this dissertation. Two types of MLP were tested: open-loop and closed-loop MLP (Fig. 2.7).

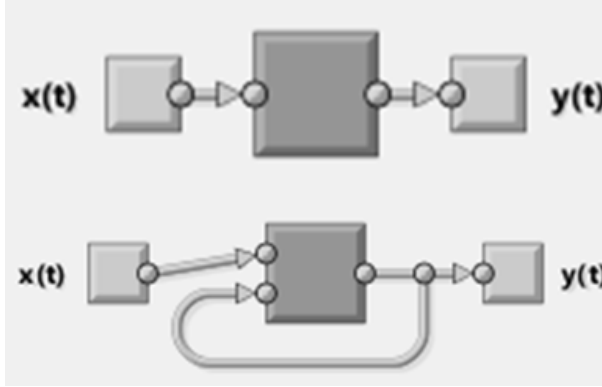


Fig. 2.7. Open loop ANN and close loop ANN

Mathematically, open loop ANN is defined as:

$$y_t = f(x_{1,t}, \dots, x_{1,t-d}, \dots, x_{n,t-d}). \quad (2.21)$$

Close loop ANN is defined as:

$$y_t = f(x_{1,t-1}, \dots, x_{1,t-d}, \dots, x_{n,t-d}, \dots, y_{1,t-1}, \dots, y_{1,t-d}). \quad (2.22)$$

In equation (2.22), a closed loop structure is proposed, and previous values of the proposed parameter are also used.

2.7. Evaluation Metrics

Different metrics are used to evaluate the prognosis accuracy of the proposed models. These metrics are used to test econometric models and ANNs-based models. Below, seven metrics are presented.

The correlation between the actual value and the prognosis value:

$$R = \frac{\frac{1}{n} \sum_{i=1}^n (y_t - \bar{y}_t)(\hat{y}_t - \bar{\hat{y}}_t)}{\sqrt{\frac{1}{n} \sum_{i=1}^n (y_t - \bar{y}_t)^2} \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_t - \bar{\hat{y}}_t)^2}}, \quad (2.23)$$

where $\hat{y}_t$ is the prognosed value at the time moment t ; $\bar{y}_t$ is the mean actual value; $\hat{\bar{y}}_t$ is the mean prognosed value. Also, R^2 – the square of the correlation between the actual and prognosed values – is sometimes used.

Forecast Error (Chukwudike et al., 2020):

$$FE_t = y_t - \hat{y}_t. \quad (2.24)$$

This value is calculated for each time moment and is not used widely.

Mean Forecast Error (Chukwudike et al., 2020):

$$MFE = \frac{\sum_{i=1}^n (y_t - \hat{y}_t)}{n}, \quad (2.25)$$

where n – number of samples. The MFE is used for the whole dataset.

Other scale-dependent metrics are not unit-free; they are favoured in machine learning evaluation (Jierula et al., 2021).

Mean Square Error (Chukwudike et al., 2020):

$$MSE = \frac{\sum_{i=1}^n (y_t - \hat{y}_t)^2}{n}. \quad (2.26)$$

MSE measures the mean squared error between the prognoses and actual values (Jierula et al., 2021).

The Root Mean Squared Error (Liu et al., 2020):

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_t - \hat{y}_t)^2}{n}}. \quad (2.27)$$

RMSE measures the average error magnitude between the prognoses and actual values (Jierula et al., 2021).

Mean Absolute Error (Kumar et al., 2021):

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_t - \hat{y}_t|. \quad (2.28)$$

The MAE sometimes called the Mean Absolute Deviation (MAD), is a metric used to measure the average magnitude of the absolute errors between the prognoses and actual values (Jierula et al., 2021). Compared with MAE, the RMSE has a relatively high weight for significant errors because the errors are squared before averaging.

Mean Absolute Percentage Error (Liu et al., 2020):

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right|. \quad (2.29)$$

The MAPE calculates the average of the percentage error and is expressed in percentage (Jierula et al., 2021):

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right| \cdot 100\%. \quad (2.30)$$

Regarding the investigation provided by Jierula et al. (2021), the sensitivity of the seven accuracy metrics is ranked as follows: $MSE > MAPE > MAE > RMSE > R^2 > R$. The more sensitive the metric is, the more suitable it is for comparing the accuracy of different prognoses.

2.8. Conclusions of the Second Chapter

1. The primary emphasis is on examining various data types and sources leveraged to prognosis freight rates and demand within road freight transportation. A key point of discussion is the significant challenges associated with accessing timely and accurate data, particularly noting that a substantial portion of European data experiences delays of up to ten months. In stark contrast, data pertaining to the US are typically attainable with a delay of less than a month, underscoring notable disparities in data accessibility across different regions. Methods that will perform under conditions as in the EU should be developed.
2. A freight rate and demand prognosis method based on mathematical models has been developed. A detailed exposition of the evolution of econometric and ANN-based models for contract pricing and demand assessment in road freight transportation is provided.
3. All prerequisites concerning data, encompassing aspects such as normalisation, stationarity, and evaluation metrics, are meticulously delineated and examined within this Chapter. These prerequisites play a pivotal role in guaranteeing the accuracy and dependability of the prognostic models and the subsequent interpretations of their results.

Analysis of Freight Rate and Demand Applying Developed Prognostic Models

In this Chapter, the technological solution developed for the European road freight transportation sector is thoroughly examined. For a case study, the transportation direction from the Netherlands to Italy was selected; however, the developed method can be adjusted to all directions in Europe. A meticulous analysis assesses the prognosis strengths of both econometric models and ANNs. To ensure robust findings, the Chapter outlines detailed protocols for data normalisation and stationarity, highlights the methodology for model selection using the AICc criterion, and scrutinises the accuracy of the ensuing prognosis. By analysing the processes behind data preparation, model selection, and prognosis evaluation, this Chapter offers a nuanced understanding of how well the chosen models capture the intricate dynamics at play in freight rates and demand within this specific transportation link. The ultimate goal is to distil insights into the relative efficiency of these modelling techniques in grasping the evolving nature of freight movements. The main research findings of this Chapter are published in two of the author's publications (Liachovičius, Skrickij, Podvieszko, 2020; Liachovičius, Šabanovič, Skrickij, 2023; Liachovičius, Kojis, Skrickij, 2024).

3.1. Results of Quantitative Univariate Econometric Models

This sub-chapter thoroughly evaluates prognostic models, focusing on normalised freight rates and demand data. The dataset utilised is internal data collected over several years, as detailed in the second Chapter. With a dataset spanning 90 months, the first 78 months were allocated for model development, while the subsequent 12 months were set aside for testing purposes; shipment demand and freight rates since January 2015 were used as input parameters. Figure 3.1 visually presents normalised monthly freight rates and demand data.

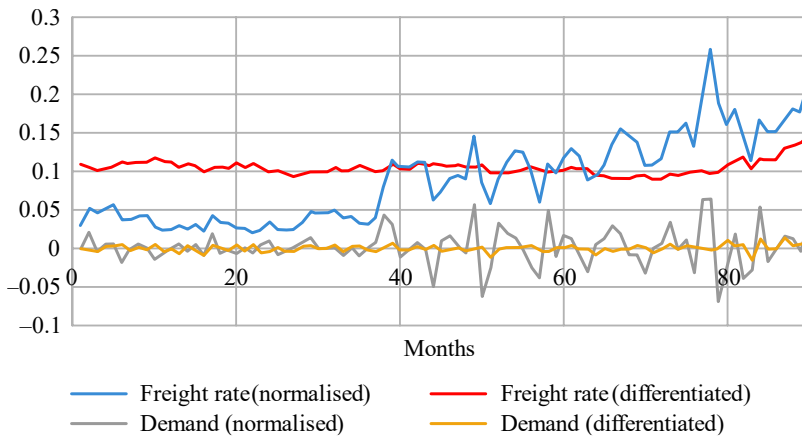


Fig. 3.1. Quantity and freight rate (price) for shipments

ADF test was used to analyse time series for stationarity; results are presented in Table 3.1. During the investigation performed by the author, it was found that the initial data were not stationary. A differentiation procedure was used to reach stationarity, and it was reached successfully. Initially, the territory of Italy was divided into eight regions (Fig. 2.4.), and eight combinations of destinations from the Netherlands to eight regions in Italy were tested. However, the need for cargo transportation in the different companies is unequal, and for some areas, developed models perform well; at the same time, they do not perform well for others where the data regarding the number of shipments are limited to a few per month. So, in the end, it was decided to test countries as a whole without the division into regions.

Table 3.1. The ADF test results

Data	Null rejected	P-value	Test statistics	Critical value	Significance level
Demand	FALSE	0.6104	-0.1056	-1.9445	0.05
Demand after differentiation	TRUE	0.01	-10.249		
Freight rate	FALSE	0.898	0.8868		
Freight rate after differentiation	TRUE	0.01	-10.707		

In the initial phase, econometric and ANNs-based models presented in the second Chapter were used to prognose the demand to develop an increasing efficiency method. The study progressed by exploring various ARIMA/SARIMA model configurations, focusing on the selection process guided by the AICc parameter to ensure optimal prognosis performance.

Multiple econometric models were tested, ranging from simple first-level AR and MA models to the more complex ARIMA (4,2,4) model (comprising 74 combinations for each dataset). A similar procedure was repeated for the SARIMA models, with the most accurate results achieved using a seasonality of 12 months. The top three ARIMA models were selected based on the minimal AICc value, and this procedure was repeated using the SARIMA models, with the results presented in Table 3.2.

Table 3.2. The most accurate econometric models for demand modelling

Model	ARIMA (2,0,4)	ARIMA (3,0,3)	ARIMA (4,0,4)	SARIMA (2,0,2)(4,0,0) ¹ ₂	SARIMA (4,0,1)(4,0,0) ¹ ₂	SARIMA (4,0,3)(4,0,0) ¹ ₂
AICc	-382.11	-381.5	-381.7	-411.5	-408.6	-414.2
RMSE for prognosed values	0.0127	0.0118	0.0155	0.03288	0.08888	0.01671

Figures 3.2 and 3.3 visually depict the proposed demand for the following 12 months (from months 79 to 90) using the models from Table 3.2, compared with actual data. Prognosis intervals are also shown in Figures 3.2 and 3.3. Notably, the ARIMA models demonstrated superior performance, with most estimated values falling within the prognosis intervals.

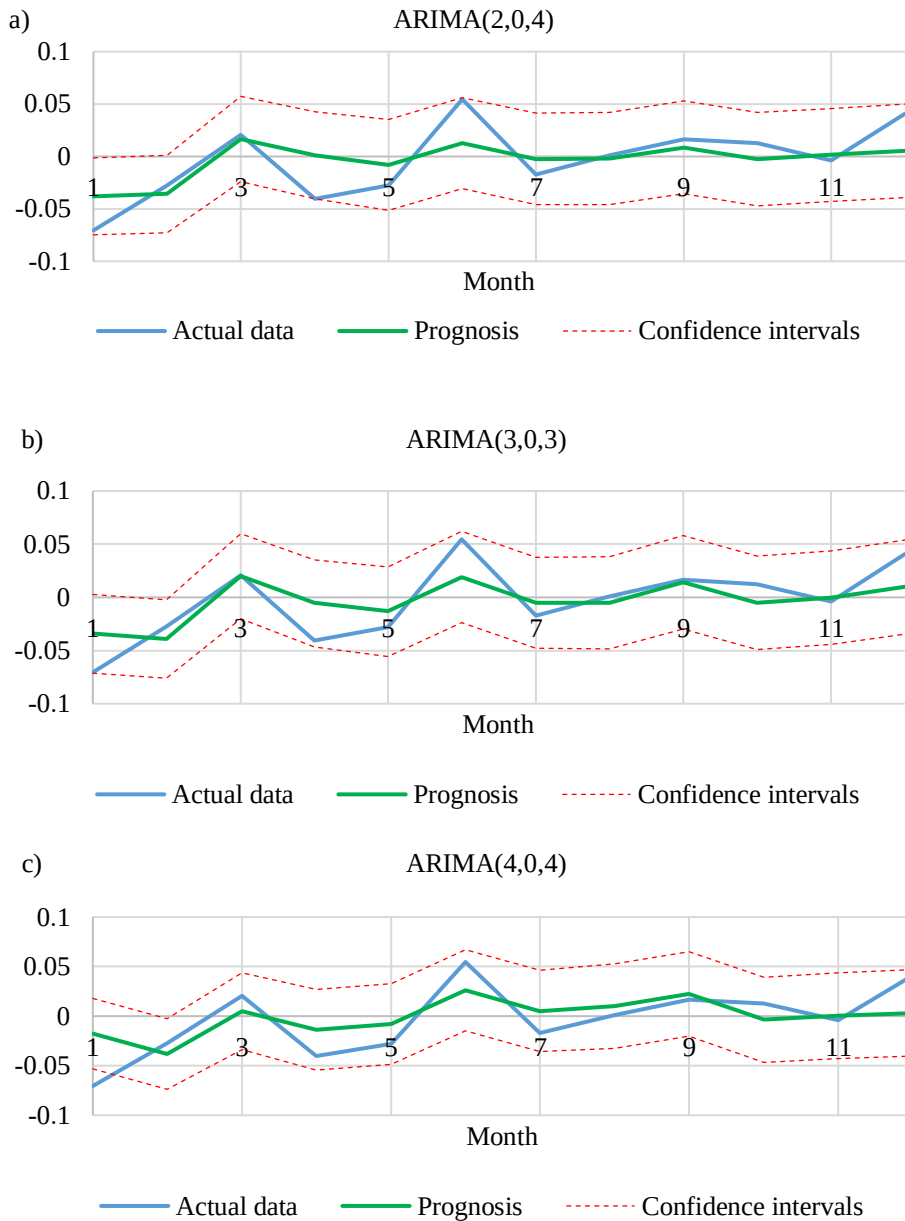


Fig. 3.2. Prognosis and confidence intervals using ARIMA models for differentiated demand data

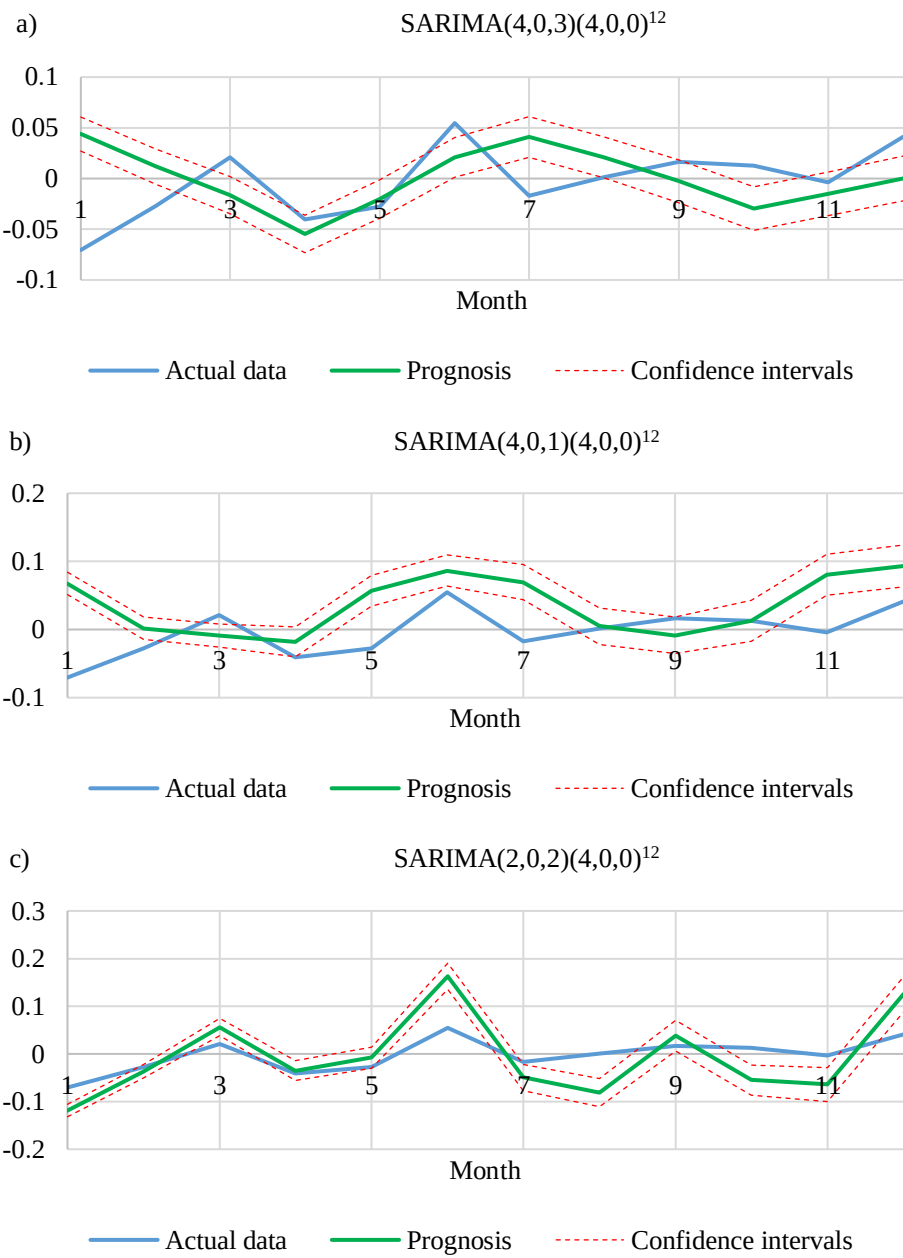


Fig. 3.3. Prognosis and confidence intervals using SARIMA models for differentiated demand data

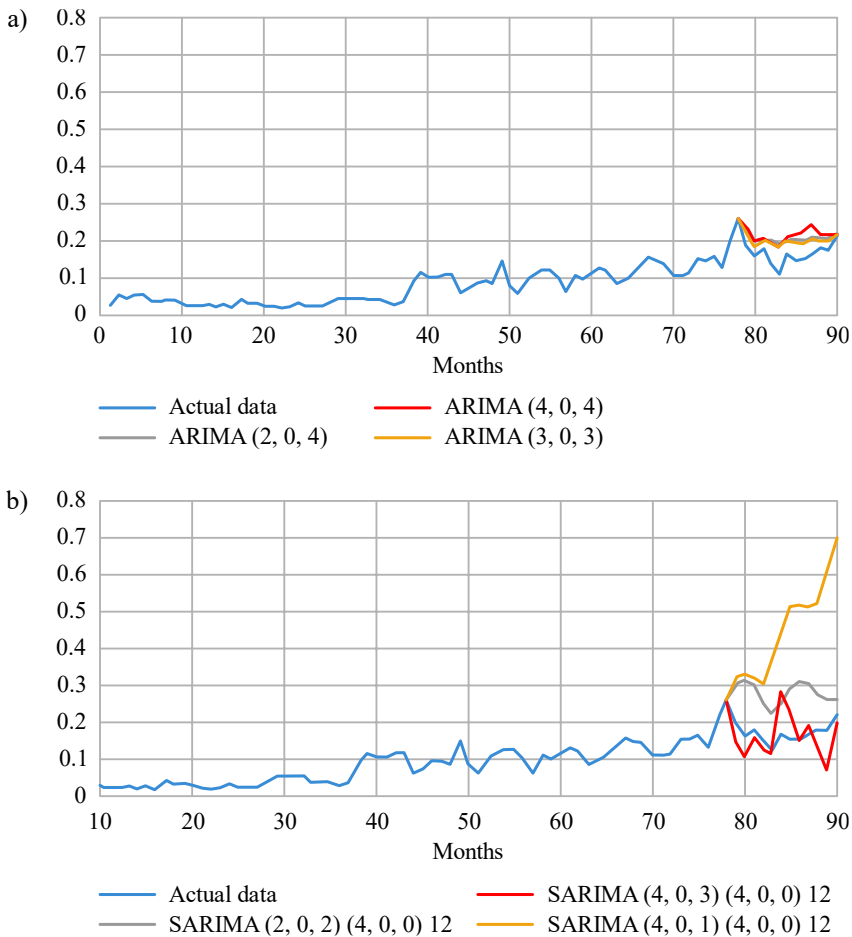


Fig. 3.4. Prognosis and actual demand data using (a) ARIMA and (b) SARIMA models

The ARIMA (3, 0, 3) model achieved the minimal RMSE value, recording a numerical value of 0.0118 (Table 3.2). The overall commendable performance of all ARIMA models was highlighted by a maximum RMSE of 0.0155. In contrast, while the SARIMA models achieved favourable results, the maximal RMSE observed was 0.08888, with the most accurate performance obtained using the SARIMA (4, 0, 3)(4, 0, 0)¹² model, yielding an RMSE of 0.01671.

After carefully selecting the most accurate econometric models with a rigorous evaluation process, the next step involved integrating the data from Figures 3.2 and 3.3 for a comprehensive analysis. The integrated data were then meticulously compared with the actual data, as illustrated in Figure 3.4. The graphical representations in Figure 3.4 vividly highlight and emphasise the superior

performance of the ARIMA model, especially when compared to the SARIMA model. These detailed results show that ARIMA models are exceptionally well-suited and highly effective for demand prognosis in road freight transportation.

A similarly thorough procedure was undertaken in the subsequent study phase to identify the rational models for freight rate prognosis. This phase utilised the freight data presented in Figure 3.1. The process was methodically divided into two main segments: the first 78 months of data were dedicated to model tuning and precise calibration, ensuring that the models were fine-tuned for accuracy. The final 12 months of data (from month 79 to month 90) were set aside for rigorous testing and validation. Using this structured approach, the study aimed to identify the most accurate and reliable models for freight rate prognosis, ultimately contributing to the overall goal of enhancing prognosis accuracy in road freight transportation. Freight rate prognoses are comprehensively depicted in Figures 3.5 and 3.6, with Figure 3.5 illustrating the results from ARIMA models and Figure 3.6 showcasing the outputs from SARIMA models. During the specified prognosis period, the performance of both ARIMA and SARIMA models proved to be suboptimal. This suboptimal performance is thoroughly documented in Table 3.3, which lists the most accurate models identified for freight rate prognosis.

Table 3.3. Most accurate econometric models for freight rate modelling

Model	ARIMA (1,0,1)	ARIMA (3,0,4)	ARIMA (4,0,4)	SARIMA (3,0,3)(4,0,0) ¹²	SARIMA (3,0,4)(4,0,0) ¹²	SARIMA (4,0,3)(4,0,0) ¹²
AICc	−652.95	−659.76	−659.68	−641.06	−631.06	−631.37
RMSE for prognosis values	0.0346	0.0312	0.0308	0.0222	0.0222	0.0225

Notably, the prognosis data consistently failed to fall within the prognosis intervals, indicating issues with prognosis accuracy.

Following this realisation, the received data were meticulously integrated, and the consolidated results are presented in Figure 3.7. An intriguing observation emerged when actual data, which had not been differentiated, was considered and depicted in Figure 3.7. In this scenario, the SARIMA model demonstrated superior performance in prognosis freight rates compared to the ARIMA model. However, the results obtained from this analysis underscore the inherent limitations of econometric models in effectively prognosis freight rates during the specified 12-month period from July 2021 to June 2022.

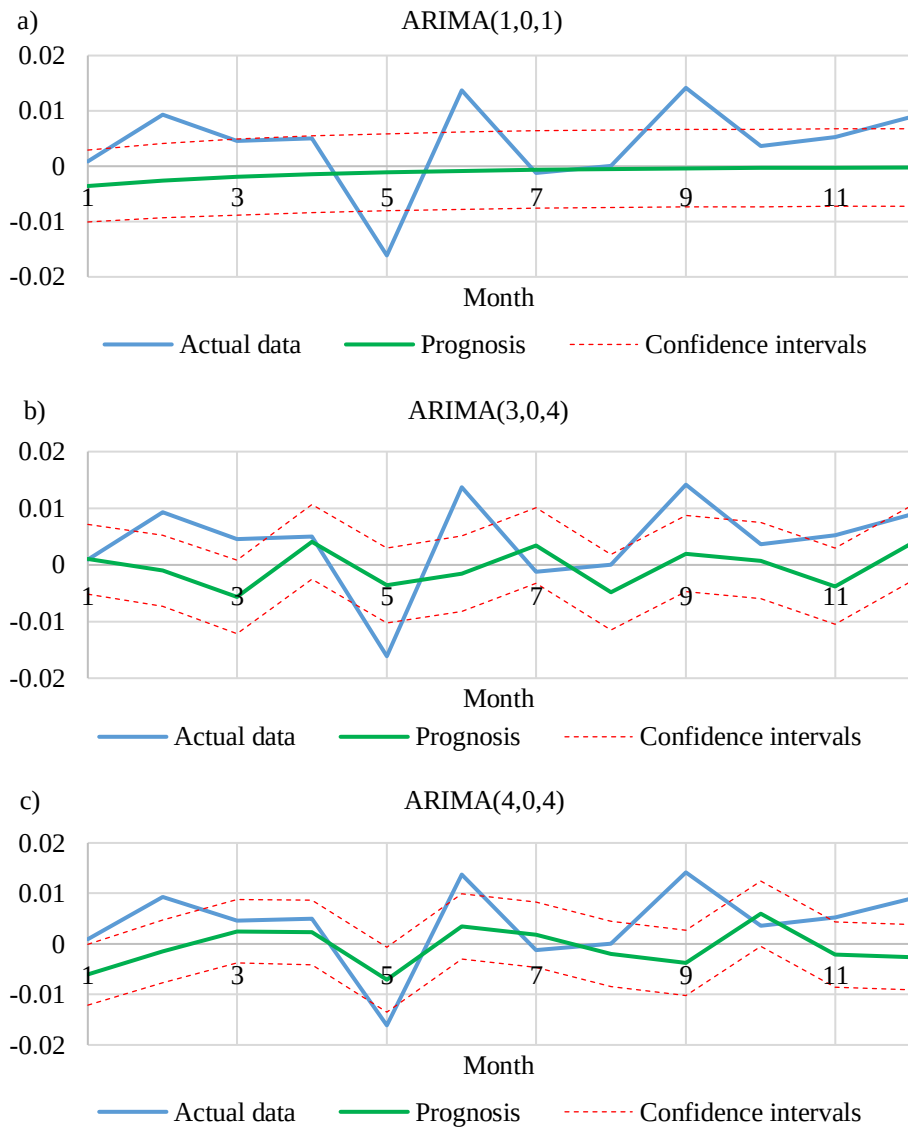


Fig. 3.5. Prognosis and confidence intervals using ARIMA models for differentiated freight rate data

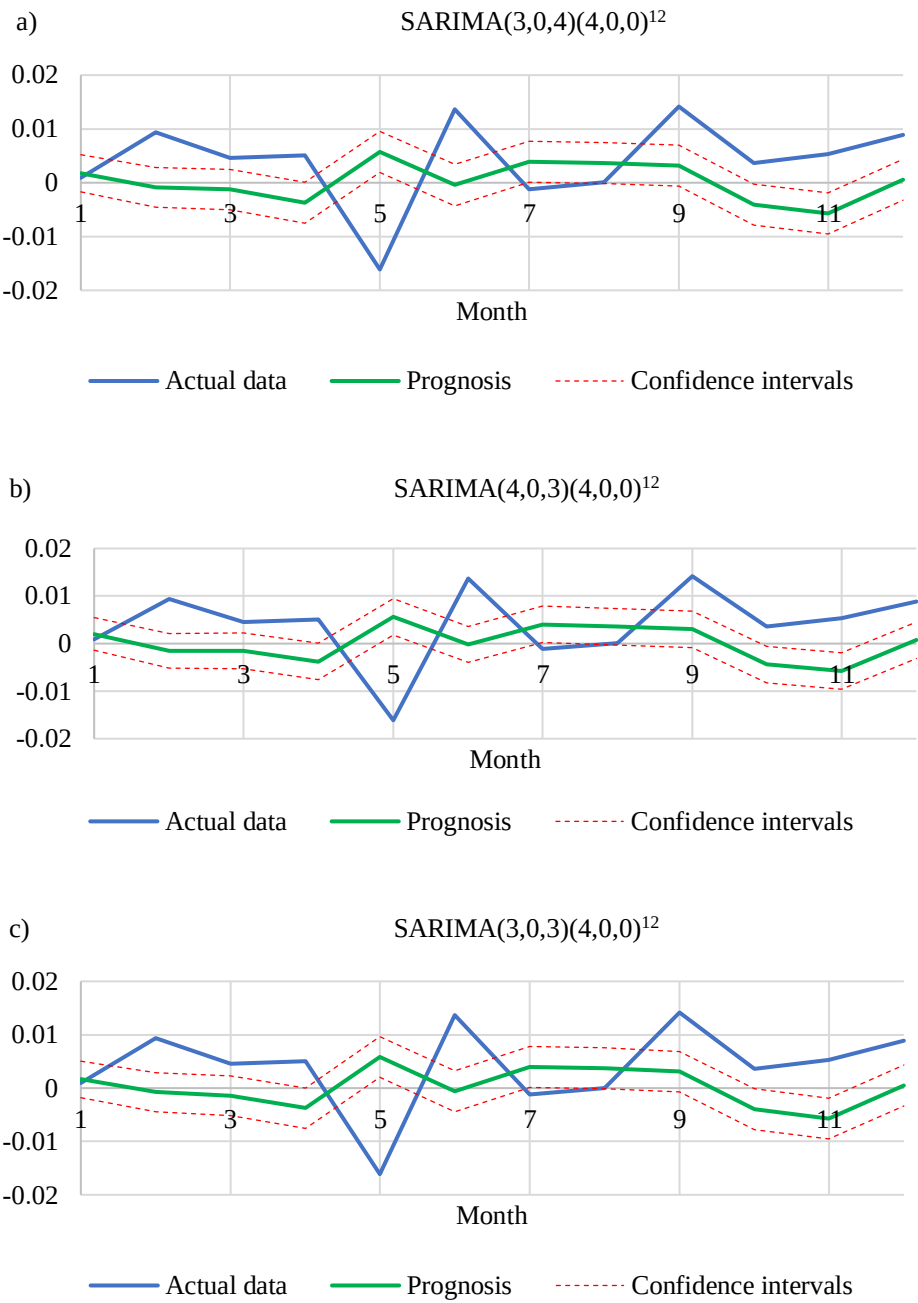


Fig. 3.6. Prognosis and confidence intervals using SARIMA models for differentiated freight rate data

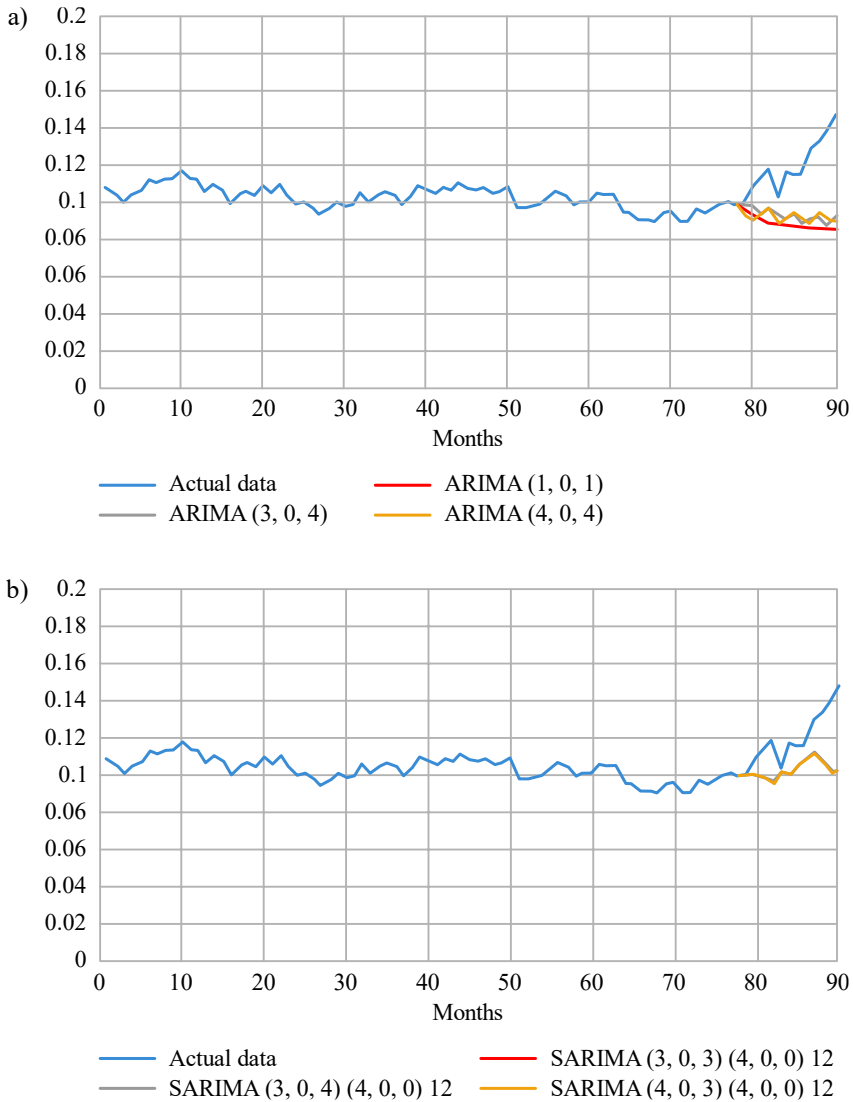


Fig. 3.7. Prognosis and actual freight rate data using (a) ARIMA and (b) SARIMA models

The achieved results, as depicted in Figures 3.5 and 3.7, indicate that during the period under investigation, econometric models failed to produce satisfactory outcomes. The performance of these models in prognosis freight rates was notably inadequate, suggesting that alternative prognosis methods should be considered for better accuracy and reliability. It is important to underscore that this analysis

and the associated prognosis were conducted during a time of significant market volatility, which was predominantly influenced by the far-reaching impacts of the COVID-19 pandemic.

The limitations observed in the performance of econometric models during this period call for a reassessment of the approaches used for freight rate prognosis. The complexities introduced by the pandemic, such as sudden changes in market demand, supply chain disruptions, and fluctuating economic conditions, posed substantial challenges for traditional prognostic models. These unprecedented conditions amplified the inherent unpredictability within the market, further straining the ability of standard econometric models to cope effectively.

Given these findings, it becomes clear that relying solely on conventional econometric approaches is insufficient in extreme market volatility. Alternative methodologies that can adapt to rapid and unforeseen changes in the market landscape are warranted. Such methodologies include more advanced statistical techniques, machine learning models, or hybrid approaches combining various prognosis paradigms to enhance robustness and accuracy.

The analysed period serves as a critical case highlighting the necessity for flexible and resilient prognosis methods that withstand and adapt to volatile market conditions. Consequently, future research and practical applications in freight rate forecasting should focus on developing and implementing dynamic models that can adapt to high levels of market uncertainty. This approach better caters to the practical needs of stakeholders within the freight and logistics sectors, particularly during periods marked by significant disruptions and instability.

3.2. Results of Quantitative Multivariate Econometric and Artificial Intelligence-Based Models

After discovering that both ARIMA and SARIMA models do not provide reliable results for freight rate prognosis, the focus shifted towards developing multivariate models. Consistent with findings in existing literature, multivariate models present a robust framework for prognosis, effectively addressing the complexities associated with multiple interrelated variables. This sub-chapter extends the analysis initiated in sub-chapter 3.1, utilising the same data set for the route from the Netherlands to Italy (Fig. 3.1). Here, the objective is to harness the prognosis power of multivariate econometric models, exploring their capability to encapsulate the intricacies of prognosis when multiple influential factors are at play.

In this research, key indicators used for freight rate prognosis included TKMs, industrial production, imports, consumer spending, and fuel prices. While multivariate models provide a comprehensive approach, a notable disadvantage is that the key indicators used for prognosis also need to be defined. Fortunately, the

data were available for this case study, and the results achieved with the developed model were compared against existing data. The prognosis was performed over 12 months (spanning months 79 to 90 in Fig. 3.1), covering July 2021 to June 2022. The only exception was the input parameter TKMs, for which data were unavailable and needed to be defined. This parameter, collected quarterly and reported by Eurostat, experiences a 6 to 9-month delay.

The FI index was employed to estimate TKMs. This indicator, defined as the ratio between TKMs and gross domestic product (GDP), was indexed in 1995 to a value of 1 for each EU country. Figure 3.8 presents the FI from the first quarter of 2015 onwards, revealing a discernible linear trend. For the Netherlands, the correlation coefficient stood at 0.87 ($R^2 = 0.76$), while for Italy, it was 0.82 ($R^2 = 0.68$). The trendlines were used to build a prognosis for the subsequent quarters. Based on the estimated FI for the prognosis period, TKM values were evaluated.

The remaining input parameters (industrial production, imports, consumer spending, and fuel prices) were readily available, facilitating the development of an econometric model using statistical data. Various combinations of ARIMAX and SARIMAX models were tested following a methodology similar to that described in the second Chapter.

Concurrently, ANN models with exogenous inputs were developed. A significant advantage of using ANNs is their ability to handle non-stationary data, allowing the use of raw data without preprocessing. The Levenberg-Marquardt algorithm was employed to train the ANN. The number of neurons in the hidden layer was varied, and results were compared using MSE as the primary metric, computed automatically via the MATLAB ANN toolbox. The most accurate results were obtained with a model featuring ten neurons in a single hidden layer. Increasing the number of neurons led to a tendency towards overlearning, where the MSE values decreased for the training dataset, while the performance deteriorated on the testing dataset.

The most accurate results were achieved using the ARIMAX (1,0,2) model and nonlinear autoregressive ANN with exogenous inputs, presented in Figure 3.9.

The smallest achieved RMSE value for prognosis was 0.01934 using the ANN model (Fig. 3.10). The ANN model provided more accurate results by the end of the prognosis period, achieving the minimal RMSE value among the different models tested for price prognosis.

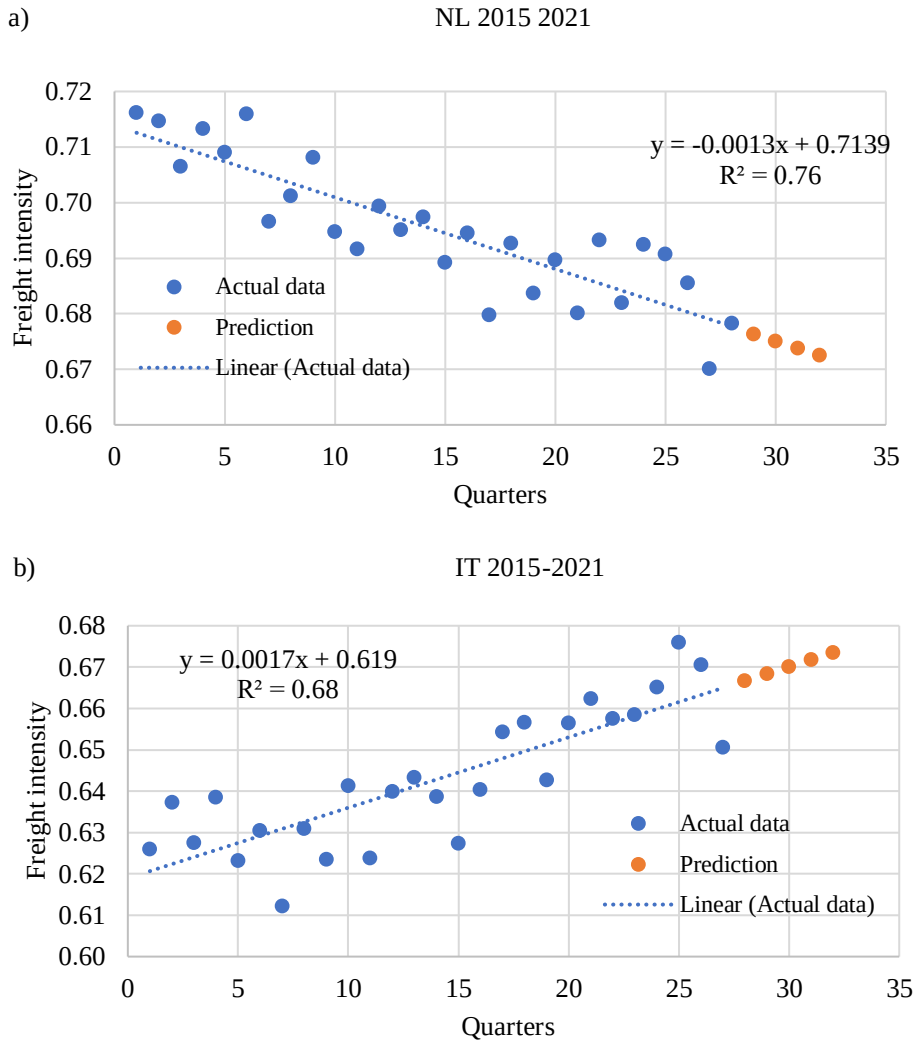


Fig. 3.8. Freight intensity: (a) Netherlands; (b) Italy

The primary drawback of implementing the proposed solution lies in the necessity to prognose five parameters, which inherently increases the potential for errors. For instance, consider the input parameter – fuel prices. In the US, transportation companies typically depend on WTI crude oil price prognosis and NY-MEX prognoses for fuel prices. This same prognostic model was employed in this investigation, given that global oil trends generally exhibit similar patterns.

However, it is crucial to note that the prognosis for 2022 turned out to be entirely incorrect. In January 2022, the prognosis predicted a decline in oil prices from nearly USD 80 per barrel, as observed the previous year, to approximately USD 60 per barrel by the end of 2022. Contrary to this prognosis, the actual price surged to nearly USD 120 per barrel by mid-year before declining to USD 80 per barrel by the end of the year Figure 3.11.

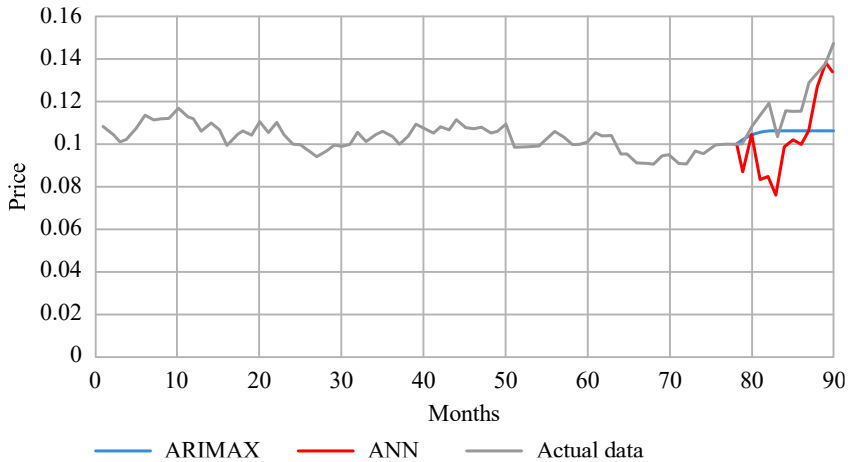


Fig. 3.9. Prognosis and actual freight rate data using ARIMAX and ANN models

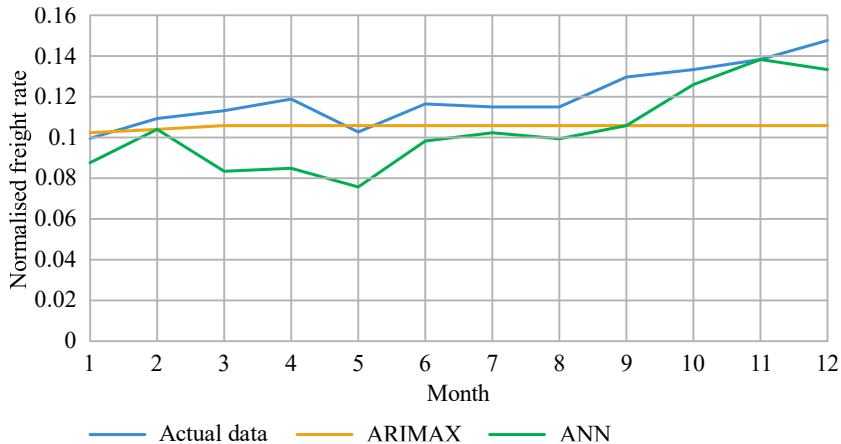


Fig. 3.10. Prognosis of freight rates using ARIMAX and ANN methods for the last 12 months (79–90)

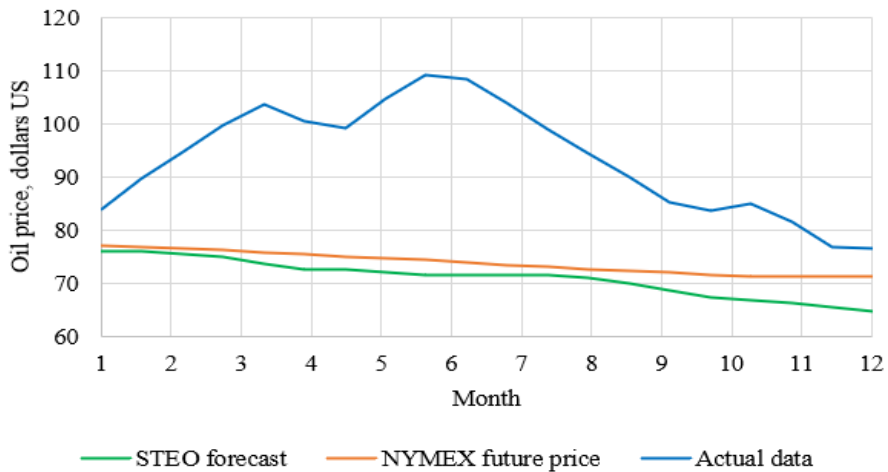


Fig. 3.11. Example of oil price prognosis for 2022 year; actual data for 2022, prepared by the author based on the US Energy Information Administration, Short-Term Energy Outlook, January 2022 and February 2023

Consequently, the notion that multivariate models would inherently outperform conventional univariate models must be approached with extreme caution, particularly considering the challenges associated with additional prognosis parameters. In times of market volatility, such an approach introduces significant uncertainty. Therefore, despite the advantages of multivariate models, a robust and efficient solution that effectively navigates these complexities is still required. Further research and innovation in prognosis methodologies are necessary to develop models that reliably and accurately prognose freight rates under volatile market conditions.

3.3. Prognosticating Contract Freight Rates Using Spot Rates

This sub-chapter examines the idea that contract freight rates correlate with spot rates after a certain delay. Previous studies in some industries have found such correlations (Jason et al., 2021). If spot rates change, contract rates are expected to follow suit over the next several months.

Spot and contract rates were separated to perform a freight rates prognosis and test this hypothesis. Unfortunately, such data separation was not previously implemented in the available dataset and only began in 2020. The data collected, separating contract and spot rates, spans 24 months for the route from the

Netherlands to Italy. After data collection, the rates were compared using the correlation coefficient (R) as the primary metric.

Table 3.4 presents the results of this analysis. A month lag of 0 indicates that the contract rate of month one is compared with the spot rate of month one (without delay), while a month lag of 1 (one month delay) means that month two's contract rate is compared with month one's spot rate, and so forth. The highest correlation was observed with a lag of six months, indicating that the contract rate curve mirrors the trends of the spot rate with this delay.

Table 3.4. Correlation of spot rates with considered contract rates

Month lag	0	1	2	3	4	5	6	7	8	9
Correlation	0.71	0.64	0.54	0.61	0.76	0.72	0.86	0.78	0.72	0.50

For the 6-month lag, the correlation coefficient is 0.86. These data are graphically represented in Figure 3.12. For the selected case study, it was found that spot rates could be used as a primary metric for evaluating contract rates. This model is particularly beneficial during periods of market volatility, where the accuracy of more advanced multivariate models tends to decrease. The main advantages of this method are its simplicity and robustness.

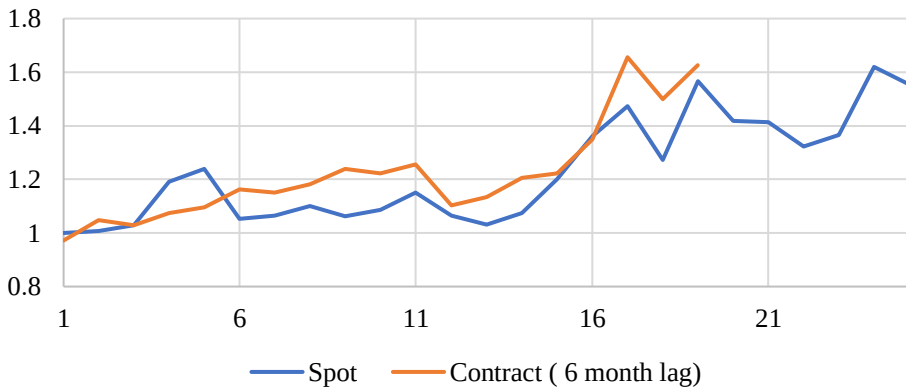


Fig. 3.12. Spot VS contract rate with a 6-month lag

As depicted in Figure 3.13, the maximal correlation coefficient value is achieved during month 6. This indicates that contract prices tend to mirror the trend of spot prices in a specified direction with a delay of six months.

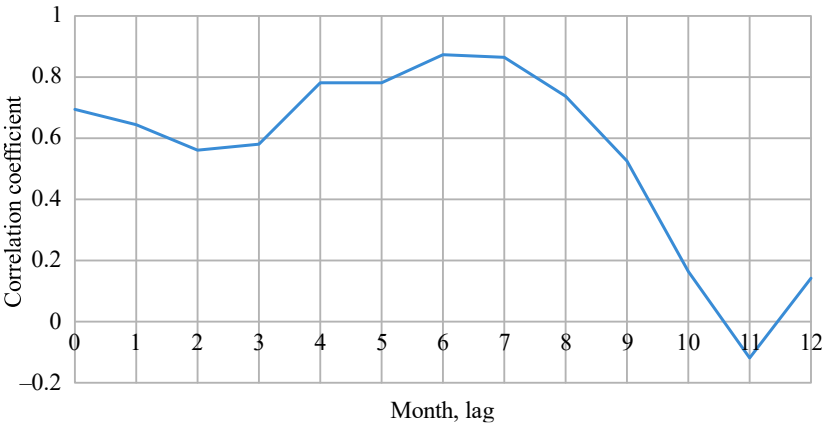


Fig. 3.13. Correlation coefficient between spot and contract rates, direction Netherlands–Italy

Similar trends were observed for other directions as well, as shown in Figure 3.14, where the direction from Spain to Italy is analysed.

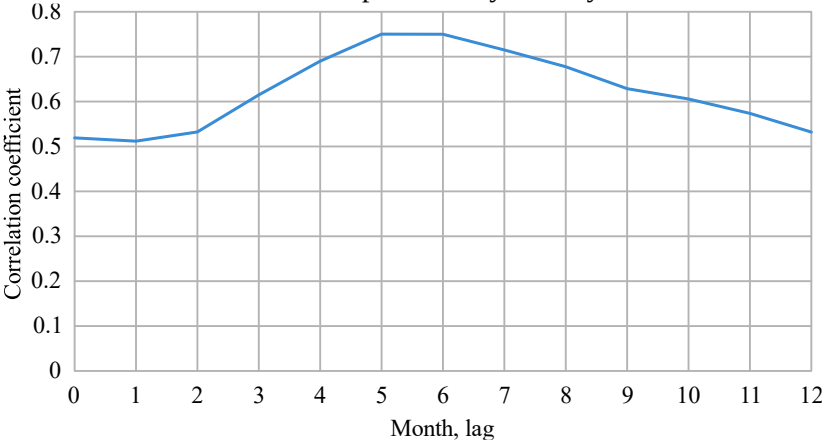


Fig. 3.14. Correlation coefficient between spot and contract rates, direction Spain–Italy

Based on Figure 3.14, in the second case study, the most optimal results were achieved with a lag of five months. This outcome indicates that the previously assumed 6-month delay is inconsistent across different scenarios and suggests that the appropriate delay should be calculated individually for each specific destination.

During this investigation, a strategic decision is made to split spot and contract rates into separate categories. The findings from this model reveal that contract rates tend to follow and mirror spot rates with a noticeable delay. Specifically, a straightforward dependency was identified between these two parameters, with contract rates typically trailing spot rates by a period ranging from 5 to 7 months. However, it is essential to note that determining this delay requires an in-depth analysis of real-world data across various destinations to achieve accurate results.

One notable drawback of this model is that it limits the prognosis horizon to a 5–7 month timeframe, in contrast to other data-driven methods that offer a prognosis of up to 12 months. Consequently, addressing this limitation necessitates the use of a combination of methodologies. Integrating different prognosis techniques can enhance the robustness and accuracy of prognoses, thereby offering a more comprehensive solution to the problem.

Future studies should aim to delve deeper into this area, focusing on exploring potential solutions and refining prognosis techniques. Such research would involve examining a more comprehensive dataset from multiple destinations to better understand the variability and develop more sophisticated models capable of providing accurate prognoses over extended periods. Additionally, investigating the underlying factors contributing to the observed delay could yield insights that would help improve the prognoses of contract rates based on spot market trends.

By advancing the understanding and improving the analytical methods used, it becomes possible to develop prognostic models that are more accurate and adaptable to varying market conditions. This comprehensive model will ultimately enhance the decision-making process, making it more responsive to the dynamic nature of freight markets.

3.4. Method for Increasing Efficiency in Road Freight Transportation

Various mathematical models were rigorously tested for their effectiveness in freight rate and demand prognosis. The study was conducted during extraordinarily challenging times, notably due to the COVID-19 pandemic, which caused unprecedented global disruptions and the considerable geopolitical shifts in Europe that altered the transportation corridors between Europe and numerous third countries. These significant upheavals profoundly affected the demand for freight transportation and the corresponding freight rates, introducing a substantial level of volatility and unpredictability to the datasets. This made the development of reliable prognostic models exceptionally difficult. However, despite these

challenging conditions, models demonstrating robust performance were identified and implemented even during these unstable periods.

During the research, it became evident that demand prognosis was a relatively simpler task compared to freight rates prognoses. Econometric and ANN-based models were employed across all test cases to tackle these prognosis challenges. The findings indicated that ANNs performed exceptionally well for demand prognosis tasks (refer to Fig. 3.15 for detailed results). The ANNs were adept at accurately prognosticating the various fluctuations in demand, capturing the intricate patterns inherent in the data.

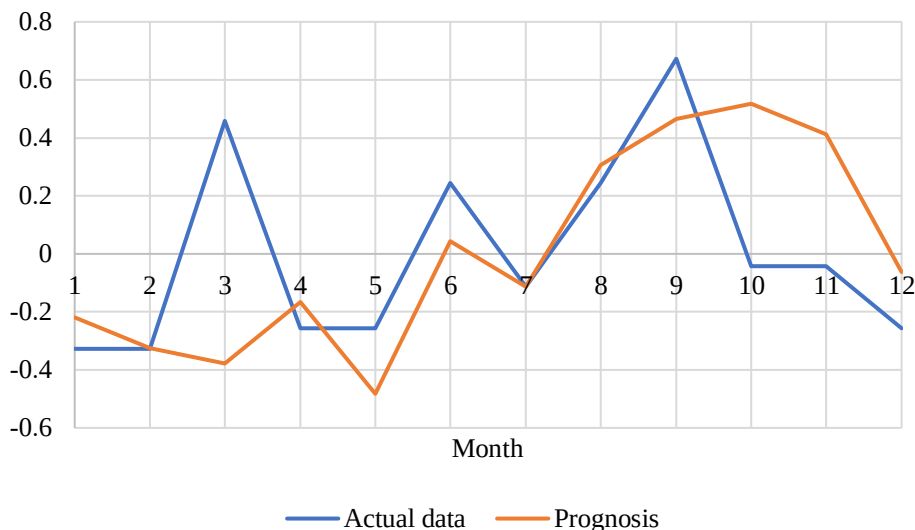


Fig. 3.15. Normalised demand prognosis between the Netherlands and one of the Italian regions using ANN

However, it should be noted that ANNs require a comprehensive set of input data for their prognoses, which needs to be selected accurately. Given this requirement, ARIMA models also performed better for demand prognosis. ARIMA models are well-suited for time series prognosis and have a proven track record of reliability in similar tasks. Consequently, utilising ARIMA models specifically for demand prognosis was deemed effective in ensuring higher accuracy and reliability. ARIMA models achieved reliable and stable demand prognosis, providing valuable insights despite the highly volatile environment brought on by the pandemic and geopolitical shifts.

It must be stated that the method developed in this dissertation is not final and should be further modified to consider different regions within countries, as

illustrated in Figure 2.4 (sub-chapter 2.2). The primary challenge faced in this research is the lack of a data aggregator in Europe that collects comprehensive information regarding demand and prices. Consequently, only internal data were used for the analysis.

Despite these limitations, the asset-based company under investigation operates a substantial fleet of nearly 10,000 trucks. However, the distribution of contracts across different regions is uneven, which introduces complexities in accurate demand prognosis and freight rates. For instance, many shipments occur between the Netherlands and Italian Region 2, as depicted in Figure 2.3 (Sub-chapter 2.2.). In this specific scenario, the freight rate prognosis for Italian Region 2 yielded very accurate results when employing the ARIMAX (1,1,1) model (Fig. 3.16).

The accurate prognoses in this case are attributed to the concentration of data and the higher volume of shipments between these two regions, which provided a more robust model creation. However, this success highlights the necessity for further refinement and regional customisation of the models. Different regions may exhibit varying demand patterns and external influencing factors, necessitating region-specific adjustments to the prognostic models to ensure their reliability and accuracy.

Without a centralised data aggregator, future research should integrate multiple data sources, possibly through collaborations with other companies or industry stakeholders, to build a more comprehensive dataset. This could enhance the model's ability to generalise across different regions and improve the overall prognosis accuracy. Additionally, future studies could explore advanced prognosis techniques and machine learning methodologies that account for regional differences more effectively.

In the studied region, more than 100 full truckloads were transported per month during the prognosis period, providing a substantial dataset for analysis and model training. This high volume of shipments allowed for accurate and reliable prognosis results, as the data were robust enough to identify and prognosticate patterns effectively. On the other hand, there were other regions where the shipment volume was significantly lower. In some of these regions, only a few shipments were performed each month, which resulted in data scarcity and made it challenging to produce reliable prognostic models. Due to the insufficient data volume in these regions, the prognosis results were deemed unacceptable, as the models could not capture meaningful trends or patterns (figures are not provided for these cases). This stark contrast in shipment volumes between regions illustrates the critical role that sufficient data plays in achieving accurate and reliable prognosis outcomes.

More comprehensive datasets would also allow for the application of more sophisticated modelling techniques that require large amounts of data to function

optimally. Conversely, datasets with limited shipment volumes suffer from sparse data, which hampers the ability of models to generalise and prognose accurately. This disparity highlights the need for adaptive strategies to handle varying data volumes and regional characteristics.

Due to the scarcity of data, it was decided against separating the datasets into regions and instead focused on analysing countries as whole units. The limited data available for some areas would not support robust and reliable regional analysis. However, developing prognosis tools specifically designed to operate at the regional level would be advantageous for practical applications. Such tools would allow for more precise and localised prognoses, addressing individual regions' unique demand and supply dynamics.

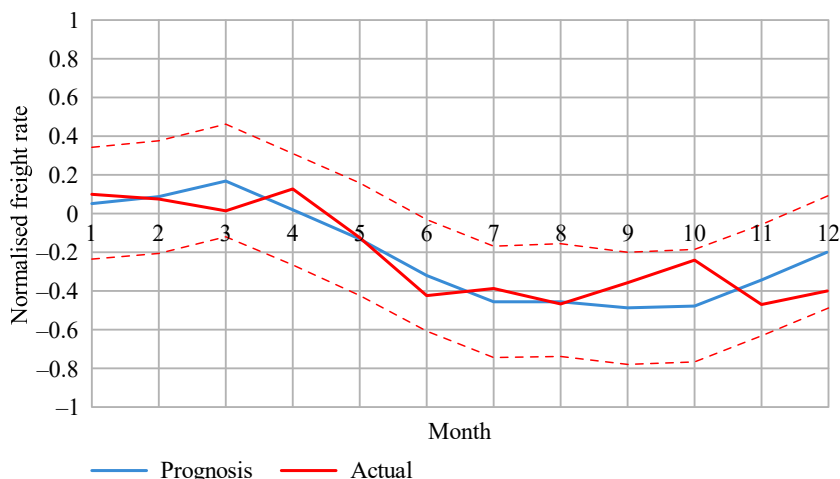


Fig. 3.16. Prognosis of freight rate with confidence intervals using ARIMAX (1,1,1) between Netherlands and Italy 2 region

The investigation revealed that no single model could universally fit all cases under consideration. Each scenario presented unique characteristics and challenges, making it clear that a one-size-fits-all approach was insufficient. Therefore, a more tailored strategy was necessary to address each case's specific needs and conditions. Presented below is the developed method aimed at improving the efficiency of operations within road freight transportation companies (Fig. 3.17). This method encompasses a range of models and techniques, each chosen for its ability to enhance performance and rationalise outcomes in various contexts. By adopting a multifaceted strategy, the companies can better navigate the complexities of road freight transportation, ensuring more reliable and effective service delivery.

For an effective analysis and enhancement of the proposed method, internal historical data are essential, focusing on freight rates with separate considerations for spot and contract rates. Additionally, access to fuel price data is crucial. Whether the data originates internally or externally is relatively inconsequential, as fuel price datasets show a high correlation coefficient of about 0.96. Access to comparable data from other companies within the same market is also vital, as larger datasets contribute to improved prognosis accuracy.

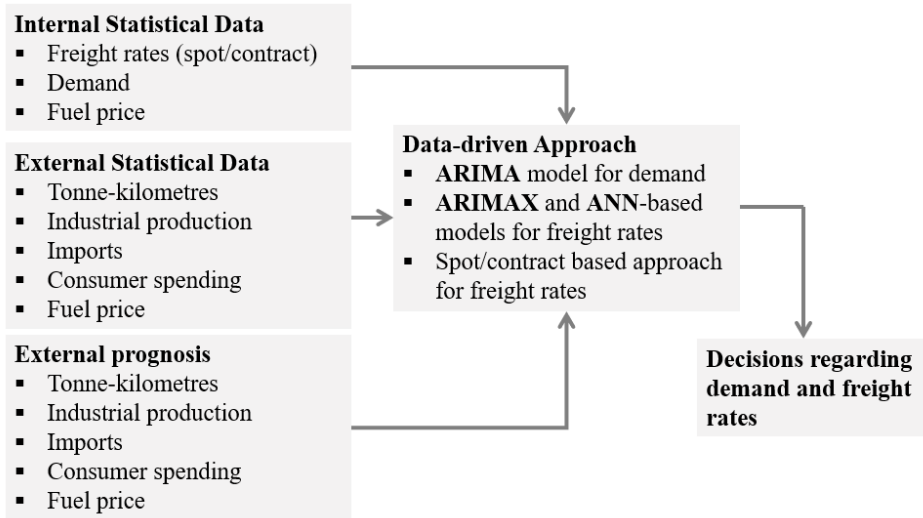


Fig. 3.17. Developed method for increasing efficiency in road transportation companies

External data requirements include TKMs, industrial production, imports, fuel prices and consumer spending. A significant drawback of this external data is the notable delay in its availability. However, the prognosis for most of these data exists, with only the TKM prognosis being performed internally during this investigation.

Upon preparation of the dataset, the proposed method is employed. Initially, ARIMA models are utilised for demand prognosis. Freight rates are prognosed using three models; two of these models determine the same parameter: the freight rate for the next twelve months with monthly discretisation. Simultaneously, contract rate trends are identified based on spot prices, with the prognosis horizon extending to about six months. Although this is insufficient for signing contracts for the coming year, it can still facilitate decision-making processes.

The proposed method aids decision-makers in assessing their company's performance for the forthcoming year. The company's overall performance is

enhanced by making informed and weighted decisions. However, the developed tool is not intended to replace human judgement altogether.

While the current method is promising, especially with abundant and specific internal data, continuous modifications and enhancements are necessary. These adjustments better address regional variations and the ever-changing nature of freight demand and pricing. Ongoing improvement and adaptation of the models will yield more precise and reliable prognosis capabilities across varied geographic and economic landscapes.

3.5. Pathway for Developed Method Implementation

For asset-based freight transportation companies, evaluating efficiency involves using various metrics presented in the second Chapter:

1. The number of available trucks;
2. The number of kilometres travelled per truck;
3. Empty kilometres per truck (%);
4. Revenue per kilometre per truck;
5. The number of shipments per truck;
6. The average daily margin per truck;
7. Operating profit.

An accurate demand prognosis is essential for the number of kilometres travelled per truck and the number of shipments per truck. This metric ensures that resources are optimally allocated and assets are utilised to their full potential, thereby minimising empty runs.

Freight rates are essential for calculating the revenue per kilometre per truck. By accurately prognosticating freight rates, companies establish competitive yet profitable pricing strategies that directly influence their revenue generation per kilometre travelled. A prognosis is used to calculate the average daily margin per truck. This calculation involves integrating the revenue per kilometre with the distance travelled and the number of shipments, resulting in a vital daily profit margin for informed decision-making.

Operating profit is then estimated based on the total revenue and expenses related to the asset's operations. By ensuring that these calculations rely on precise demand and rate forecasts, companies can anticipate financial outcomes more accurately.

If the actual results deviate from the expected values, a reassessment of the number of available trucks is undertaken. This evaluation includes operational adjustments, such as reallocating trucks to higher-demand routes, leasing additional vehicles, or even reducing the fleet size to better align with demand and maximise profitability.

The developed method offers an exceptional opportunity for proactive company management. It equips decision-makers to enhance efficiency, reduce costs, and maximise profitability by enabling the real-time monitoring of key metrics and facilitating prompt operational adjustments. By utilising predictive analytics, businesses can stay ahead of market fluctuations, maintaining a competitive advantage.

Moreover, this method fosters continuous environment improvement. By regularly analysing and revisiting the key performance metrics, areas for improvement are identified, and best practices are established across the fleet. This iterative process guarantees that the company meets and exceeds its operational and financial goals.

In conclusion, integrating these metrics into a cohesive analytical framework transforms asset-based freight transportation companies' operations. Through meticulous demand and rate prognosis, the companies can make data-driven decisions, optimise their fleet utilisation, and maintain robust financial health. This bolsters current performance and paves the way for sustained growth and operational excellence in the highly competitive logistics industry.

3.6. Conclusions of the Third Chapter

1. For demand prognosis, the most accurate results were achieved using the ARIMA model. It is not a universal solution, and a specific model should be selected for each considered direction. SARIMA models provide the least accurate results for all the cases under investigation.
2. Freight rate prognosis was different due to the geopolitical situation, as rates changed dramatically. Standard ARIMA and SARIMA models do not provide satisfactory results. Using multivariate models, such as ARIMAX, SARIMAX, and ANN, considering TKMs, industrial production, imports, consumer spending, and fuel prices, better results were achieved compared to previously described methods. However, results obtained using input values in practical applications may not perform accurately, as the parameters required for the model are also forecasted with an error.
3. Freight rate prognosis is needed for transportation companies to sign one-year period contracts. Freight rate prognosis helps in decision-making. To solve the task, rates were collected, freight type was separated into spot and contract, and data were collected for 24 months. Analysis showed that contract rates repeat the tendency of spot rates with a 6-month delay. For the case under investigation, the correlation coefficient between spot and contract rates is equal to 0.86.

4. The dissertation rigorously tested various mathematical models for their effectiveness in prognosticating freight rates and demand during the extraordinary challenges posed by the COVID-19 pandemic and significant geopolitical shifts in Europe. These global disruptions caused considerable volatility and unpredictability in the datasets, which complicates the development of reliable prognostic models. Despite these challenges, robust performance models were identified and successfully implemented in these unstable periods. Based on the findings, a decision-making method has been developed.
5. The study highlighted the critical need for data accumulation to ensure reliability and accuracy, given the varying demand patterns and influencing factors across different regions. An example was the successful application of the ARIMAX (1,1,1) model for the Italian Region 2, which benefitted from concentrated, voluminous data. However, the lack of a comprehensive data aggregator in Europe, which led to reliance on internal company data, presented a significant limitation.

General Conclusions

1. Road freight transportation companies lack forecasting tools, even though the digitalisation of the sector and data accumulation offer opportunities for their development. A literature analysis indicated that this problem remains unresolved, and the methods proposed by the scientific community are often concentrated on other sectors or fail to provide a sufficient forecasting horizon.
2. The developed method integrates econometrics, ANNs, and statistical models to increase the efficiency of companies. Econometric models and ANNs were chosen to forecast freight transport rates and demand. Various types of data and sources used for forecasting freight rates and demand were examined. All necessary actions were carried out while working with the data, including data normalisation, stationarity analysis, and the application of evaluation metrics.
3. During the research, it was found that the most accurate results in forecasting demand were achieved by applying ARIMA models. In the case under investigation, which evaluated the direction of transportation from the Netherlands to Italy, the most effective results were obtained using the ARIMA (3,0,3) model, which had the lowest RMSE value of 0.0118. The ARIMA (2,0,4) and ARIMA (4,0,4) models performed slightly worse, with RMSEs of 0.0127 and 0.0155, respectively. In all cases, the predicted

values fell within the confidence interval for the entire 12-month period. It should be noted that the ARIMA (3,0,3) model is not necessarily the most accurate for all directions; different ARIMA models must be tested for each direction under consideration. Investigation revealed that it is generally not worthwhile to use models more complex than ARIMA (4,2,4).

4. Forecasting freight rates was complicated by the significant impact of COVID-19 and geopolitical factors, which caused substantial fluctuations in rates during the study period (2021–2022). Standard ARIMA and SARIMA models were found to perform this task inadequately. Multivariate models, such as ARIMAX, SARIMAX, and ANN, were employed to forecast rates, incorporating input data including ton-kilometres, industrial production, imports, consumer spending, and fuel prices. Improved results were achieved compared to the previously discussed ARIMA and SARIMA models, as the forecast values fell within the confidence intervals. Among the econometric results, the ARIMAX (1,0,2) model yielded the most accurate outcomes. Moreover, the results obtained using ANNs produced even better outcomes, with an RMSE of 0.01934. These results were achieved using only the actual values of additional input data. In practice, using forecast values for these parameters may lead to incorrect model performance due to inaccuracies in the input data.
5. Forecasting freight rates pose challenges due to the high uncertainty of input parameters. Therefore, a two-stage approach to forecasting freight rates is proposed. First, it is advisable to use ANN models in stable conditions. Second, when confronted with volatile market conditions, it becomes crucial to analyse and consider spot contract rates in the forecasting process. By combining ANN models during stable market situations with an analysis of short-term contract rates in highly volatile conditions, a comprehensive and reliable freight rate forecasting system can be established.
6. The developed method, which incorporates various mathematical models selected according to a rule-based algorithm, offers companies a significant opportunity for real-time management, allowing them to monitor indicators and rapidly adapt to changes. The growth cycles of companies align with market cycles. This method integrates updated historical data, and the forecasting models are continuously refined during the training process. Future research should focus on integrating multiple data sources in collaboration with other companies and stakeholders to create a more comprehensive dataset, thereby increasing the accuracy of predictions.

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List of Scientific Publications by the Author on the Topic of the Dissertation

Papers in the Reviewed Scientific Journals

Liachovičius Edvardas; Skrickij Viktor; Podvieszko Askoldas. (2020). MCDM evaluation of asset-based road freight transport companies using key drivers that influence the enterprise value. *Sustainability*. Basel: MDPI. ISSN 2071-1050. vol. 12, iss. 18, p. 1–17. <https://doi.org/10.3390/su12187259>.

Liachovičius, Edvardas, Šabanovič, Eldar; Skrickij, Viktor. (2023). Freight rate and demand prognosis in road freight transportation using econometric and artificial intelligence methods. *Transport*, 38(4), 231–242. <https://doi.org/10.3846/transport.2023.20932>.

Papers in Other Editions

Liachovičius Edvardas; Skrickij Viktor. (2020). The challenges and opportunities for road freight transport. *Transbaltica XI: Transportation science and technology: Proceedings of the international conference Transbaltica*, May 2–3, 2019, Vilnius, Lithuania. Cham: Springer. ISBN 9783030386658, p. 455–465. DOI:10.1007/978-3-030-38666-548.

Liachovičius Edvardas, Kojis Paulius, Skrickij Viktor. (2024). Efficiency improvement in asset-based freight transportation company. *Transport Problems*. XVI International Scientific Conference, 19–21 June 2024, Katowice, Poland. Katowice: Silesian University of Technology. ISBN 9788395974281, p. 331–338.

Summary in Lithuanian

Įvadas

Problemos formulavimas

Nuosavą parką turinčios kelių transporto įmonės vykdo veiklą konkurencingoje rinkoje, kur nuolatos keičiasi teisiniai reikalavimai. Transporto sektoriaus skaitmenizavimas ir duomenų prieinamumas suteikė naujų galimybių diegti duomenimis grįstus metodus, siekiant pagerinti technologinius procesus ir bendrą įmonės efektyvumą. Paklausos ir vežimo tarifų prognozavimas yra svarbus pasaulinis krovinių transportavimo iššūkis, neišspręstas dėl duomenų trūkumo ir jų kintamumo.

Šioje disertacijoje sprendžiamas uždavinys, tyrinėjant ir naudojant duomenimis grįstus modelius bei pasiūlant IT pagrindu sukurtą technologinį sprendimą – metodą, gerinantį kelių krovinių transporto sektoriaus efektyvumą.

Darbo aktualumas

Tiksli sutartinių krovinių vežimo tarifų ir paklausos prognozė padeda įmonės vadovams priimti sprendimus dėl kainodaros, išteklių paskirstymo ir pajėgumų planavimo, todėl padidėja efektyvumas ir pelningumas. Dėl duomenų stokos šis uždavinys iki šiol nebuvo pakankamai išnagrinėtas mokslo bendruomenės, todėl nebuvo aišku, kurių metodų taikymas leis išspręsti šį uždavinį. Disertacijoje pateikiama naujų įžvalgų ir žinių, kaip taikyti duomenimis grįstus metodus siekiant padidinti efektyvumą, tobulinti sritį ir suteikti pagrindą būsimiems tyrimams. Taikydama sukurtą metodą krovinių vežimo įmonė įgyja konkurencinį pranašumą.

Tyrimo objektas

Tyrimo objektas – krovinių vežimo keliais procesai ir jų efektyvumo didinimo būdai.

Darbo tikslas

Disertacinio darbo tikslas – sukurti duomenimis grįstą sprendimų priėmimo metodą, leidžiantį prognozuoti sutartinius krovinių vežimo tarifus ir paklausą krovinių vežimo keliais srityje, bei įvertinti jo efektyvumą, naudojant realius duomenis.

Darbo uždaviniai

Siekiant išspręsti nurodytą problemą, buvo suformuluoti šie uždaviniai:

1. Atlikus literatūros analizę, nustatyti mokslinį neapibrėžtumą ir pasirinkti tinkamus modelius bei metodus problemai spręsti.
2. Sukurti ekonometrinis ir dirbtiniu neuronų tinklu pagrįstus matematinius modelius paklausos ir krovinių tarifams prognozuoti.
3. Įvertinti sukurtų modelių efektyvumą ir veiksmingumą, naudojant realius duomenis.
4. Sukurti metodą, pasitelkiant sukurtus matematinius modelius, transportavimo procesui gerinti ir kelių transporto įmonių efektyvumui didinti.

Tyrimų metodika

Atliktas teorinis tyrimas, orientuotas į analizę ir sintezę, jis leidžia gerinti krovinių vežimo efektyvumą kelių transportu. Tyrimas apėmė mokslinių publikacijų analizę ir prognozavimo modelių bei metodų apžvalgą, su tikslu nustatyti neapibrėžtumus literatūroje. Pasirinkti pažangiausi sprendimo metodai, taikant matematinę modeliavimą. Įrankiai apėmė ekonometrijos modelius, tokius kaip ARIMA, sezoninis ARIMA (SARIMA) ir jų vertinimo rodikliai. Tyrimo metu buvo sukurti individualūs ir daugiamačiai prognozavimo modeliai, naudojant dirbtinių neuronų tinklus (angl. ANN). Sukurti modeliai buvo testuojami naudojant realius duomenis, naudojant Microsoft Office ir MATLAB programinę įrangą.

Mokslinis naujumas

1. Sukurti nauji statistiniai, ekonometriniai ir dirbtinių neuronų tinklais grįsti modeliai, krovinių vežimo tarifams ir paklausai prognozuoti.
2. Nustatyti esminiai išoriniai parametrai, skirti tarifų prognozavimo modeliams, ir jie buvo panaudoti kuriant metodą.
3. Sukurtas naujas metodas, pagrįstas realių duomenų naudojimu, krovinių vežimo keliais efektyvumo didinimui.

Darbo rezultatų praktinė reikšmė

Krovinių vežimas keliais yra reikšmingas pasaulinės ekonomikos sektorius, jo efektyvumo didinimas yra svarbus uždavinys. Šiame darbe sukurtas metodas yra svarbus krovinių vežimo keliais transporto sektoriui. Sukurtas metodas bus taikomas kaip pagrindinis elementas ilgalaikių sutarčių tarifų ir paklausos vertinimo procese, taip tobulinant transportavimo efektyvumą.

Ginamieji teiginiai

1. Ekonometriniai ir dirbtinių neuronų tinklų modeliai gali būti efektyviai naudojami krovinių vežimo tarifams ir paklausai prognozuoti, taip padidinant krovinių pervežimo efektyvumą.
2. Naudojant daugiamačius modelius, atsižvelgiant į ekonominius parametrus, gausiami geresni rezultatai, palyginti su anksčiau naudotais modeliais.
3. Ilgalaikių sutarčių krovinių vežimo tarifai seka trumpalaikių sutarčių tendencijas su kelių mėnesių vėlavimu, todėl trumpalaikių sutarčių tarifai gali būti naudojami prognozavimui.

Darbo rezultatų aprobavimas

Pagrindiniai disertacijos rezultatai paskelbti 4 moksliniuose leidiniuose: 2 straipsniai – žurnaluose, referuojamuose *Web of Science* duomenų bazėje su citavimo indeksu; 1 straipsnis – *Web of Science* duomenų bazės konferencijos pranešimų medžiagoje; 1 straipsnis – konferencijos pranešimų medžiagoje.

Autorius skaitė 2 pranešimus tarptautinėse, mokslinėse konferencijose:

- „*Transbaltica*“, plenarinė sesija 2019 m. gegužės 2 d., Vilnius, Lietuva, Vilniaus Gedimino technikos universitetas.
- „*Transport Problems*“, 2024 birželio 19 d., Katovica, Lenkija, Silezijos technologijos universitetas.

Disertacijos struktūra

Disertaciją sudaro įvadas ir trys pagrindiniai skyriai.

Pirmajame skyriuje nagrinėjama aktuali mokslinė literatūra apie krovinių transportavimo procesus, įmonės efektyvumą ir prognozavimo modelius bei metodus.

Antrajame skyriuje analizuojami technologiniai krovinių transportavimo proceso aspektai, sutelkiant dėmesį į efektyvumo didinimo uždutį, ir pristatytas kuriamas metodas, kuris skirtas efektyvumui didinti bei pagrįstas krovinių vežimo tarifų ir paklausos prognozavimo modeliais.

Trečiajame skyriuje įvertinami matematinio modeliavimo rezultatai, naudojant realius duomenis jų tikslumui ir veiksmingumui patikrinti. Šiame skyriuje pateikiama išsami rezultatų analizė ir įvertinamos modelių privalumai bei trūkumai. Remiantis atliktu tyrimu, pasiūlytas efektyvumo didinimo metodas, kurį sudaro prognozavimo modelių

rinkinys ir jų parinkimo algoritmas. Analizuojamos metodo įgyvendinimo galimybės krovinių vežimo transporto įmonėse.

Disertacija užbaigiama išvadomis ir pateikiamas literatūros šaltinių sąrašas. Išvadosse pateikiami visi esminiai rezultatai, parodant tyrimo svarbą ir indėlį į krovinių transportavimo proceso efektyvumo didinimą.

Disertacijos apimtis 108 puslapiai, juose yra 31 lygtis, 26 paveikslai, 6 lentelės ir 105 bibliografiniai šaltiniai.

1. Krovinių vežimo keliais naujausios technologijos ir efektyvumo gerinimo analizė

Remiantis literatūros apžvalga, buvo išnagrinėti kokybiniai, kiekybiniai ir hibridiniai prognozavimo metodai ir modeliai, kurie gali būti naudojami prognozavimo uždaviniui spręsti.

Kokybiniai metodai apima dvi grupes. Pirmoji grupė apima individualius metodus. Scenarijų kūrimo metodai apima istorijų su tikėtinomis priežasties ir pasekmės sąsajomis kūrimą, ateities sąlygų susiejimą su dabartimi, iliustruojant pagrindinius sprendimus, įvykius ir pasekmes (Glenn, 2009; Retek, 2021). Prognozei gali būti naudojama paprasta turimų duomenų šaltinių apžvalga, analizuojant ekonominę situaciją regione. Antrasis pogrupis apima kolektyvinius metodus, kuriems reikia komandos pastangų. Plačiai taikomi interviu tyrimo metodai, kai dalyvauja apklausiami ekspertai ir pateikiami specifiniai klausimai. Klientų apklausos dažnai naudojamos prognozavimui (Claveria et al., 2017). Vienas iš tokių apklausos metodų yra *Delphi* metodas, apimantis kelis apklausų etapus, kai respondentai gali komentuoti anketas, o jų atsakymus galima koreguoti po rezultatų analizavimo. Po kelių etapų pastebima tam tikra konvergencija (Kauko & Palmroos, 2014). Sudėtinis pardavimo pajėgų metodas apima pardavimų vadybininkus, prognozuojančius pardavimus atitinkamose savo teritorijose, kurios yra konsoliduojamos filialo, regiono ar srities lygmeniu, kad būtų parengta bendra įmonės pardavimo prognozė (Mahlamäki et al., 2020). Šį metodą galima pritaikyti skirtingoms sritims, iš pradžių atliekant žemo lygio (angl. *low level*) prognozes, o po to apibendrinant rezultatus aukštesniu lygiu. Tai galima padaryti taikant vadovų nuomonės metodą (Wang & Chaovalitwongse 2011). Įvairiose srityse dirbantys įmonių vadovai susirenka ir prognozuoja vadovaudamiesi savo patirtimi, žiniomis ir esama situacija rinkoje.

Prognozavimui plačiai taikomi kiekybiniai modeliai. Prognozuojant plačiai naudojami MA ir jo modifikacijos, tokios kaip kasdienė MA, normalizuoti MA ir kiti rodikliai, pagrįsti praeities duomenimis (Wen et al. 2022). Paprastas eksponentinis išlyginimas (angl. *exponential smoothing*) tinka situacijoms be sezoninių svyravimų ar tendencijų prognozuoti, kai reikia nustatyti tik paklausos lygį (Dekker et al., 2004). Regresinė analizė pagrįsti modeliai taip pat gali būti naudojami prognozavimui (Wang & Chaovalitwongse, 2011), tačiau labiausiai paplitę ekonometriniai modeliai. ARIMA modelis, apimantis AR, I ir MA komponentus, yra klasikinis ir plačiai paplitęs modelis, tinkamas stacionariems duomenims. Sezoniniams duomenims gauti naudojami SARIMA modeliai, o jei prognozavimo duomenys priklauso nuo kelių įvesties parametų, galima naudoti daugiamačius modelius, tokius kaip ARIMAX arba SARIMAX.

Kita kiekybinių modelių grupė yra ANNs pagrįsti modeliai. ANN yra duomenimis pagrįstas modelis, kuris išmoksta iš pačių duomenų, todėl jam nereikia matematinio modelio (Goodfellow et al., 2016). ANN, kaip dirbtinio intelekto modelių dalis, išpopuliarėjo (Falatouri et al., 2022) ir dažnai pranoksta įprastus modelius, nes gali išmokyti duomenimis pagrįstus modelius, jungiančius įvesties ir numatomus prognozės duomenis (Lecun et al., 2015). ANN modelius taip pat galima atnaujinti naudojant papildomus mokymus (He et al. 2019). ANN pagrįstiems modeliams reikia daug istorinių duomenų, tačiau ne visi proceso duomenys yra prieinami tyrėjams (Chen et al., 2018).

Pastaraisiais metais išaugo hibridinių modelių, jungiančių ekonometrinius modelius, Kalmano filtravimą ir AI modelius, diegimas (Shukur & Lee 2015). Kalmano filtrui naudoti reikalingas matematinis modelis. Mišrus modelis, pagrįstas įprastų ekonometrinių ir ANN modelių deriniu, gali veikti geriau nei bet kuris iš atskirai naudojamų modelių (Ruiz-Aguilar et al., 2014). Kartu didėja tokių sprendimų sudėtingumas, o praktinis pritaikymas tampa vis sudėtingesnis.

Vilutienė et al. (2020) apibrėžė reikalavimus, kuriuos turi atitikti prognozavimo modeliai: 1) jie turi būti pakankamai paprasti, kad juos būtų galima pritaikyti praktiškai; 2) stebimo reiškinio tendencijos ateityje turi išlikti tokios pat kaip ir stebėjimo laikotarpiu; 3) galimybė atnaujinti modelius naujais duomenimis; 4) modelis turi būti daugiamatis; atskiri modeliai gali tik atsitiktinai atspindėti galimą proceso raidą; 5) modeliai turi įvertinti pradinių duomenų stochastinį pobūdį; 6) vertinant įverčius reikšminga specialistų patirtis ir intuicija. Paskutinis punktas gali būti taikomas tik kai kuriems kokybiniais modeliams.

Yra keletas mokslinių darbų, skirtų krovininių vežimo prognozavimo tematikai. Sprendimai atsirado dėl sektoriaus skaitmenizavimo ir duomenų bazių atsiradimo. Batchelor et al. (2007) analizavo VAR, ekonometrinį ir vektorinį autoregresijos prognozavimo modelius. Nustatyta, kad trumpalaikių ir ilgalaikių sutarčių atveju ARIMA pasirodė tiksliau. Schramm ir Munim (2021) naudojo ekonometriją ir VAR modelius krovinio tarifams prognozuoti. Jie išsiaiškino, kad ARIMAX modelyje pateiktas logistikos pasitikėjimo indeksas labai pagerina prognozių našumą. Tačiau šis indeksas taikomas oro ir vandens transporto rūšims, o ne kelių transportui. Coyote Logistics (2022b) sukūrė krovininių vežimo tarifų prognozavimo modelį, pagrįstą metiniais pirkimais, sezonine paklausa ir rinkos pajėgumais. Jų daugiamatis modelis naudoja penkis rodiklius: sunkvežimių krovininių kieki, pramonės gamybą, importą, vartotojų išlaidas ir pardavimų bei atsargų santykį. Jis tenkina daugiamatę sąlygą, kurią paminėjo Vilutienė et al. (2020). Tačiau nėra detalių apie faktinį modelį, kuris naudojamas prognozavimui, prognozavimo tikslumo analizė taip pat neatliekama.

Kai kurie mokslininkai analizavo trumpalaikių sutarčių tarifų priklausomybę nuo sutartinių, ir atvirkščiai. Ankstyvuosiuose darbuose, skirtuose laivybos pramonei, Kavussanos et al. (2004a) rodo, kad sutarties tarifai 1 ir 2 mėnesius iki termino pabaigos paprastai yra nešališkos realių trumpalaikių tarifų prognozės. Tai atskleidžia ilgalaikių sutarčių prognozavimo problemą. Kavussanos et al. (2004b) teigia, kad sutartyje nustatytas frachto tarifas turi bendrą stabilizuojančią įtaką trumpalaikių tarifų svyravimui. Jasonas et al. (2021) nustatė trumpalaikės ir ilgalaikės sutarties priklausomybę. Kai trumpalaikiai tarifai didėja 20 %, turėtų būti tikimasi, kad bendri sutarčių tarifai per ateinančius kelis mėnesius padidės maždaug 4 %, jeigu kiti parametrai išliks nepakitę. Panašių rezultatų pasiekia

Coyote Logistics (2022a, b) sukurtas modelis, nuolat teikiantis sunkvežimių krovinių rinkos prognozes su trijų mėnesių prognozavimo horizontu. Pažymėtina, kad didžioji dalis krovinių vežimo keliais prognozavimo sprendimų (Jason et al., 2021, Coyote Logistics, 2022a,b, Hassan et al., 2020) atliekami JAV rinkai. Europoje vis dar kyla problemų, susijusių su duomenų prieinamumu. Visų pirma, nėra duomenų repozitorijų, kurie renka duomenis. Statistinių duomenų saugyklose duomenys pateikiami labai stipriai vėluojant. Pavyzdžiui, kai kurie šiame darbe naudojami įvesties duomenys pasirodo vėluodami iki 10 mėnesių, JAV analogiškai duomenys prieinami esant mažesniai nei 1 mėnesio vėlavimui.

Išnagrinėjus esamą literatūrą, tampa akivaizdu, kad ekonometriniai ir ANN modeliai yra plačiai naudojami prognozavimo uždaviniams transporte. Tačiau pagrindinis mokslinėje literatūroje aptinkamų prognozavimo modelių apribojimas yra tas, kad jie visų pirma yra skirti praeities laiko intervalams prognozuoti, kai įvesties rodikliai yra žinomi. Darbuose neatsižvelgiama į poreikį prognozuoti šiuos parametrus, o tai yra labai svarbu praktikoje. Su duomenimis susijusių iššūkių sprendimas yra labai svarbus Europos rinkai ir turi būti išspręstas, kad sukurti prognozavimo modeliai galėtų būti veiksmingai įgyvendinti realiuose scenarijuose.

Šioje disertacijoje nagrinėjami krovinių vežimo tarifų ir paklausos prognozavimo modeliai. Prognozavimo metodas yra sukurtas ir ištirtas.

2. Ilgalaikių krovinių tarifų ir paklausos prognozavimo metodika

ARIMA yra ekonometrinio modelio tipas, dažnai naudojamas laiko eilutės prognozuoti. Tokio tipo modeliai yra paprasti ir lengvai pritaikomi skirtingiems atvejams. ARIMA modeliai taikomi stacionariams duomenims, atliekant tam tikras matematines operacijas. Jei stacionarumo sąlyga neįvykdoma, naudojamas duomenų diferencijavimas. AR modelio lygtis (Kumar et al., 2021):

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t. \quad (S2.1)$$

MA modelio apibendrinta lygtis:

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q}. \quad (S2.2)$$

ARIMA modelio apibendrinta lygtis (Markevičiūtė et al. 2022):

$$y_t = c + \phi_1 y_{t-1} + \dots + \phi_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q}. \quad (S2.3)$$

ARIMA(p, d, q) modelis perrašytas:

$$\phi_p(B)(1-B)^d y_t = c + \theta_q(B)\varepsilon_t. \quad (S2.4)$$

Parametras B aprašomas:

$$B^k y_t = y_{t-k}. \quad (S2.5)$$

Nesezoninis AR polinomas:

$$\phi_p(B) = 1 - \phi_1(B) - \phi_2(B^2) - \dots - \phi_p(B^p). \quad (S2.6)$$

Nesezoninis MA polinomas:

$$\Theta_q(B) = 1 + \Theta_1(B) + \Theta_2(B^2) + \dots + \Theta_q(B^q). \quad (\text{S2.7})$$

Logistikoje dažnai pastebimas sezoniškumas; tokius uždavinius galima analizuoti įtraukiant sezoninius svyravimus į klasikinius ARIMA modelius, į sezoninius atsilikimus apibūdinančius parametrus. Sezoninis autoregresijos integruotas slenkamojo vidurkio modelis $SARIMA(p, d, q)(P, D, Q)^S$ išreikštas forma (Kumar et al. 2021):

$$\Phi_p(B^S)\phi_p(B)(1 - B^S)^D(1 - B)^d y_t = \Theta_q(B^S)\Theta_q(B)\varepsilon_t. \quad (\text{S2.8})$$

Sezoninis narys AR modelyje:

$$\Phi_p(B^S) = 1 - \Phi_1(B^S) - \Phi_2(B^{2S}) - \dots - \Phi_p(B^{PS}). \quad (\text{S2.9})$$

Sezoninis narys MA modelyje:

$$\Theta_q(B^S) = 1 + \Theta_1(B^S) + \Theta_2(B^{2S}) + \dots + \Theta_q(B^{QS}). \quad (\text{S2.10})$$

Kai prognozuojamas parametras priklauso nuo kitų parametrų, naudojamas ARI-MAX modelis:

$$\phi_p(B)(1 - B)^d y_t = c + \Theta_q(B)\varepsilon_t + \sum_{i=1}^n X_{i,t}\beta_i. \quad (\text{S2.11})$$

Sezoninis, t. y. SARIMAX modelis, pateiktas kaip:

$$\Phi_p(B^S)\phi_p(B)(1 - B^S)^D(1 - B)^d y_t = \Theta_q(B^S)\Theta_q(B)\varepsilon_t + \sum_{i=1}^n X_{i,t}\beta_i. \quad (\text{S2.12})$$

Ekonometriniai modeliai turi būti patikrinti modelio veikimo efektyvumui nustatyti (Kumar et al., 2021). Tai daroma naudojant Bajeso informacijos kriterijų (BIC):

$$BIC = k \ln(n) - 2 \ln(\hat{B}). \quad (\text{S2.13})$$

Kitas geriausio modelio parinkimo metodas yra Akaike informacijos kriterijaus (AIC) taikymas:

$$AIC = 2k - 2 \ln(\hat{B}). \quad (\text{S2.14})$$

Dėl konkrečios tiriamos užduoties duomenų rinkiniai yra nedideli. Todėl taikomas Akaike informacijos kriterijus, modifikuotas mažiems duomenų rinkiniams (AICs) (Markevičiūtė et al. 2022):

$$AIC_c = AIC + \frac{2k^2 + 2k}{n - k - 1} = 2k - 2 \ln(\hat{B}) + \frac{2k^2 + 2k}{n - k - 1}. \quad (\text{S2.15})$$

Prieš naudojant anksčiau aprašytus ekonometrinius modelius, reikia patikrinti laiko eilučių duomenų stacionarumą. Jei duomenys nėra pastovūs, duomenų diferencijavimas (vienkartinis arba dvigubas) daugeliu praktinių atvejų išsprendžia problemą. Paprastai išplėstinis Dickey–Fuller (ADF) testas naudojamas taikomojoje statistikoje ir ekonometrijoje, siekiant analizuoti laiko eilutes dėl stacionarumo. ADF tikrina nulinę hipotezę (H_0), kad duomenyse yra vieneto šaknis.

Dirbtiniai neuronų tinklai taikomi prognozavimo uždaviniams spręsti. Darbe šiai problemai spręsti parinktas MLP ANN. Šiame tyrime taikomas MLP turi vieną paslėptą

neuronų sluoksni. Kiekvienas neuronas turi svertinį ryšį su visomis įvestimis, o kiekvieno neurono išėjimas yra prijungtas prie išvesties neurono sluoksnio. Ryšio svoriai derinami mokymosi procese. ANN modelio trūkumas yra didelis skaičiavimo sudėtingumas, nes kiekvienam ryšiui reikia papildomo dauginimo. Šiam atvejo tyrimui duomenų kiekis yra gana mažas, todėl skaičiavimo resursai ir laikas yra maži. Hiperbolinio tangento (tanh) aktyvavimo funkcija buvo taikoma visiems šio tinklo MLP sluoksniams suaktyvinti.

3. Krovinių vežimo tarifų ir paklausos analizė naudojant sukurtus prognozavimo modelius

Šiame skyriuje gilinamasi į Europos krovinių vežimo keliais rinkos analizę. Rezultatų analizei pasirinkta kryptis iš Olandijos į Italiją. Sukurti ekonometriniai ir ANN modeliai, vertinamos prognozavimo paklaidos. Šioje dalyje siekiama ištestuoti naudojamų modelių efektyvumą fiksuojant krovinių vežimo tarifų ir paklausos dinamiką pasirinktoje kryptyje.

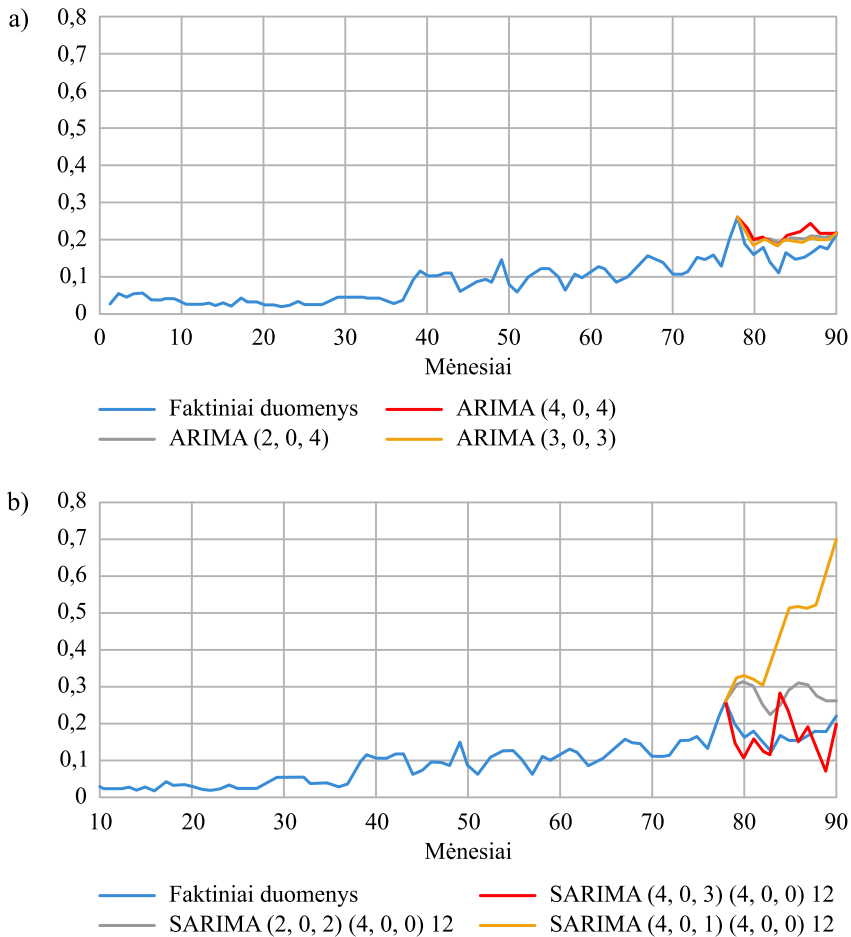
Pirmaisiais etapais paklausai prognozuoti buvo naudojami ekonometriniai modeliai, pateikti antrame skyriuje. Tyrimas atliktas įvertinus įvairias ARIMA modelio konfigūracijas, naudojant AICc kriterijų tiksliausių modelių atrankai. Buvo išbandyta keliasdešimt ekonometrinų modelių, pradedant nuo paprastų pirmojo lygio AR ir MA modelių iki ARIMA(4,2,4). Panašiai procedūra buvo pakartota SARIMA modeliams. Tiksliausi rezultatai buvo pasiekti naudojant 12 mėnesių sezoniškumą.

Trys tiksliausi ARIMA modeliai buvo atrinkti pagal minimalią AICc vertę, ta pati procedūra buvo pakartota naudojant SARIMA modelius. ARIMA modeliai pasižymi didesniu tikslumu, dauguma apskaičiuotų verčių patenka į patikimumo intervalus. Minimali RMSE reikšmė buvo gauta naudojant ARIMA(3,0,3) modelį, fiksuojant skaitinę reikšmę 0,0118. Svarbu pabrėžti bendrą visų ARIMA modelių tikslumą, maksimalus RMSE 0,0155. Naudojant SARIMA modelius tiksliausias rezultatas buvo gautas naudojant SARIMA(4,0,3),(4,0,0)12 modelį (RMSE = 0,01671).

Pasirinkus tiksliausius ekonometrinius modelius, duomenys buvo integruoti ir lyginami su faktiniais duomenimis (S1 pav.). Grafiniai modeliavimo rezultatai pateikti S3.1 paveiksle.

Kitame etape panaši procedūra buvo pakartota, siekiant išsiaiškinti tiksliausius sutarčių tarifų prognozavimo modelius. Panašiai modeliui derinti buvo naudojami 1–78 mėnesių duomenys, o testuoti – paskutinių 12 mėnesių (nuo 79 iki 90 mėnesių).

Pasirinktu laikotarpiu tiek ARIMA, tiek SARIMA modeliai davė nepatenkinamus rezultatus. Prognozuojami duomenys nepateko į prognozavimo intervalus. Vėliau gauti duomenys buvo integruoti, o rezultatai pateikti S2 paveiksle. Įdomu tai, kad įvertinus faktinius duomenis (S3.2 pav.), SARIMA modelis pranoko ARIMA pagal vežimo tarifų prognozę. Tačiau gauti rezultatai pabrėžia ekonometrinių modelių ribotumą prognozuojant krovinių tarifus nurodytu 12 mėnesių laikotarpiu (2021 m. liepos mėn. – 2022 m. birželio mėn.). Labai svarbu pažymėti, kad šis laikotarpis pasižymėjo padidėjusiu rinkos nepastovumu, kurį pirmiausia lėmė COVID-19 pandemija ir geopolitinis neapibrėžtumas. Todėl tokiomis neramiomis rinkos sąlygomis reikalingi alternatyvūs modeliai, kad galima būtų tiksliau prognozuoti sutarties tarifus.



S3.1 pav. Prognozuojama ir faktinė paklausa naudojant a) ARIMA ir b) SARIMA modelius

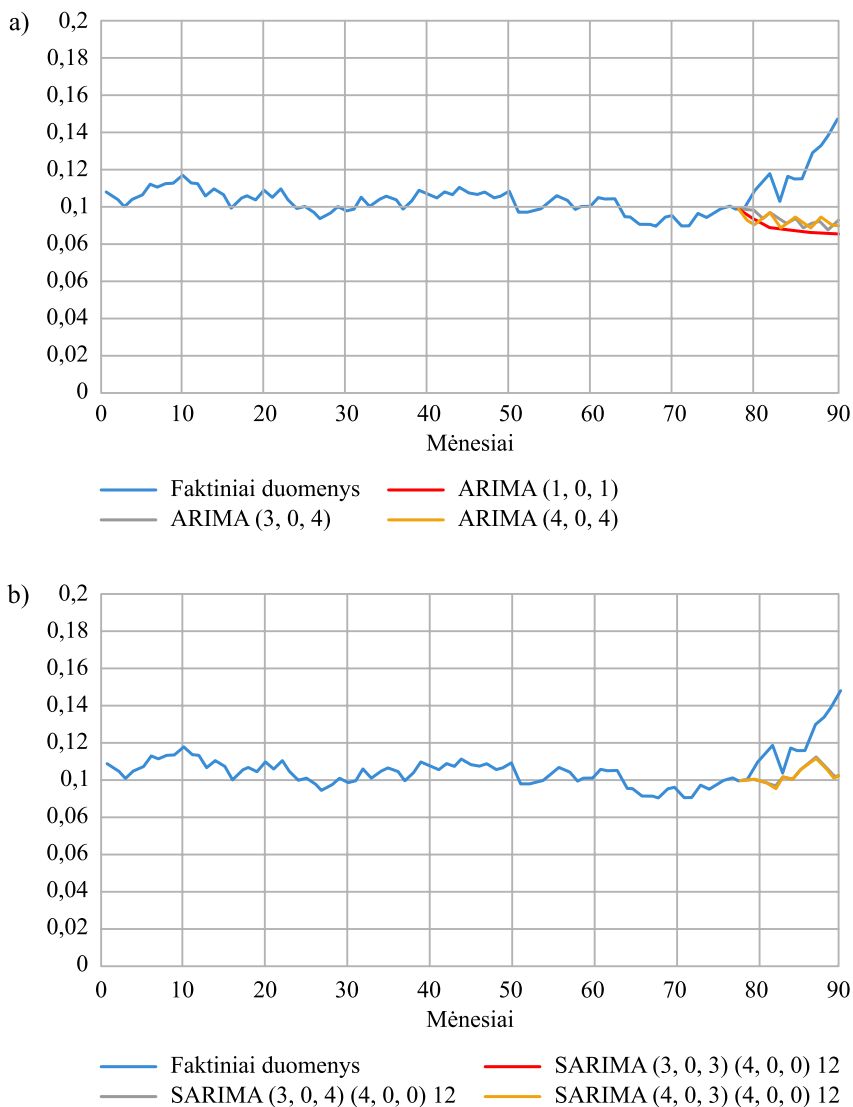
Buvo išbandyti įvairūs ARIMAX ir SARIMAX modelių deriniai. Pasiiekti rezultatai parodė, kad pasirinkto atvejo tyrimo metu ARIMAX modelis veikė tiksliau nei SARIMAX. Tiksliausi rezultatai pasiekti naudojant ARIMAX (1,0,2) modelį.

Tuo pačiu metu buvo sukurti MLP modeliai. Pagrindinis skirtumas naudojant ANN modelius yra tas, kad jiems negalioja pradinių duomenų stacionarumo sąlyga. Taigi duomenis galima naudoti be jokių papildomų procedūrų. Apmokyti buvo naudojamas Levenbergo–Marquardo algoritmas. Paslėptame sluoksnyje buvo keičiamas neuronų skaičius, o rezultatai lyginami naudojant MSE kaip pagrindinę metriką, kuri automatiškai apskaičiuojama naudojant MATLAB ANN programinę įrangą.

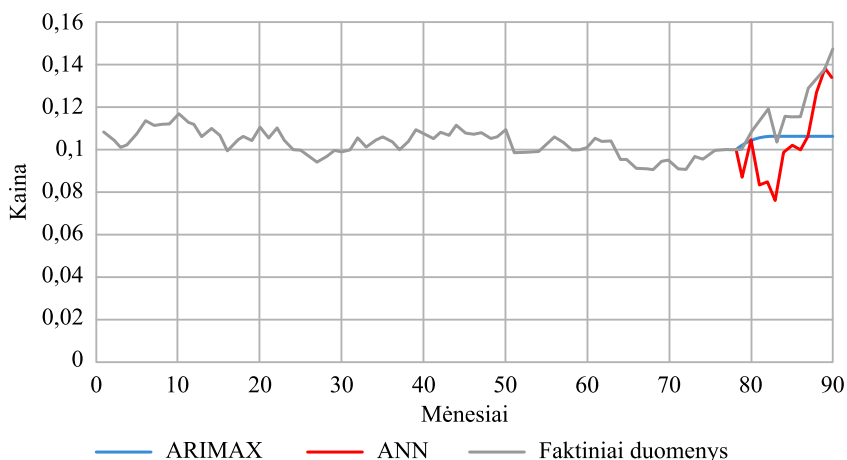
Tiksliausi rezultatai buvo pasiekti su 10 neuronų ANN paslėptame sluoksnyje. Naudojant daugiau neuronų, buvo pastebima ANN tendencija persimokinti. Mokymosi

duomenų rinkinio MSE reikšmės sumažėjo, tačiau naudojant testavimo duomenų rinkinį rezultatai buvo nepatenkinami.

Ilgalaikių sutarčių krovinių vežimo tarifų prognozavimas naudojant du tiksliausius modelius MLP ir ARIMAX pateiktas S3.3 paveiksle.



S3.2 pav. Prognozuojami ir esami tarifai naudojant a) ARIMA; b) SARIMA modelius



S3.3 pav. Prognozavimo ir faktiniai krovininių tarifų duomenys naudojant ARIMAX ir ANN modelį

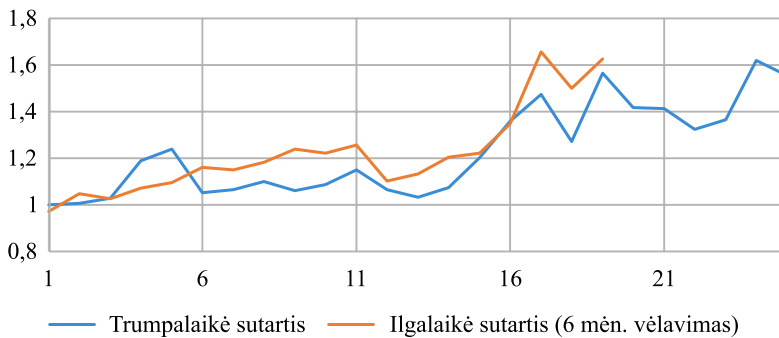
Mažiausioji pasiekta RMSE vertė yra 0,01934 naudojant ANN modelį. Matyti, kad ANN pateikia tikslesnius rezultatus prognozės laikotarpio pabaigoje. Pagrindinis siūlomo sprendimo įgyvendinimo trūkumas yra būtinybė naudoti penkis įvesties parametrus, o tai padidina klaidų galimybę.

Kitas bandymas atlikti vežimo tarifų prognozavimą buvo atskirti trumpalaikių ir ilgalaikių sutarčių tarifus. Deja, toks duomenų atskyrimas tiriamojoje įmonėje anksčiau nebuvo naudojamas ir pradėtas naudoti tik 2020 metais. Duomenys buvo renkami atskiriant ilgalaikių ir trumpalaikių sutarčių tarifus, galutinį rinkinį sudarė 24 mėnesių laikotarpis. Kryptis ta pati (iš Olandijos į Italiją). Po to rodikliai buvo lyginami naudojant koreliacijos koeficientą R kaip pagrindinę metriką. S1 lentelėje pateikti rezultatai. Mėnesio delsa 0 reiškia, kad pirmojo mėnesio ilgalaikės sutarties tarifai lyginami su pirmojo mėnesio trumpalaikės sutarties tarifais, mėnesio delsa 1 reiškia, kad antrojo mėnesio sutarties tarifai lyginami su pirmojo mėnesio trumpalaikės sutarties tarifais ir t. t. Matoma, kad pasiekama didžiausia koreliacija su 6 mėnesių vėlavimu. Ilgalaikių sutarčių vežimo tarifų kreivė atkartoja trumpalaikės sutarties tendencijas.

S3.1 lentelė. Koreliacijos koeficientas tarp trumpalaikių ir ilgalaikių sutarčių vežimo tarifų

Vėlavimas (mėn)	0	1	2	3	4	5	6	7	8	9
Koreliacijos koeficientas	0,71	0,64	0,54	0,61	0,76	0,72	0,86	0,78	0,72	0,50

Šėsių mėnesių vėlavimo atveju koreliacijos koeficientas yra lygus 0,86; šie duomenys pateikti S4 paveiksle.



S3.4 pav. Trumpalaikių ir ilgalaikių sutarčių tarifai esant 6 mėn. vėlavimui

Tyrimo metu buvo nustatyta, kad trumpalaikių sutarčių tarifai turi būti naudojami kaip pagrindinė metrika vertinant ilgalaikių sutarčių tarifus. Visų pirma, toks priėjimas turi būti taikomas esant rinkos nepastovumui, kai pažangesnių daugiamačių modelių tikslumas mažėja. Tačiau tai nėra universalus sprendimas visais atvejais. Kai kuriose kryptyse galimas 12 mėnesių sezoniskumas – pavyzdžiui, kryptys kur vaisiai ar daržovės bus pagrindinės vežimo prekės. Kadangi šie produktai yra sezoniniai, o sezonas kartojasi kas 12 mėnesių, nustatytas 6 mėnesių vėlavimas neveiks. Prieš taikant sukurta metodiką, reikia atlikti pirminį tyrimą ir nustatyti tendencijas konkrečiu atveju.

Atlikus šį tyrimą paaiškėjo, kad nėra universalaus prognozavimo sprendimo, kuris būtų tinkamas visiems rinkos scenarijams. Ekonometriniai modeliai gerai veikia prognozuojant paklausą, nes rinkos nepastovumo metu paklausa svyruoja mažiau, palyginti su tarifais. Šiame darbe ANN modelis demonstravo didesnę tikslumą nustatant krovinių vežimo tarifus, palyginti su rezultatais, gautais naudojant ekonometrinius modelius. Kitas svarbus aspektas, ypač Europos rinkoje, yra vėluojantis statistinių duomenų prieinamumas, palyginti su JAV rinka. Didelis rinkos nepastovumas yra reikšmingas trūkumas prognozavimo procese, dėl kurio gali atsirasti netikslumų įvesties parametruose, kurie patys yra prognozuojami. Trumpalaikių sutarčių tarifų analizė yra galinga priemonė sutarčių tarifams prognozuoti. Tačiau būtina atsižvelgti į vežamų prekių pobūdį. Pavyzdžiui, dėl sezoninių produktų šis metodas tampa mažiau veiksmingas. Sukurtas metodas leidžia sujungti sukurto ir ištirtus matematinius modelius į bendrą sistemą ir pasitelkiant taisyklėmis grįstą algoritmą spręsti prognozavimo užduotis.

Bendrosios išvados

1. Transporto įmonėms, užsiimančioms krovinių vežimu keliais, trūksta prognozavimo įrankių, nors sektoriaus skaitmenizavimas ir duomenų kaupimas suteikia galimybes juos kurti. Literatūros analizė rodo, kad ši problema nėra išspręsta, o mokslo bendruomenės siūlomi metodai dažniausiai orientuoti į kitus sektorius arba nesuteikia pakankamo prognozavimo horizonto.
2. Sukurtas metodas įmonės efektyvumui didinti jungia ekonometrijos, dirbtinių neuronų tinklų ir statistinius modelius. Ekonometrijos ir dirbtinių neuronų tinklų

modeliai buvo parinkti krovininių vežimo tarifams ir paklausai prognozuoti. Ištirti duomenų tipai ir šaltiniai, naudojami krovininių vežimo tarifams bei paklausai prognozuoti krovinių kelių transporto sektoriuje. Dirbant su duomenimis buvo atlikti visi būtini veiksmai, įskaitant duomenų normalizavimą, stacionarumo analizę ir rezultatų vertinimo metrikų taikymą.

3. Tyrimų metu buvo nustatyta, kad prognozuojant paklausą tiksliausių rezultatų pasiekta taikant ARIMA modelius. Nagrinėjamu atveju, vertinant vežimo kryptį iš Olandijos į Italiją, tiksliausi rezultatai gauti naudojant ARIMA (3,0,3) modelį, gauta mažiausioji RMSE vertė 0.0118. Kiek prasčiau pasirodė ARIMA (2,0,4) ir ARIMA (4,0,4) modeliai, kurių RMSE buvo 0,0127 ir 0,0155 atitinkamai. Visais atvejais prognozuojamos reikšmės visų 12 mėnesių pataikė į pasiklivimo intervalo rėžius. ARIMA (3,0,3) modelis nėra tiksliausias visoms kelionių kryptims. Kiekvieną kartą skirtingi ARIMA modeliai turi būti išbandyti kiekvienai nagrinėjamai kryptčiai. Eksperimentiniu būdu buvo nustatyta, kad praktiškai neverta naudoti sudėtingesnių modelių nei ARIMA (4,2,4).
4. Krovininių vežimo tarifų prognozavimas buvo sudėtingas dėl didelio COVID-19 poveikio ir geopolitinių veiksnių, sukėlusių didelių tarifų svyravimus tiriamuoju laikotarpiu (2021–2022 m.). Standartiniai ARIMA ir SARIMA modeliai šią užduotį atliko nepatenkinamai. Daugiakriteriai modeliai, tokie kaip ARIMAX, SARIMAX ir ANN, buvo panaudoti tarifams prognozuoti, įtraukiant įvesties duomenis: tonkilometrus, pramonės gamybą, importą, vartotojų išlaidas ir degalų kainas. Gauti tikslesni rezultatai, lyginant su anksčiau aprašytais ARIMA ir SARIMA modeliais, t. y. prognozuojamos vertės pateko į pasiklivimo intervalus. Iš ekonometrinių rezultatų tiksliausi rezultatai gauti naudojant ARIMAX (1,0,2) modelį. Rezultatai, gauti taikant dirbtinius neuronų tinklus, davė dar tikslesnius rezultatus, RMSE 0,01934. Šie rezultatai buvo pasiekti tik naudojant faktines papildomų įvesties duomenų vertes. Prognozuojamų šių parametrų verčių (papildomų įvesties duomenų) naudojimas praktikoje gali sukelti netinkamą prognozavimo modelių veikimą dėl netikslumų įvestyje.
5. Krovininių vežimo tarifų prognozavimas kelia iššūkių dėl didelio įvesties parametrų neapibrėžtumo. Atsižvelgiant į tai, siūlomas dvipakopis metodas vežimo tarifams prognozuoti. Pirma, rekomenduojama naudoti ANN modelius stabiliose situacijose. Antra, kai susiduriama su nepastoviomis rinkos sąlygomis, prognozavimo procese tampa labai svarbu analizuoti ir atsižvelgti į trumpalaikių sutarčių tarifus. Sujungiant ANN modelius, esant stabiliai situacijai rinkoje ir įtraukiant trumpalaikių sutarčių tarifų analizę, kai yra didelio nepastovumo rinkos sąlygos, sukuriami išsami ir patikima krovininių vežimo tarifų prognozavimo sistema.
6. Sukurtas metodas, apimantis skirtingus matematinius modelius ir jų parinkimą pagal taisyklėmis grįstą algoritmą, suteikia įmonėms reikšmingą galimybę valdyti realiuoju laiku, stebint rodiklius ir greitai prisitaikant prie pokyčių. Įmonių augimo ciklai suderinami su rinkos ciklais. Šis metodas integruoja atsinaujinančius istorinius duomenis, o prognozavimo modeliai nuolat tobulinami atliekant mokymo procesą. Ateities tyrimais turėtų būti siekiama integruoti kelis duomenų šaltinius, bendradarbiaujant su kitomis įmonėmis ir suinteresuotosiomis šalimis, siekiant sukurti išsamesnį duomenų rinkinį, didinant prognozių tikslumą.

Annexes

Annex A. External input data for multivariate models

Annex B. Comparison of open loop and closed loop ANN

Annex A. External input data for multivariate models

Normalised data		Fuel price	Consumer spending		Industrial production	
Year	Month		Netherlands	Italy	Netherlands	Italy
0.994074	0.083333	0.420713	-0.28971	-0.11195	0.186809	-0.04175
0.994074	0.166667	0.454632	-0.28971	-0.11195	-0.09319	-0.0677
0.994074	0.25	0.416295	-0.28971	-0.11195	0.413475	-0.08965
0.994074	0.333333	0.347555	-0.28971	-0.1377	0.106809	-0.07368
0.994074	0.416667	0.305685	-0.28971	-0.1377	0.166809	-0.0657
0.994074	0.5	0.305993	-0.28971	-0.1377	-0.09986	-0.02378
0.994074	0.583333	0.351375	-0.2639	-0.12912	-0.05986	-0.05372
0.994074	0.666667	0.366477	-0.2639	-0.12912	-0.01319	-0.07568
0.994074	0.75	0.404695	-0.2639	-0.12912	0.133475	-0.03975
0.994074	0.833333	0.345165	-0.23165	-0.12912	0.013475	0.010148
0.994074	0.916667	0.309099	-0.23165	-0.12912	0.180142	0.032104
0.994074	1	0.336339	-0.23165	-0.12912	0.146809	0.000168
0.994568	0.083333	0.308209	-0.28326	-0.12912	-0.21319	0.040088
0.994568	0.166667	0.304641	-0.28326	-0.12912	-0.39319	0.028112
0.994568	0.25	0.276271	-0.28326	-0.12912	-0.55319	0.016136
0.994568	0.333333	0.283356	-0.2639	-0.1377	-0.07986	0.052064
0.994568	0.416667	0.284066	-0.2639	-0.1377	-0.05986	-0.01979
0.994568	0.5	0.295215	-0.2639	-0.1377	-0.03319	0.02412
0.994568	0.583333	0.284743	-0.2639	-0.11195	0.240142	-0.00183
0.994568	0.666667	0.271998	-0.2639	-0.11195	0.120142	0.010148
0.994568	0.75	0.262796	-0.2639	-0.11195	-0.03319	-0.02378
0.994568	0.833333	0.188077	-0.18649	-0.09049	-0.03319	-0.03376
0.994568	0.916667	0.133	-0.18649	-0.09049	-0.19319	-0.01979
0.994568	1	0.003361	-0.18649	-0.09049	-0.09319	0.02412
0.995062	0.083333	-0.21775	-0.14778	-0.06474	0.133475	-0.0158
0.995062	0.166667	-0.14119	-0.14778	-0.06474	0.233475	0.012144
0.995062	0.25	-0.03456	-0.14778	-0.06474	-0.01319	0.042084
0.995062	0.333333	-0.02068	-0.10261	-0.01753	-0.36652	0.026116
0.995062	0.416667	0.031535	-0.10261	-0.01753	-0.31986	0.070028
0.995062	0.5	0.005086	-0.10261	-0.01753	-0.06652	0.016136
0.995062	0.583333	-0.05756	-0.11552	-0.00036	-0.17319	0.066036

Normalised data		Fuel price	Consumer spending		Industrial production	
Year	Month		Netherlands	Italy	Netherlands	Italy
0.995062	0.666667	-0.18978	-0.11552	-0.00036	-0.44652	0.06404
0.995062	0.75	-0.23475	-0.11552	-0.00036	-0.25986	0.052064
0.995062	0.833333	-0.2606	-0.09616	0.021098	-0.07319	0.062044
0.995062	0.916667	-0.26477	-0.09616	0.021098	-0.17986	0.080008
0.995062	1	-0.33768	-0.09616	0.021098	-0.43319	0.02412
0.995556	0.083333	-0.50145	-0.08326	0.033973	-0.09319	0.09398
0.995556	0.166667	-0.54537	-0.08326	0.033973	-0.01986	0.04408
0.995556	0.25	-0.45734	-0.08326	0.033973	0.206809	0.04408
0.995556	0.333333	-0.4405	-0.09616	0.033973	0.366809	0.062044
0.995556	0.416667	-0.34046	-0.09616	0.033973	0.213475	0.012144
0.995556	0.5	-0.26663	-0.09616	0.033973	0.173475	0.000168
0.995556	0.583333	-0.30053	-0.03165	0.055433	0.046809	0.01414
0.995556	0.666667	-0.34175	-0.03165	0.055433	0.186809	0.109949
0.995556	0.75	-0.31074	-0.03165	0.055433	0.066809	0.058052
0.995556	0.833333	-0.23998	0.039321	0.076892	-0.03319	0.070028
0.995556	0.916667	-0.25342	0.039321	0.076892	0.180142	0.076016
0.995556	1	-0.17	0.039321	0.076892	0.446809	0.155857
0.996049	0.083333	-0.07915	0.032869	0.115518	0.060142	0.028112
0.996049	0.166667	-0.07458	0.032869	0.115518	0.293475	0.07402
0.996049	0.25	-0.1097	0.032869	0.115518	0.126809	0.091984
0.996049	0.333333	-0.11566	0.097385	0.128394	-0.02652	0.04408
0.996049	0.416667	-0.15758	0.097385	0.128394	0.086809	0.091984
0.996049	0.5	-0.22713	0.097385	0.128394	0.093475	0.145877
0.996049	0.583333	-0.24609	0.161902	0.141269	0.113475	0.109949
0.996049	0.666667	-0.20758	0.161902	0.141269	0.180142	0.155857
0.996049	0.75	-0.16687	0.161902	0.141269	0.253475	0.080008
0.996049	0.833333	-0.11651	0.15545	0.154145	0.320142	0.084
0.996049	0.916667	-0.07088	0.15545	0.154145	0.200142	0.095976
0.996049	1	-0.06759	0.15545	0.154145	0.120142	0.125917
0.996543	0.083333	0.011184	0.232869	0.175604	0.353475	0.109949
0.996543	0.166667	-0.01729	0.232869	0.175604	0.093475	0.076016
0.996543	0.25	-0.03898	0.232869	0.175604	0.200142	0.085996
0.996543	0.333333	0.040295	0.252224	0.18848	0.153475	0.056056

Normalised data		Fuel price	Consumer spending		Industrial production	
Year	Month		Netherlands	Italy	Netherlands	Italy
0.996543	0.416667	0.152206	0.252224	0.18848	0.193475	0.062044
0.996543	0.5	0.187208	0.252224	0.18848	0.140142	0.04408
0.996543	0.583333	0.16454	0.265127	0.18848	0.020142	-0.00582
0.996543	0.666667	0.174481	0.265127	0.18848	0.126809	-0.00183
0.996543	0.75	0.223813	0.265127	0.18848	0.080142	0.046076
0.996543	0.833333	0.303995	0.284482	0.201355	0.060142	0.040088
0.996543	0.916667	0.304263	0.284482	0.201355	0.026809	-0.03376
0.996543	1	0.158036	0.284482	0.201355	-0.21986	-0.08965
0.997037	0.083333	0.052139	0.310289	0.205647	0.006809	0.022124
0.997037	0.166667	0.10272	0.310289	0.205647	-0.05986	0.042084
0.997037	0.25	0.158031	0.310289	0.205647	-0.04652	-0.00582
0.997037	0.333333	0.176892	0.348998	0.214231	-0.00652	-0.00382
0.997037	0.416667	0.219779	0.348998	0.214231	0.013475	0.01414
0.997037	0.5	0.140156	0.348998	0.214231	-0.08652	0.000168
0.997037	0.583333	0.118672	0.368353	0.218523	0.060142	0.010148
0.997037	0.666667	0.095664	0.368353	0.218523	0.000142	-0.00981
0.997037	0.75	0.118497	0.368353	0.218523	0.133475	-0.0158
0.997037	0.833333	0.129257	0.419966	0.218523	0.086809	-0.02578
0.997037	0.916667	0.127802	0.419966	0.218523	-0.05319	0.012144
0.997037	1	0.141079	0.419966	0.218523	-0.01986	-0.06171
0.997531	0.083333	0.206607	0.232869	-0.17204	0.000142	0.016136
0.997531	0.166667	0.098614	0.232869	-0.17204	0.040142	-0.02977
0.997531	0.25	-0.10483	0.232869	-0.17204	-0.05319	-0.5667
0.997531	0.333333	-0.31627	-0.58003	-0.78148	-0.46652	-0.84414
0.997531	0.416667	-0.39863	-0.58003	-0.78148	-0.51986	-0.39105
0.997531	0.5	-0.32084	-0.58003	-0.78148	-0.47986	-0.25732
0.997531	0.583333	-0.26241	0.013514	-0.19779	-0.23986	-0.14554
0.997531	0.666667	-0.25918	0.013514	-0.19779	-0.21319	0.01414
0.997531	0.75	-0.3155	0.013514	-0.19779	-0.32652	-0.07768
0.997531	0.833333	-0.33386	0.013514	-0.19779	-0.11319	-0.0178
0.997531	0.916667	-0.31445	0.013514	-0.19779	-0.05319	-0.0637
0.997531	1	-0.23253	0.013514	-0.19779	0.060142	-0.01979

Normalised data		Freight Intensity		Import	
Year	Month	Netherlands	Italy	Netherlands	Italy
0.994074	0.083333	0.577113	0.600583	-0.07582	-0.01389
0.994074	0.166667	0.577113	0.600583	-0.19285	-0.1199
0.994074	0.25	0.577113	0.600583	-0.05333	-0.06194
0.994074	0.333333	0.577113	0.600583	-0.16933	-0.11197
0.994074	0.416667	0.577113	0.600583	-0.05262	-0.07035
0.994074	0.5	0.577113	0.600583	-0.12689	-0.11823
0.994074	0.583333	0.577113	0.600583	-0.1246	0.026371
0.994074	0.666667	0.577113	0.600583	-0.27845	-0.45744
0.994074	0.75	0.577113	0.600583	-0.1493	-0.02994
0.994074	0.833333	0.577113	0.600583	0.003917	0.02079
0.994074	0.916667	0.577113	0.600583	-0.12444	-0.13541
0.994074	1	0.577113	0.600583	-0.18367	-0.22572
0.994568	0.083333	0.518081	0.116765	-0.15057	-0.11387
0.994568	0.166667	0.518081	0.116765	-0.28059	-0.15113
0.994568	0.25	0.518081	0.116765	-0.07764	-0.08197
0.994568	0.333333	0.518081	0.116765	-0.14138	-0.15053
0.994568	0.416667	0.518081	0.116765	-0.13489	-0.04756
0.994568	0.5	0.518081	0.116765	-0.14661	-0.08734
0.994568	0.583333	0.518081	0.116765	-0.04193	0.006654
0.994568	0.666667	0.518081	0.116765	-0.34148	-0.55697
0.994568	0.75	0.518081	0.116765	-0.08334	0.033104
0.994568	0.833333	0.518081	0.116765	-0.01271	-0.00049
0.994568	0.916667	0.518081	0.116765	-0.2041	-0.12889
0.994568	1	0.518081	0.116765	-0.22389	-0.24062
0.995062	0.083333	0.152412	0.019459	-0.43531	-0.17001
0.995062	0.166667	0.152412	0.019459	-0.4152	-0.13452
0.995062	0.25	0.152412	0.019459	0.01722	0.093606
0.995062	0.333333	0.152412	0.019459	-0.17432	-0.00753
0.995062	0.416667	0.152412	0.019459	-0.24258	-0.041
0.995062	0.5	0.152412	0.019459	-0.07305	0.113499
0.995062	0.583333	0.152412	0.019459	-0.14162	0.070714
0.995062	0.666667	0.152412	0.019459	-0.39999	-0.53011
0.995062	0.75	0.152412	0.019459	-0.21732	0.056677

Normalised data		Freight Intensity		Import	
Year	Month	Netherlands	Italy	Netherlands	Italy
0.995062	0.833333	0.152412	0.019459	-0.16767	0.002753
0.995062	0.916667	0.152412	0.019459	-0.22057	-0.04846
0.995062	1	0.152412	0.019459	-0.17812	-0.18528
0.995556	0.083333	-0.02789	-0.26694	-0.46706	-0.20237
0.995556	0.166667	-0.02789	-0.26694	-0.34837	-0.08931
0.995556	0.25	-0.02789	-0.26694	-0.23775	0.005704
0.995556	0.333333	-0.02789	-0.26694	-0.29626	-0.08173
0.995556	0.416667	-0.02789	-0.26694	-0.29674	-0.03909
0.995556	0.5	-0.02789	-0.26694	-0.14827	0.009177
0.995556	0.583333	-0.02789	-0.26694	-0.36967	-0.07439
0.995556	0.666667	-0.02789	-0.26694	-0.33665	-0.41449
0.995556	0.75	-0.02789	-0.26694	-0.1322	0.012662
0.995556	0.833333	-0.02789	-0.26694	-0.15065	-0.02652
0.995556	0.916667	-0.02789	-0.26694	-0.03528	0.054746
0.995556	1	-0.02789	-0.26694	-0.09364	-0.0902
0.996049	0.083333	-0.20044	-0.01108	-0.0466	0.010293
0.996049	0.166667	-0.20044	-0.01108	-0.11335	0.045067
0.996049	0.25	-0.20044	-0.01108	0.257857	0.279191
0.996049	0.333333	-0.20044	-0.01108	-0.16854	-0.09065
0.996049	0.416667	-0.20044	-0.01108	0.108914	0.260064
0.996049	0.5	-0.20044	-0.01108	0.040421	0.175059
0.996049	0.583333	-0.20044	-0.01108	-0.13624	0.099639
0.996049	0.666667	-0.20044	-0.01108	-0.05191	-0.30809
0.996049	0.75	-0.20044	-0.01108	-0.01912	0.091106
0.996049	0.833333	-0.20044	-0.01108	0.079775	0.158448
0.996049	0.916667	-0.20044	-0.01108	0.257144	0.219104
0.996049	1	-0.20044	-0.01108	0.048418	-0.02528
0.996543	0.083333	-0.21803	0.189803	0.23624	0.175172
0.996543	0.166667	-0.21803	0.189803	0.051031	0.065568
0.996543	0.25	-0.21803	0.189803	0.278444	0.280095
0.996543	0.333333	-0.21803	0.189803	0.095453	0.08328
0.996543	0.416667	-0.21803	0.189803	0.231331	0.288453
0.996543	0.5	-0.21803	0.189803	0.24107	0.275005

Normalised data		Freight Intensity		Import	
Year	Month	Netherlands	Italy	Netherlands	Italy
0.996543	0.583333	-0.21803	0.189803	0.18968	0.291517
0.996543	0.666667	-0.21803	0.189803	0.24107	-0.20853
0.996543	0.75	-0.21803	0.189803	0.192214	0.207363
0.996543	0.833333	-0.21803	0.189803	0.532938	0.44303
0.996543	0.916667	-0.21803	0.189803	0.383362	0.297626
0.996543	1	-0.21803	0.189803	0.148664	0.056931
0.997037	0.083333	-0.33027	-0.19912	0.382332	0.209803
0.997037	0.166667	-0.33027	-0.19912	0.177249	0.126751
0.997037	0.25	-0.33027	-0.19912	0.460406	0.273921
0.997037	0.333333	-0.33027	-0.19912	0.419865	0.192634
0.997037	0.416667	-0.33027	-0.19912	0.464128	0.347716
0.997037	0.5	-0.33027	-0.19912	0.249226	0.173652
0.997037	0.583333	-0.33027	-0.19912	0.357073	0.33278
0.997037	0.666667	-0.33027	-0.19912	0.157849	-0.27529
0.997037	0.75	-0.33027	-0.19912	0.338623	0.252608
0.997037	0.833333	-0.33027	-0.19912	0.530721	0.320909
0.997037	0.916667	-0.33027	-0.19912	0.432059	0.175549
0.997037	1	-0.33027	-0.19912	0.326271	0.02563
0.997531	0.083333	-0.42289	-0.39942	0.398644	0.225758
0.997531	0.166667	-0.42289	-0.39942	0.158166	0.117692
0.997531	0.25	-0.42289	-0.39942	0.282879	-0.10751
0.997531	0.333333	-0.42289	-0.39942	-0.23276	-0.48362
0.997531	0.416667	-0.42289	-0.39942	-0.25168	-0.38077
0.997531	0.5	-0.42289	-0.39942	0.112477	-0.13314
0.997531	0.583333	-0.42289	-0.39942	0.066155	0.02311
0.997531	0.666667	-0.42289	-0.39942	-0.13592	-0.45206
0.997531	0.75	-0.42289	-0.39942	0.247642	0.121512
0.997531	0.833333	-0.42289	-0.39942	0.259599	0.151104
0.997531	0.916667	-0.42289	-0.39942	0.29919	0.114638
0.997531	1	-0.42289	-0.39942	0.273297	-0.00405

Annex B. Comparison of open loop and closed loop ANN

Below, results for freight rate prognosis are provided analysing NI and IT2 destinations.

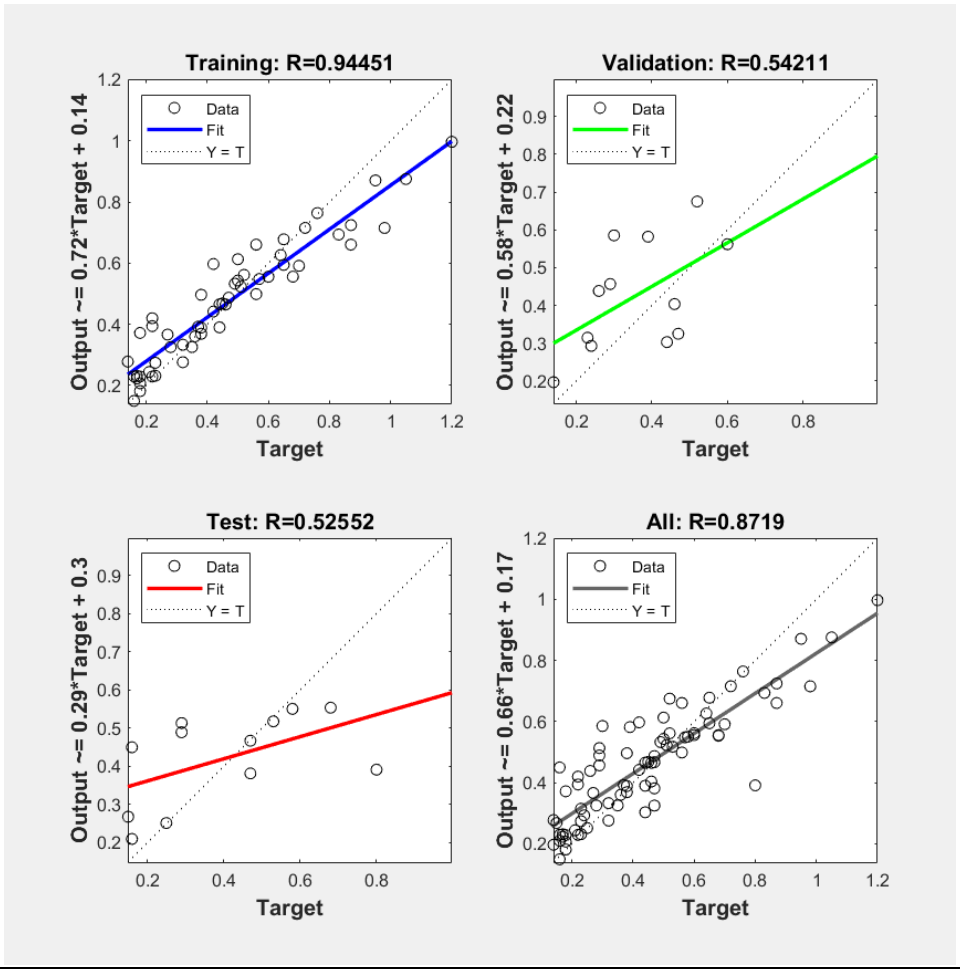


Fig. B1. Metrics using open loop neural network

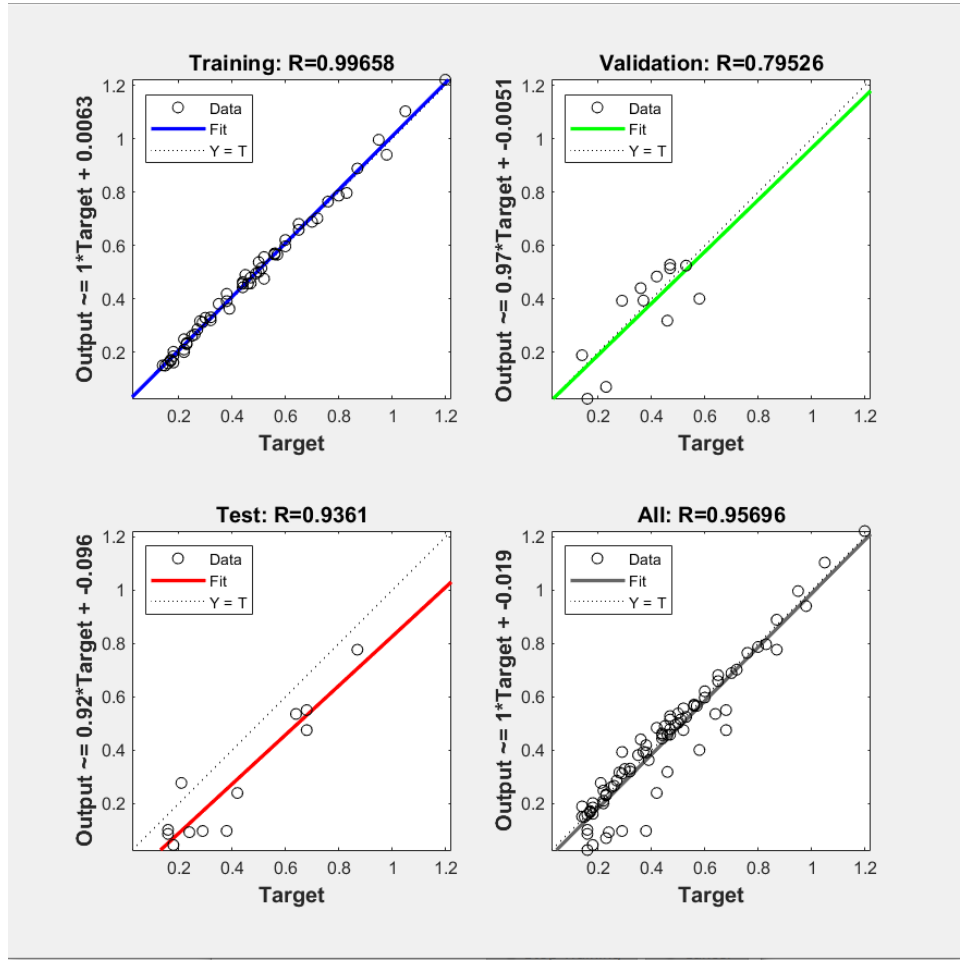


Fig. B1. Metrics using close loop neural network

Closed loop ANN outperforms open loop ANN, using correlation coefficient as the main metric.

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