Estimating the demand for railway freight transportation in Kazakhstan: a case study

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Abstract

Accurate demand forecasting is essential for effective resource planning in organizations. In railway freight transportation, many factors can influence future volume and turnover, and traditional expert methods may no longer meet the requirements of the time. This article compares the accuracy of demand forecasts made using two different methods with the actual results. The theoretical research methods used are autoregressive integrated moving average (ARIMA) and expert methods. The results are compared using percentage mean absolute error (MAPE) and mean absolute error (MAE). The study found that time series analysis using ARIMA can significantly improve the accuracy of demand forecasts for railway freight transportation in Kazakhstan. The comparison of the results shows great promise for the use of time series analysis in improving demand forecasting quality. The implementation of time series analysis techniques can benefit the largest enterprises in Kazakhstan, including those in the transportation industry. By improving the efficiency of demand forecasting, organizations can better plan their operations, resulting in improved resource allocation and overall business success. Thus, this study suggests that time series analysis should be integrated into the practice of enterprises to improve their demand forecasting capabilities.

Keywords. demand forecasting, railway freight transportation, regression analysis, quality assessment of forecasts.

JEL codes: R41

1 Introduction

Demand estimates are crucial for effective planning and decision-making in any organization, providing key input for various departments such as marketing, production, distribution, and finance, to support short-to-long term forecasts (Punia, Shankar, 2022). Despite the complexity and execution of forecasting processes across different businesses, the main purpose remains the same: to obtain a fairly accurate estimation of future demand for a product or service based on historical data and the current state of the environment, including political, social, and economic factors, to plan and organize businesses accordingly (Merkuryeva et al., 2019).

In the case of transport companies, forecasting future demand for transport services is critical for success and provides basic input for planning and control of functional areas such as transport operations planning, marketing, and finance (Milenković et al., 2018). One such company is Joint Stock Company “National Company “Kazakhstan Temir Zholy” (KTZ), a transport and logistics holding engaged in rail transportation, with its main sources of income coming from income generated by freight and passenger transportation. KTZ's corporate portfolio includes 44 organizations, and its main subsidiaries and structural organizations operate in the segments "Main railway network services", "Rail freight transportation", "Passenger rail transportation," and "Freight cars operations." The length of railway lines (unfolded length) is more than 21 thousand km, the fleet of freight cars is about 46 thousand units, the fleet of passenger cars is more than 2 thousand units, and the fleet of locomotives is more than 1.8 thousand units. The company is the country's largest employer (over 112,000 employees).

In 2021, the cargo turnover amounted to 233 billion t-km, exceeding the level of 2020 by 0.7%. Income from freight traffic increased by 11.5% compared to the fact of 2020, mainly due to an increase in freight turnover by 0.7%; changes in the exchange rate (Swiss franc) for the calculation of income from transit traffic; increase in income from changes in the average level of tariff increases, etc. The share of income from freight traffic is 89% of the total income of the KTZ.

The demand for railway transportation services is primarily assessed based on the volume of cargo transportation in tons multiplied by the distance transported in kilometers, known as freight turnover. The tariff freight turnover, which takes into account the shortest distance between the points of loading and unloading, is used to calculate demand and becomes the basis for calculating future revenues from freight traffic.

To generate accurate forecasts, a variety of forecasting methods have been developed based on two well-known approaches: qualitative and quantitative. Qualitative methods, such as Executive opinions, Delphi technique, Sales force polling, and Customer services, generate forecasts based on judgments or opinions, while quantitative techniques rely on historical data forecasts (e.g., Naive method, Trend Analysis, Time Series Analysis, Holt’s and Winter’s models) or associative forecasts that identify causal relationships between variables using Simple, Multiple or Symbolic regression. Mixed or combined models enable the integration of both approaches (Borucka et al., 2021).

2 Literature review

Numerous research centers have conducted studies on constructing models to describe demand for rail services. For instance, Milenković et al. (2018) utilized the SARIMA model to predict monthly passenger flows on Serbian railways, while Roos et al. (2017) developed a dynamic Bayesian network-based approach to forecast short-term passenger flows on the Parisian urban rail network. Zhang et al. (2019) utilized a LSTM (Long short-term memory) network to analyze the transport performance of the urban rail transit network in Beijing, while Tang et al. (2017) combined a backpropagation neural network and the glow-worm swarm optimization algorithm to analyze passenger traffic. Namiot et al. (2018) described methods of forecasting passenger traffic in Moscow based on network topology analysis. However, most of these studies are limited to the analysis of cities, where increasing demand for rail transport is due to urban sprawl and deteriorating road transport conditions, such as congestion, traffic jams, and increased vehicle emissions leading to smog.

Fewer models have been developed to assess the functioning of larger national rail networks, such as those in Sweden and India (Andersson et al. 2017; Prakaulya et al. 2017). Furthermore, Markovits-Somogyi (2011) reviewed the application of data envelopment analysis (DEA) in the transport sector, investigating the inputs and outputs used in 69 DEA models reported in the literature. Although DEA is a tool for evaluating the performance of decision-making units, it is sensitive to measurement errors and noise in data.

Most research in this area focuses on a specific mathematical model without considering alternative solutions, leading to a low effectiveness of proposed methods of analysis. However, Banerjee et al. (2020) propose various models to forecast demand in the regular passenger transport industry and compare them to choose the best one.

Demand analyses and forecasts are crucial for developing transport policies, but demand data are not always available due to a lack of appropriate mathematical models for generating forecasts. Thus, it is essential to analyze railway systems in various countries to select appropriate methods for forecasting transport performance. The objective of this study is to identify parameters of a mathematical model of rail cargo transport performance based on historical data to make reliable forecasts of future demand. In this paper, we investigate the national (Kazakhstan) railway system, propose several models dedicated to this type of empirical data, establish selection criteria, identify the best model, and assess its accuracy and effectiveness.

3 Methodology

The planning of demand for cargo transportation by rail at KTZ currently relies heavily on the expertise of an individual in cargo transportation marketing who uses MS Excel and MS Access to make forecasts. The Marketing and Tariff Policy Department (hereinafter, MTPD) is responsible for demand forecasting and uses expert estimates and extrapolation to make their predictions. However, extrapolation has significant drawbacks as it does not consider changes in the external environment and the impact of external factors on the forecast. This method relies heavily on the judgment and experience of the MTPD expert, which can be time-consuming and may result in a deterioration in the quality of forecasts.

The MTPD expert spends most of their time on routine operations, such as downloading data from KTZ systems, uploading to personal computers, generating summary tables, preparing data, generating reports, graphs, tables, preparing paper questionnaires for shippers, and manually processing survey results. They use Microsoft Excel and Microsoft Access to process large data arrays, but their capabilities for processing large data arrays are severely limited, which can lead to simplifications and averaging, and thus, a deterioration in the quality of forecasts.

To improve the process of demand forecasting, KTZ needs to automate the process using modern software to analyze data and solve problems. This would allow the expert to spend more time on analysis rather than compilation of statistics. Special software products such as SAP HANA (High-Performance Analytic Appliance) and IBS SPSS (Statistical Package for the Social Sciences) can be used to analyze data and solve problems due to the high performance of database management systems and built-in libraries of algorithms, which would save time on mechanical tasks. KTZ has decided to conduct a pilot study or experiment on the planning and forecasting of future traffic and freight turnover using specialized software that processes and analyzes large volumes of data and compares the quality of the forecast made by the software with the forecast made by the MTPD experts using the methodology described in the methods section of this article.

The experiment consisted of multiple stages. Initially, data from KTZ systems on the volume and turnover of freight railway transportation were collected for each nomenclature of goods UTSNG (unified tariff and statistical nomenclature of goods) and 13 aggregated nomenclatures of goods, as well as for all types of communication. This data was analyzed and forecasted using a specialized program.

Next, macroeconomic indicators that could potentially correlate with the historical volumes of transportation or cargo turnover were collected and loaded into the program. The program was designed to assess the degree of correlation between the data on volume and turnover over a five-year period with macro indicators, and to determine the presence or absence of correlation between them.

A model was created and tested using 2012-2016 test data, and then it generated a monthly forecast for 2017. This forecast was compared with the 2017 results and with the forecast made by MTPD experts in 2016 for 2017, separately for each aggregated nomenclature of cargo and for each type of communication.

Finally, the quality of the forecast was assessed using the MAPE or MAE method. The MAPE/MAE indicator was derived for both the manual forecast made by MTPD experts and for the forecast made by specialized software by comparing the forecast with the actual value of the time series. MAE was used if the actual value of the indicator was zero.

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{|Z(t)-X(t)|}{Z(t)} * 100\% \quad (1)$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|Z(t)-X(t)| \quad (2)$$

SPSS, a specialized software for data analysis and forecasting, was selected due to its top ranking in the Gartner 2017 Data Science platform category. With numerous statistical and mathematical forecasting methods available in SPSS, the challenge was to determine the most effective approach. Consequently, three techniques - ARIMA model, neural net model, and autofitting - were utilized, and the best model was ultimately chosen.

In the design study, two models were utilized: a neural network and ARIMA. The neural network is a simplified model of the nervous system in living organisms, which uses interconnected processing elements to represent neurons. The network is trained by presenting it with records and adjusting the weights until it can accurately predict outcomes. After training, the neural network can be used to predict outcomes for new observations. On the other hand, ARIMA is used to create autoregressive integrated moving average models for time series simulations. It is capable of modeling trend and seasonal components, and can include predictor variables in the model. By setting the order of autoregressive, differential, and moving average components, as well as their seasonal equivalents, the ARIMA model can be fine-tuned. However, determining optimal values for these components can be time-consuming and require extensive trial and error.

The experiment involved analyzing five years of monthly historical data on traffic volume and freight turnover for 13 aggregated cargo categories using SPSS. The data included information on the Unified Tariff and Statistical Nomenclature of Goods (UTSNG) cargo code, as well as the country of consignor and consignee. Additionally, macro indicators from various countries with trade relations with Kazakhstan, such as production volume, export/import volume, prices, and exchange rates, were loaded into the system in a monthly format for the same period as the historical data.

The correlation between the macro indicators and historical data was analyzed using special tools in SPSS, and the impact of predictors on historical data was estimated. The model was trained on the training sample and tested on the test data of 2012-2016. Using three different methods (ARIMA, neural net, and auto selection), a forecast was created by month for 2017 for all 13 cargo nomenclatures by traffic volume and cargo turnover. The best forecast generated by SPSS (ARIMA) was compared with the actual data for 2017 and the MTPD forecast generated by the old method described in the introduction section of the article.

4 Results and Discussion

The main results of the research work and the experiment in graphical form are presented below.

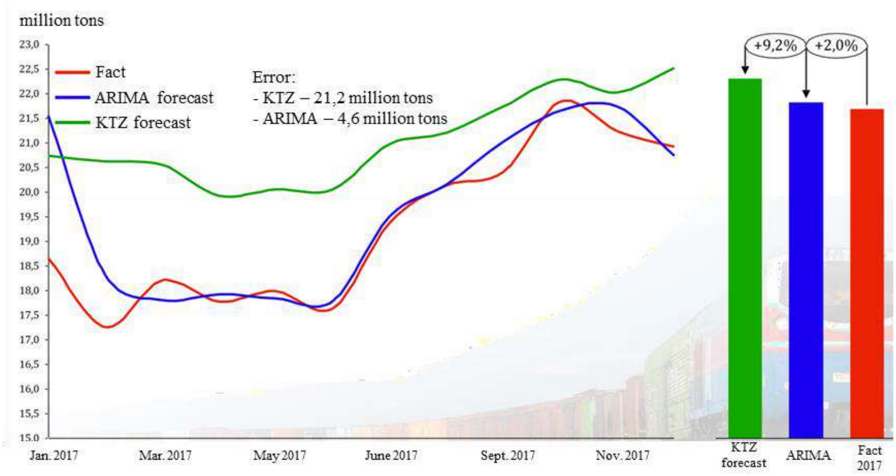

Figure 1: Cumulative traffic forecast for all nomenclature and message types compared to the 2017 fact and MTPD KTZ forecast.

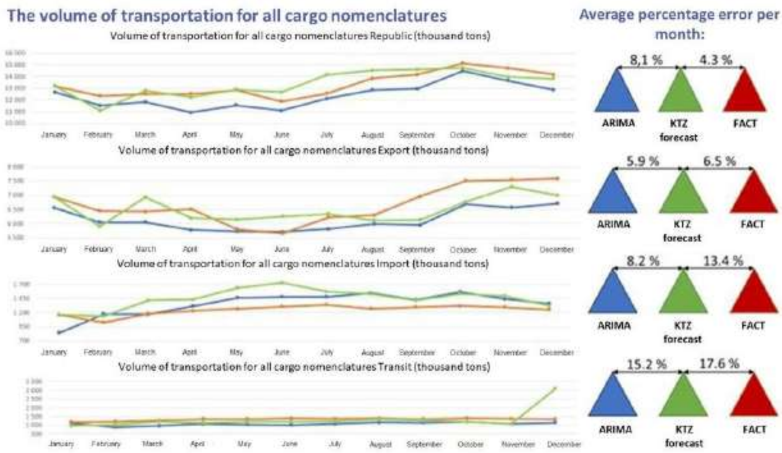

Figure 2. Thousand tones traffic forecast compared to 2017 actual: where ARIMA forecast is the forecast made by IBM SPSS Modeler by applying the ARIMA model to the forecast; FACT is actual data for 2017; KTZ forecast is a forecast made by MTPD experts in 2016 for 2017 using an expert method

Figure 2 shows that the MAPE score of the forecast made using ARIMA is better for all types of traffic except domestic traffic. In Import, especially in the second half of 2017, the blue line and the green line almost coincide, that is, the forecast turned out to be almost equal to the fact, while the red line, symbolizing the forecast made manually by MTPD experts, lies much lower than the fact. In general, it can be seen that MTPD experts somewhat overestimated the forecasts for transportation within the country and in exports, while imports were underestimated. In transit, everything is relatively “stable”, even seasonal fluctuations are not felt, but in December there is an “anomalous” jump in traffic volumes.

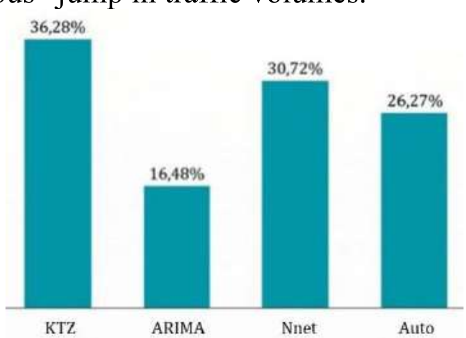

Figure 3. The indicator of the average monthly error per month for all types of cargo, all types of forecasts (volume and cargo turnover), all types of messages when using various forecasting methods

Figure 3 shows that the ARIMA predictive model gives much better results compared to even the neural network model. However, the neural network model (Nnet in Figure 4) requires more “fine” tuning, and has the potential for improvement.

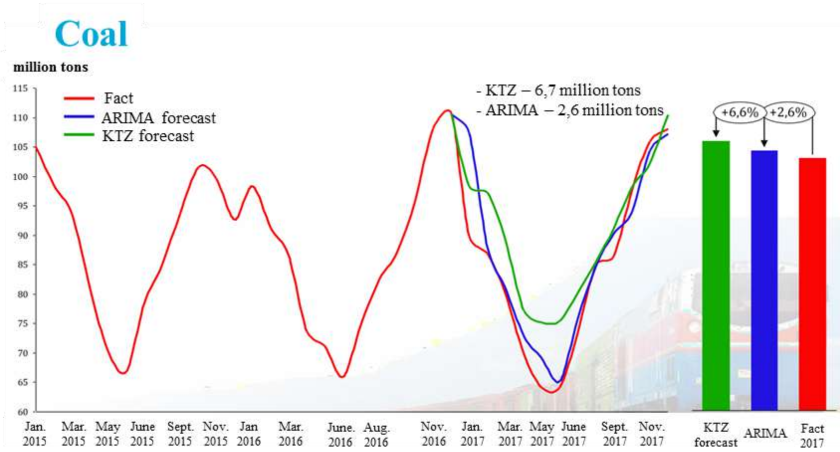

Figure 4: Comparison of fact with MTPD experts' forecast and SPSS simulation result (ARIMA model) on the total coal transportation volume in all modes of communication.

The ARIMA model provided a more accurate forecast for coal traffic, which is the main freight transported by KTZ. This is due to the high correlation between traffic volumes and macro indicators, as well as the seasonality of coal traffic. IBM SPSS Modeler's "predictor screening" feature can help identify the most important predictors for accurate forecasting. By using data on the correlation between specific predictors and traffic volume, along with forecasts from leading agencies, the quality and accuracy of the forecast can be greatly improved. By utilizing data that demonstrates a correlation between particular predictors and traffic and cargo turnover volume, which includes predictions from global and national agencies, it is feasible to enhance the precision and quality of the forecast considerably. For the purpose of this study, 260 indicators were collected from diverse sources of data (such as national statistical agencies of Kazakhstan's trading partners, global statistical agencies like Bloomberg, BMI Research, Reuters, and others). To perform an accurate correlation analysis, macro indicators with the right format and frequency, which matched the historical traffic data period and frequency (monthly data), were acquired. This resulted in more than 15,000 values for all predictors or a monthly data set for a five-year period (60 values) being loaded into the IBM SPSS interface for each predictor. Through a specific tool, IBM SPSS automatically detected the existence of a correlation and the degree of influence of predictors on traffic volume or cargo turnover and compiled a list of up to 5-7 predictors that have the best correlation with the predicted indicators. This allowed for a focus on seeking predictions for specific macro indicators, saving valuable research time.

Using the methods and models described above has several advantages for KTZ's planning system. Firstly, it reduces the time for making forecasts and plans from 3 months to a maximum of 3-5 days, saving more than 1,000 man-days or 8,000 man-hours of work. Secondly, it allows for the development of many more forecasting scenarios, considering various scenarios of economic sectors' development. Thirdly, it presents an opportunity to reduce the average monthly error in forecasts from 36% to a potentially ambitious 10% or less. This will enable more accurate forecasting of KTZ's freight revenues and variable costs, which are dependent on freight performance. Fourthly, it enables more accurate calculation of the volume of demand and timing of purchases and deliveries of diesel fuel and electricity. Finally, combining the advantages of automation and MTPD experts' knowledge can result in significant progress in the speed and quality of demand forecasts and overall business planning at KTZ.

Here are the main areas for improvement when using a forecasting system with the aforementioned models and methods (ARIMA):

1. IBM SPSS forecasting results were found to be inferior to KTZ forecast results in some cases due to inadequate data for forecasting certain goods and message types, such as low volumes of crude oil transportation in import and transit. The accuracy of the forecast in any system for data analysis and forecasting depends on the availability and quality of data. In cases where historical data is insufficient, the "expert" forecasting method may be the only alternative.

2. Although the system can generate automatic forecasts, corrections by an expert may still be necessary. Only an expert can fully comprehend the forecast, evaluate its reasonableness and compare it with insider information that they may have from the largest shippers in the industry. Any changes made by an expert to the "automatic" forecast in the system must be documented and saved for future system training.

3. The study only utilized 260 predictors, which may not be sufficient for accurate forecasting. The quality of the forecast can be influenced by the number of predictors used, and a larger number of predictors can potentially improve the accuracy of the forecast. However, the quantity and frequency of macro- and microeconomic indicators by sectors of the economy in the Republic of Kazakhstan are quite limited, which is a natural limitation of the system.

4. Maintenance and updates are required for any data analysis and forecasting system to receive and upload new traffic data and predictors, which can be time-consuming and financially demanding. The benefits of using the system should outweigh the costs of maintaining it.

5 Conclusion

The aim of the study was to evaluate the accuracy of two forecasts for freight transportation in comparison to actual data for Kazakhstan Temir Zholy (KTZ). The study used historical data from 2012 to 2016, and macroeconomic indicators from Kazakhstan and its trading partners, which were loaded into IBM SPSS Modeler for analysis and forecasting. The forecasts generated by SPSS were compared to both the actual data for 2017 and the forecast data created by MTPD experts in 2016 for 2017, for all types of cargo and services in terms of tonnes of traffic and tonne-kilometres of freight turnover. The study found that modern mathematical and statistical models, such as SPSS, produced comparable results to those created by MTPD experts, especially for those goods and types of communication with complete, uninterrupted data and with historical transportation volume over the previous five years.

The study's conclusions suggest that modern mathematical and statistical models should be implemented in Kazakhstan's largest enterprises, including the transport industry. The experiment demonstrated that using these methods in practice for data analysis and forecasting can save up to 8,000 man-hours of work for MTPD experts, allowing them to concentrate on analysis rather than manual data processing. The experiment used real data, and the results were presented to KTZ management, leading to the launch of the "Integrated Planning System" project. The study's methodology, results, and recommendations were implemented in practice at KTZ.

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