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EFFICIENCY IMPROVEMENT IN ASSET-BASED FREIGHT TRANSPORTATION COMPANY

Summary. The logistics industry operates cyclically, requiring companies, especially those with tangible assets, to harmonise their growth strategies with market fluctuations. This paper explores the impact of market cycles on asset-based companies, highlighting the challenges and opportunities they encounter during both low and high cycles. During low cycles, growth constraints can lead to resource underutilization, operating at suboptimal costs, and significant financial setbacks. Conversely, high cycles often bring challenges related to delayed readiness and resource scarcity, hindering companies from fully capitalising on market opportunities and achieving strategic objectives promptly. By employing predictive models for demand and freight rate forecasting, companies can proactively manage their resources and investments to navigate through market fluctuations and gain a competitive edge. Leveraging digitisation and data-driven approaches presents new avenues for enhancing operational efficiency in the logistics sector. However, accurately forecasting demand and freight rates for full truckloads in road freight transportation remains a daunting task due to data complexity and variability. This paper seeks to tackle this challenge by proposing data-driven models to enhance effectiveness in the road freight transportation domain.

1. INTRODUCTION

The logistics industry operates within the cyclic nature of markets, requiring companies, particularly asset-based, to adapt their growth strategies to the changing dynamics of the market. During periods of low market activity, incorrect decisions stemming from growth strategies often lead to resource underutilisation, operational inefficiencies, and significant financial losses. Conversely, during market peaks, challenges such as delayed responsiveness and resource scarcity can hinder companies from fully capitalising on market opportunities and achieving strategic goals on time.

Employing mathematical models for demand and freight rate forecasting enables companies to make weighted management decisions, proactively allocate resources and investments, and effectively navigate through market fluctuations to gain a competitive edge.

The emergence of digitisation and data-driven methodologies presents promising avenues for enhancing operational efficiency within the logistics sector. However, accurately predicting demand and freight rates for full truckloads in road freight transportation remains challenging due to the complexity and variability of available data. As the largest asset-based road transportation companies still hold a relatively small market share [1, 2], relying solely on internal data may not suffice, and external data often comes with delays.

Consequently, the development of tools for practical applications is constrained by various limitations, including requirements for robustness and stringent requirements for available input data.

This paper aims to address these challenges by proposing an innovative data-driven approach to enhance effectiveness in the domain of road freight transportation.

The rest of the paper is divided as follows. In Section 2, a literature review is presented, the performance of supply chains and companies is analysed, and the difference between performance and efficiency is described. Forecasting of freight rates is analysed as a task for effectiveness improvement. In Section 3, methods used for forecasting are presented. In Section 4 results are provided and analysed. Finally, Section 5 concludes this paper.

2. RELATED WORKS

The performance of a supply chain can be measured using different metrics that fall into several categories: customer service [3], operational efficiency [4], financial [5], innovation and learning [6]. Customer service metrics might include on-time delivery percentage, cargo travel time, consistent quality of the service, and others, which may depend on the type of cargo defined by the customer. Operational metrics could involve warehouse or/and vehicle utilisation rates, and minimisation of empty kilometres. Previously profit was the overall objective of any logistics system [7] and the main financial metric. Currently, with changes in business models, situations have changed and a few metrics appeared, which are: cost per unit, total supply chain cost, and revenue of the company, all the time it depends on the case under investigation. Innovation and learning metrics could measure the rate of new product introduction or employee training levels [6].

Different indexes are used for performance measurement. The Logistics Performance Index (*LPI*) is one of the widely used Key Performance Indicators (*KPIs*) for performance measurement proposed by the World Bank [8]. It is based on 6 indicators:

1. The efficiency of the customs and border management clearance;
2. The quality of trade and transport infrastructure;
3. The ease of arranging completely 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.

Calculation of this index is based on surveys and often is criticised due to subjectiveness [9], there are proposals to improve the calculation methodology by adding statistical data. In any case, this index is used to compare countries, not companies.

The Supply Chain Operations Reference (*SCOR*) model, recommends 12 supply chain metrics for performance evaluation [10, 11]:

1. Delivery performance;
2. Fill rate;
3. Order fulfilment lead time;
4. Perfect order fulfilment;
5. Supply chain responsiveness;
6. Production flexibility;
7. Total logistic 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 main five groups described at the beginning of this section. Another way to measure supply chain performance is through the Average Logistic Index (*ALI*) [12]:

$$ALI = PEI(1 - SCCI), \tag{1}$$

where *PEI* is the Performance External Index, calculated by multiplying the Delivery Precision Index, Lead time Index, and Customer Satisfaction Index. *SCCI* is the Supply Chain Cost Index, calculated by summarising total supply chain cost divided by net sales. *ALI* should be high, which means closer to 1, or 100% than zero. This means that the company needs to have a low *SCCI*, at the same time as they have a high *PEI*. *ALI* can be calculated for all the companies involved in the supply chain. Some companies earn the most money with a low price and others with a high external performance. In some cases, a company can charge for excellent customer service. Value 0.4 of *ALI* in one company may be more successful than *ALI* 0.6 in another company [12].

It is important to separate performance and efficiency, according to the classification used for the calculation of the Organizational Performance Index (*OPI*) [13], the overall performance of organisations is measured in four main domains:

1. Effectiveness - the ability of the company to carry out programs to a high standard and continuously improve its operation, following its vision, mission, objectives, and goals.
2. Efficiency - the ability of an organisation to plan and budget for its interventions, with technical and financial efficiency analyses.
3. Relevance - the ability of an organisation to respond to the actual and current needs of its beneficiaries and to remain alert to any changes that might influence this capacity.
4. Sustainability - the ability of an organisation to ensure that its programs 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.

The main focus of this paper is on efficiency. Generally, efficiency can be described as minimising costs and maximising the output [14]. Beamon [15] provided another definition, efficiency is the measure of how well the resources expended are utilised. By employing predictive models for demand and freight rate forecasting, companies can proactively manage their resources and investments to navigate through market fluctuations and gain a competitive edge.

Forecasting can be performed using three main groups of techniques: qualitative, quantitative, and hybrid.

Qualitative approaches mostly are used to supplement quantitative forecasts, especially in situations involving the prognosis of the demand, for example during new product launches or market disruptions [16].

Quantitative forecasting methods include time series analysis, which involves examining historical data to identify patterns and trends [17]. Techniques such as moving averages, exponential smoothing, and autoregressive integrated moving average (*ARIMA*) models are commonly employed for short and long-term forecasting [18]. These methods provide a solid foundation for forecasting demand and resource requirements.

In recent years, the digitisation of the logistics sector has intensified. As a result, the implementation of machine learning algorithms has gained prominence as they can handle large datasets and capture complex patterns. Support vector machines, random forests, and Artificial Neural Networks (*ANN*) are among the machine learning techniques applied in supply chain forecasting [19]. These algorithms offer flexibility and accuracy, particularly in scenarios with nonlinear relationships and when datasets are available.

Furthermore, hybrid forecasting approaches, combining statistical quantitative and *ANN* techniques, have shown promising results. For instance, the combination of Autoregressive Integrated Moving Average (*ARIMA*) models with *ANN*, known as *ARIMA-ANN*, enhances forecasting accuracy by leveraging the strengths of both approaches [20].

There are several papers where forecasting tasks in the field of transportation were addressed [21-23]. However, some of them analyse only demand forecasting, and others do not take into account road freight transport, or provide a solution for the United States market, which may not be applied in Europe due to issues with data. In our previous research work [18] we showed that for demand forecasting *ARIMA* technique provides very good results, the main problem is with freight rates.

Analysing literature, it was found that performance improvement of the company and supply chain as a whole is an important topic, where efficiency increase is a separate task. Different indexes may be used for performance and effectiveness evaluation. Forecasting tools for demand and freight rate forecasting can increase company effectiveness. There are quantitative forecasting techniques that can be used for freight and demand forecasting in transportation. However, this task is not properly addressed in the literature and is not solved in asset-based road freight companies performing in Europe.

3. FORECASTING TECHNIQUES FOR EFFICIENCY IMPROVEMENT

Every business operates within its unique parameters, and road freight transportation is no exception. In this sector, the most significant costs for asset-based road freight companies are typically related to drivers and fuel. Additionally, expenses such as vehicle leasing, insurance, maintenance, tolls, vehicle taxes, and office overheads play a role. These costs vary across Europe; for instance, driver expenses can range from 17% to nearly 50%, while fuel prices can fluctuate between 25% and over 36% [1]. Another critical consideration is the nature of the cargo being transported, which can either entail a full truckload or partial shipments where multiple orders are consolidated to fill the vehicle. For this analysis, only full truckloads are examined. The origin and destination regions of the cargo also merit attention. Often regions are categorise based on the first two digits of *ZIP* codes. It's crucial to assess the likelihood of securing a follow-up order at the destination region. If satisfactory compensation is received for the current order but obtaining a subsequent order would entail a significant wait, it could result in financial losses. Similarly, driving a vehicle to the next point without any cargo can incur costs.

Furthermore, it's essential to consider the types of transportation agreements between customers and carriers, such as short-term spot agreements and long-term contracts. Long-term contracts, typically spanning one-year, present challenges, as inaccurate fuel price forecasts or economic downturns in the destination region can lead to losses. To enhance the effectiveness of asset-based transport companies, the development of forecasting tools for demand and freight rates is crucial.

Previous investigations showed that demand forecasting can be solved using econometric models. For non-seasonal time series data $ARIMA(p, d, q)$ can be formulated using the formula from [24]:

$$y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \varepsilon_t + \Theta_1 \varepsilon_{t-1} + \cdots + \Theta_q \varepsilon_{t-q}, \tag{2}$$

where y_t – current time-series value; c – intercept; ϕ_i – an auto-regressive model coefficient; y_{t-1}, $y_{t-2} \dots y_{t-p}$ – past time-series values; ε_t – model innovations (random error); Θ_q – the moving average polynomial. Also, the *ARIMA* model can be presented in a different form:

$$\Phi_P(B)(1-B)^d y_t = c + \Theta_q(B)\varepsilon_t, \tag{3}$$

where: $\Phi_P(B)$ – non-seasonal auto-regressive polynomial; $\Theta_q(B)$ – non-seasonal moving average polynomial; polynomial B is defined as the backshift operator, sometimes in literature it is called the lag operator:

$$B^k y_t = y_{t-k}. \tag{4}$$

In real-world cases one system parameter usually depends on others, using multivariate models the forecasting accuracy may be increased, ARIMA with explanatory variables *ARIMAX* can be used. *ARIMAX* model is described as follows:

$$\Phi_P(B)(1-B)^d y_t = c + \Theta_q(B)\varepsilon_t + \sum_{i=1}^{n} X_{i,t}\beta_i, \tag{5}$$

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

Before using the econometric methods described above, time-series data was tested for stationarity, and it was found that the data was not stationary. The Augmented Dickey-Fuller test was used to analyse time series for stationarity. Data differentiation solved an issue.

Together with econometric methods, *ANN* was used for investigation. Multilayer Perceptron (*MLP*) with one hidden layer of neurons is chosen to solve this problem. Each neuron has a weighted connection to all inputs and each neuron's output is connected to the output neuron layer. The connection weights are tuned during the learning process. The hyperbolic tangent (*tanh*) function was used to activate all *MLP* layers in this paper. Data since January 2015 were available and were used as input parameters for model training, with 78 samples of data. It covers a 6.5-year period before the middle of 2021. Data from months 79th to 90th (12 months) was used to analyse the accuracy of developed forecasting models.

4. RESULTS

In this section, the findings of the investigation are presented. Fig. 1 displays the forecasting of freight rates, covering the period from July 2021 to June 2022. Direction from the Netherlands to Italy was selected for investigation. External data such as tonne-km, industrial production, imports, consumer spending, and fuel prices were used as inputs to forecast 12 values for the subsequent 12-month period. Both the *ARIMAX* model and the *ANN-based* model were developed during this investigation. However, it was observed that the *ANN* model yielded superior results, aligning more closely with actual price fluctuations.

It is noteworthy that the input parameters were not themselves forecasted; instead, actual values of external data were utilised. Furthermore, only tonne-km was prognosed due to significant delays in obtaining actual data.

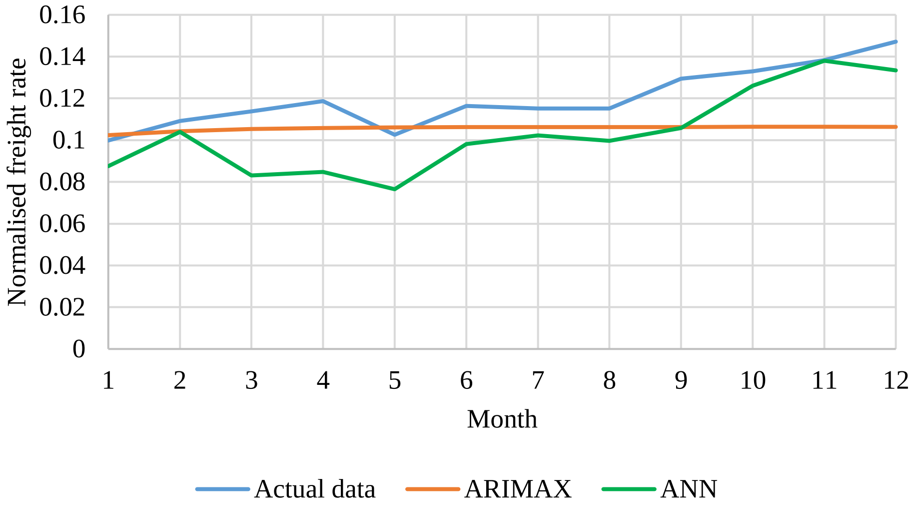

Fig. 1. Forecasting of freight rates using ARIMAX and ANN methods

For practical implementation, it is imperative to forecast all external data. Typically, this information is readily available, obviating the need to generate forecasts for the required data. Nonetheless, a key concern arises regarding the accuracy of forecasting the required parameters, which may not always meet standards. Fig. 2 depicts the forecasting of oil prices by *STEO* and *NYMEX* from January 2022 to December 2022. The prognosis was not entirely accurate. Incorporating such data into the investigation would likely have a detrimental effect on the precision of freight rate prognoses.

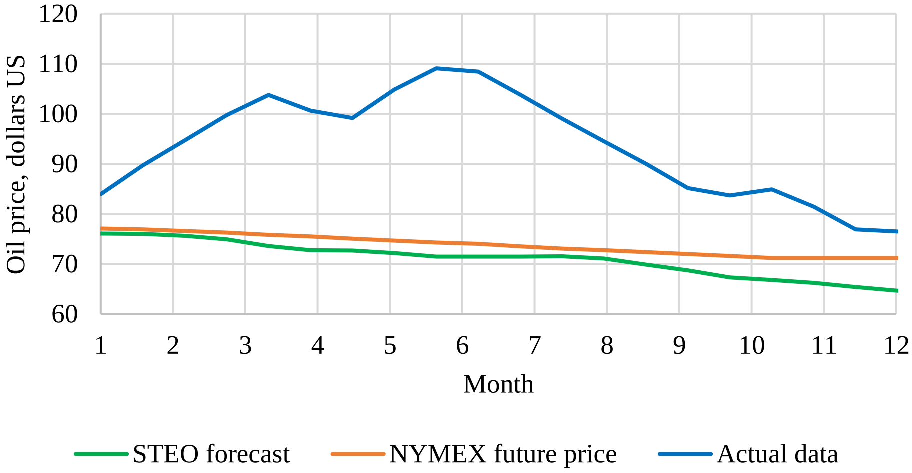

Fig. 2. Comparison of oil prices, forecasting VS actual data

ANN-based approaches provide the best results. However, are more complex, and require a lot of input data. There are a lot of challenges in receiving real-world data in the European market, and as a result application of *ANN-based* techniques is complicated.

In the subsequent stages, it was decided to analyse spot and contract rates separately. The hypothesis was that contract rates might correlate with spot rates, as proven in other sectors, such as the energy industry. However, there were issues with internal data, as previous records lacked differentiation based on contract type. Therefore, data categorised into spot and contract types has been available since July 2020.

Contract rates were then compared to spot rates with some delay. Specifically, month lag 1 means that the contract rate of month 2 is compared with the spot rate of month 1, etc. Introducing a lag parameter k meant that spot prices during month n were compared to contract rates during month $n+k$. Calculations were performed with lag values ranging from 0 to 12 months. The correlation coefficient was utilised for comparison.

As depicted in Fig. 3, 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 6 months.

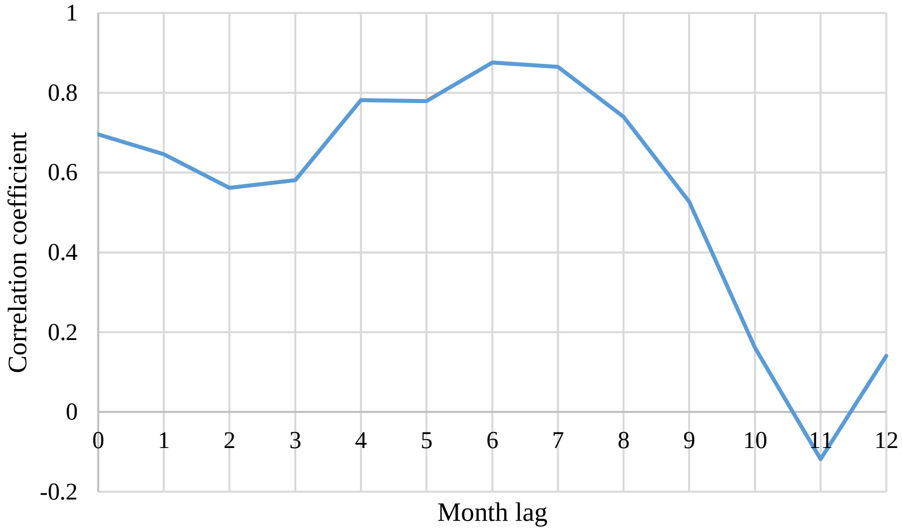

Fig. 3. Correlation coefficient between spot and contract rates, direction Netherlands-Italy

In Fig. 4 comparison of spot vs contract freight rates in the direction of Netherlands-Italy, with a lag of 6 months is presented. Normalised values of rates are used for representation, the spot price at month one was equal to 1, and all the rest values were compared to this value.

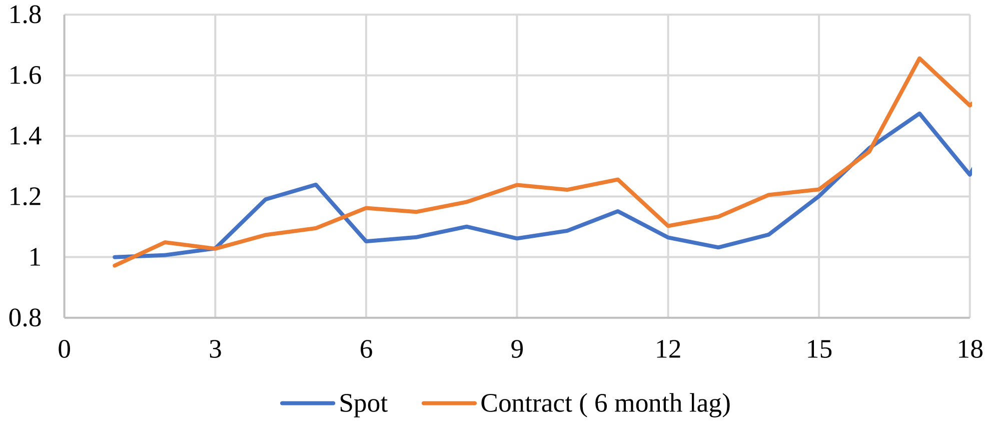

Fig. 4. Comparison of contract and spot rates with a 6-month lag, direction Netherlands-Italy

Similar trends were observed for other routes as well, as shown in Fig. 5, where the direction from Spain to Italy is analysed.

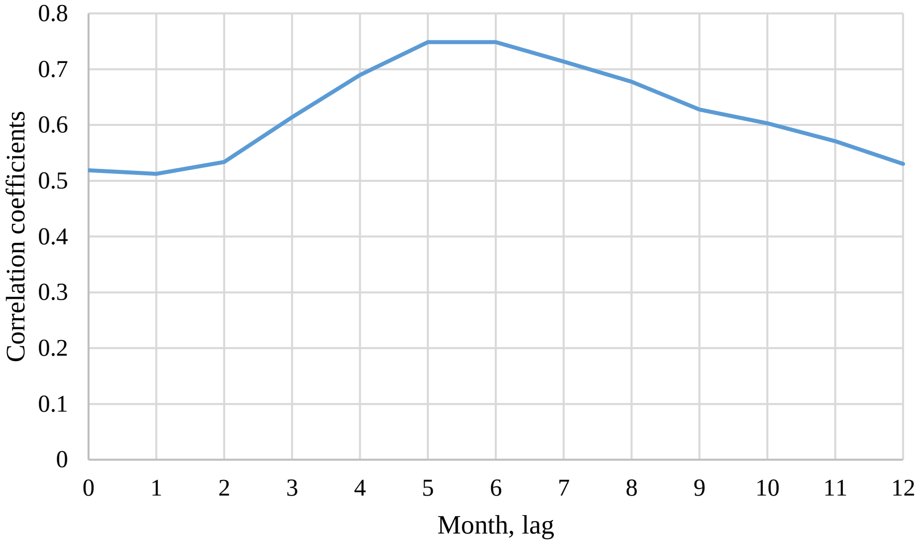

Fig. 5. Correlation coefficient between spot and contract rates, direction Spain-Italy

It can be observed (Fig. 5) that in the second case, the most optimal results were attained with a lag of 5 months. This suggests that the 6-month delay is not consistent, and the delay should be calculated individually for each destination.

5. CONCLUSIONS

The logistics industry operates within economic cycles, requiring companies to synchronise their growth strategies with market fluctuations. Understanding and adapting to these cycles is paramount for sustained success and enhanced operational efficiency. Central to this task is the forecasting of demand and freight rates, a critical aspect of logistics management. While previous studies have demonstrated the efficacy of econometric models for demand forecasting, the landscape is markedly different when it comes to predicting freight rates. The utilisation of more intricate econometric models incorporating external input parameters holds promise as a potential solution. However, challenges persist concerning input data, necessitating practical proposals for application.

In the investigation, a decision was made to segregate spot and contract prices. The findings reveal that contract rates tend to mirror spot rates with a discernible delay. Specifically, a dependency between these parameters was observed, with contract rates trailing spot rates by 5-7 months. Notably, the determination of this delay analysis of real-world data across various destinations needs to be performed.

A notable drawback of this approach is the limitation of prognostication to a 5-7 month horizon, unlike other data-driven methods offering forecasts for up to 12 months. Consequently, a combination of methodologies must be employed to address this limitation and facilitate problem-solving. Future studies will delve deeper into this area to explore potential solutions and refine forecasting techniques.

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