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Improvement of the demand planning system for freight transportation on the mainline railway transport

Abstract.

Object. Demand forecasting is a vital step for optimal organization resource planning. Many factors may influence the future volume and turnover of railway freight transportation. The quality of forecasts made by expert methods no longer meet the requirements of the time. The purpose of this article is to compare the accuracy of the forecasts by two different methods with the fact.

Methods. This article uses theoretical research methods, such as auto regressive integrated moving average (ARIMA) and expert methods for forecasting and comparing the results using the percentage mean absolute error (MAPE) and mean absolute error (MAE).

Findings. The results of the comparison show great promise for using time series analysis to improve the quality of the demand forecasts for railway freight transportation in Kazakhstan.

Conclusions. Time series analysis can be introduced into the practice of the largest enterprises in Kazakhstan, including in the transportation industry. These techniques can significantly improve the efficiency of enterprises through better planning of their operations.

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

Introduction

Demand estimates act as a primary input for effective planning and decision making in any organization. A firms marketing, production, distribution, and finance departments use short-to-long term forecasts to support different decisions. Being such a pivotal input to business decision-making, the quality of forecasts is very important (Punia, Shankar, 2022).

Demand forecasting is an integral part of business process management. Despite complexity and execution of forecasting processes across different businesses, the intended purpose stays the same: obtaining a fairly accurate estimation of future demand for a product or service given historical data and the current state of the environment (e.g., political, social, economic) to plan and organize businesses accordingly (Merkuryeva et al., 2019).

Forecasting of future demand for transport service represent important element of success for a transport company. Forecasting also provides basic input for planning and control of functional areas including transport operations planning, marketing and finance (Milenković et al., 2018).

Joint Stock Company “National Company “Kazakhstan Temir Zholy”” (hereinafter referred to as KTZ) is a transport and logistics holding engaged in rail transportation. The sole shareholder is JSC “Samruk-Kazyna”, which delegates the general management of the group's activities to the KTZ's Board of Directors. The sole shareholder of JSC “Samruk-Kazyna” in turn is the Government of the Republic of Kazakhstan.

KTZ's corporate portfolio of assets at the end of 2019 included 56 organizations, including 1 organization in trust management.

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The main subsidiaries and structural organizations of the KTZ operate in the segments “Main railway network services”, “Rail freight transportation”, “Passenger rail transportation” and “Freight cars operations”.

KTZ's main sources of income are income from freight and passenger transportation. The share of income from freight transportation is 86% of total income and consists of all components that provide transportation activities: services of the main railway network, locomotive traction services, freight commercial work and the provision of wagons.

The length of railway lines (unfolded length) is more than 21 thousand km, the fleet of freight cars is about 54 thousand units, the fleet of passenger cars is more than 2 thousand units, the fleet of locomotives is more than 1.6 thousand units. KTZ is the country's largest employer (over 115,000 employees).

Transportation is the basis for obtaining the revenue of a freight carrier. In freight railway transport in Kazakhstan, the volume of applications is almost equal to the volume of traffic. Therefore, the volume of cargo transportation in tons assess the demand for the services of a railway carrier, as well as the volume of cargo transportation in tons, multiplied by the distance transported in kilometers, the so-called freight turnover. At the same time, when calculating demand, it is precisely the tariff freight turnover that is taken into account, in which the tariff (that is, the shortest) distance between the points of loading and unloading is taken and multiplied by the volume of traffic. Freight turnover, in turn, becomes the basis for calculating future revenues from freight traffic, or, in other words, income from the main activity of freight transportation.

A variety of forecasting methods have been developed based on two well-known approaches to forecasting: qualitative and quantitative. Correspondingly, qualitative methods such as Executive opinions, Delphi technique, Sales force polling and Customer services generate forecasts based on judgements or opinions, while quantitative techniques may be grouped under historical data forecasts, e.g., Naive method, Trend Analysis, Time Series Analysis, Holt’s and Winter’s models, or under so called associative forecasts which identify causal relationships between variables using Simple, Multiple or Symbolic regression. In addition, mixed or combined models enable integration of both approaches (Borucka et al., 2021).

Literature Review

Multiple research centers have conducted studies on constructing models to describe demand for rail services. For instance, Milenković et al. (2018) employed 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. In another study, Zhang et al. (2019) utilized a LSTM network to analyze the transport performance of the urban rail transit network in Beijing. Meanwhile, Tang et al. (2017) presented a method that 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 (hereinafter, DEA) in the transport sector, investigating the inputs and outputs used in 69 DEA models reported in the literature. DEA is a tool for evaluating the performance of decision-making units, but it has a drawback of being sensitive to measurement errors and noise in data.

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

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 the railway systems of 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.

Methods

The current process of planning of demand on cargo transportation by rail completely depends on a person — an expert in the field of cargo transportation marketing who makes his forecasts using MS Excel and MS Access solutions. KTZ's Marketing and Tariff Policy Department (hereinafter, MTPD) is responsible for demand forecasting in KTZ. The following methods are used in demand forecasting:

1) Expert estimates based on an assessment of the current moment and development prospects. MTPD managers form a forecast by analyzing the established fact of transportation for several years, studying the factors that have influenced freight transportation in past periods, forecasts of major shippers (if available), and opinions of leading experts in the industries to which the range of cargo being transported relates.

2) Extrapolation — distribution of established in the past trends for the future period (extrapolation is used for prospective calculations of transportation of consignors who are not included in the surveyed group).

Thus, the main scientific method used for forecasting by MTPD staff is extrapolation. The other methods are expert, empirical, and depend on the judgment and experience of the MTPD expert. Extrapolation as it is known in mathematics and statistics is a special type of approximation, in which the function is approximated outside a given interval, rather than between given values. In other words, extrapolation is an approximate determination of values of a function f(x) in points x lying outside the interval [x0, xn] by its values in points $x0<x1<...<xn$. In a more general sense, extrapolation is the transfer of conclusions made about some part of objects or phenomena to the whole set of these objects or phenomena, as well as to some other part of them. The method of linear extrapolation is most often used.

However, this method used by MTPD experts has significant drawbacks, namely extrapolation does not consider changes in the external environment and the impact of external factors on the forecast. For example, changes in the exchange rate of the national currency to foreign currencies can have a strong impact on the volume and geography of transportation, but the extrapolation method does not take this into account.

The following conclusions can be drawn from the description of the current process of planning and forecasting freight demand:

1) MTPD expert is the key link in the process at all stages of forming the freight demand forecast. In the scientific literature, this method of forecasting is called an expert method. “Expert” in Latin means “experienced”. The forecast is based on the opinion of a specialist or team of specialists based on professional, scientific and practical experience. Expert methods are applied in the following cases: if the object of research is extremely simple or, on the contrary, in case of extreme complexity of the object of prediction, its novelty, uncertainty of formation of some essential features, insufficient completeness of information and impossibility of complete mathematical formalization of the process of solving the problem set. The main principle underlying the methods of individual expert evaluations is the maximum possibility of using individual abilities of the expert. Since, when forecasting demand, MTPD experts must deal with a rather large amount of available and complete data on transportation in the past, the expert method of forecasting, as follows from the previous narrative, is not optimal.

2) MTPD experts spend most of their time on such operations 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. That is, most of the MTPD expert's working time is spent on routine operations.

3) Processing of large data arrays from various KTZ systems is carried out in MS Excel or MS Access, capabilities of which for processing large data arrays are severely limited. For example, MS Excel does not allow to create tables with more than 1 048 576 rows and 16 384 columns, while the analysis by thousands of cargo codes from the unified tariff and statistical nomenclature of goods (further — UTSNG) by hundreds of stations of departure and destination and by hundreds of shippers may potentially create the need for tables with tens of millions of rows and columns. In addition, MS Excel and MS Access are limited in the number of available libraries for forecasting methods, so MTPD experts use only the extrapolation method available in MS Excel. The lack of technical capability of the MTPD expert to perform the most detailed analysis of the input historical information and the inability to use many other methods of mathematical or statistical analysis besides extrapolation leads to the need for simplifications, averaging and, consequently, to a deterioration in the quality of forecasts.

There is a logical conclusion — it is necessary to automate the process of demand forecasting based on modern software and thus accelerate the process of getting and loading data, analysis of large arrays of data using a variety of methods, but not to replace the expert with the program, but to increase productivity and speed of the expert. It is necessary for the expert to spend more time on the analysis, rather than on the compilation of statistics. This requires the use of special software products such as SAP HANA, IBS SPSS, and others to analyze data and solve problems, due to the high performance of database management systems (hereinafter — DBMS) and built-in libraries of algorithms, in which computing and processing data occurs in a matter of seconds, which saves time on mechanical tasks.

KTZ 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 with the forecast made by the MTPD experts using the methodology described in the methods section of this article.

The experiment was divided into several stages:

1. The actual historical data on the volume and turnover of freight railway transportation from 2012 to 2016 by month for each nomenclature of goods UTSN Gand 13 aggregated nomenclatures of goods and for all types of communication (export, import, transit and domestic traffic) were loaded from the KTZ systems into a specialized program for analysis, data research and forecasting.

2. Macroeconomic indicators were found and loaded into a specialized program (in fact, 260 indicators in the right format and with the right periodicity of data were collected), which could potentially correlate with the historical volumes of transportation or cargo turnover. To assess the degree of correlation between the data on volume and turnover over a five-year period with macro indicators, it was required that all macro indicators should also be found monthly. That is, the so-called granularity of the data had to be observed. The presence or absence of correlation between macro indicators and historical volumes of transportation and historical cargo turnover had to be assessed.

3. A model was created and tested on test data for 2012-2016, and then the model automatically generated a monthly forecast for 2017, which was then compared with the 2017 results and with the forecast made by MTPD experts in 2016 for 2017. The comparison was made for each aggregated nomenclature of cargo and for each type of communication (republic, export, import and transit) separately and in the aggregate for loading and cargo turnover.

4. The assessment of the quality of the forecast was carried out according to MAPE — mean absolute percentage error or MAE — mean absolute error, because these are the most common methods of assessment used in forecasting and checking the quality of forecast models. Formulas for calculating MAPE and MAE are presented below, where Z(t) is the actual value of the time series and X(t) is the forecast value. MAE is applied if the actual value of the indicator is zero. We compared the forecast with the fact and derived the MAPE/MAE indicator both for the manual forecast made by MTPD experts and for the forecast made by specialized software.

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

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

IBM SPSS Modeler (hereinafter referred to as SPSS) was chosen as a specialized software for data analysis and forecasting, because IBM product was ranked first in the category of Data Science platforms in the Gartner ranking in 2017.

Since many statistical and mathematical forecasting methods are available in SPSS, there was an additional task to choose the best method among those available for use in SPSS. As the result, forecasting was done using three approaches — ARIMA model (integrated autoregressive moving average model, model and time series analysis methodology), neural net model (Nnet, neural network, neural network) and autofitting (a combination of neural network methods, C&R tree, CHAID model, linear regression and support vector mechanism), from which the best model was selected further.

Models used in the design study.

Neural network. Neural networks are simplified models of the nervous system of living organisms. The basic units are called neurons and are usually grouped into layers. A neural network uses a simplified model of how the human brain processes information. Neural networks work by counting many interconnected processing elements, which represent an abstract version of neurons. The neural network is trained by looking at records; for each record, the neural network generates a prediction and, if the prediction is incorrect, adjusts the weights. The process is repeated many times, and the accuracy of the predictions gradually improves until one of the stopping criteria is triggered. At the beginning all weights are random and neural network responses to input signals are likely to be meaningless. The neural network is trained. Examples, for which output values are known, are repeatedly presented to the neural network, and each time its response is compared with the known response. The information from this comparison is fed back into the neural network, gradually changing the weights. As it learns, the neural network begins to produce responses that more and more accurately reproduce the known response. After training, the neural network is applied to future observations for which the outcome is unknown.

ARIMA. ARIMA can be used to create an autoregressive integrated moving average model suitable for fine-tuning time series simulations. ARIMA models provide more sophisticated methods for modeling trend and seasonal components than exponential smoothing models and allow (as an additional advantage) to include independent (predictor) variables in the model. Using the ARIMA method it is possible to fine-tune the model by setting the order of autoregressive, differential and moving average, as well as the seasonal equivalents of these components. Determining optimal values for these components manually can be time-consuming with extensive use of trial and error.

Description of Experiment Progress.

Historical traffic volume and freight turnover data for 13 aggregated cargo nomenclatures over a five-year period (2012 to 2016), presented on a monthly scale, were loaded into SPSS. For each aggregated nomenclature of goods combinations were selected — Unified Tariff and Statistical Nomenclature of Goods (UTSNG) cargo code, country of consignor and country of consignee. Then macro indicators from various countries that have trade relations with Kazakhstan were found and loaded into the system, such as the volume of production of coal, oil, ore, electricity, etc.; the volume of export/import of goods; prices for various types of raw materials; exchange rates against local currencies. All macro indicators are found in a monthly format for the same period as the historical data on transportation loaded into SPSS. Using special tools in SPSS, the presence and degree of correlation relations between macro indicators (predictors) and historical data were analyzed, and the impact of predictors on historical data was estimated. Then the model was trained on the training sample and tested on the test data of 2012-2016, and then formed a forecast by month for 2017 for all thirteen cargo nomenclatures by traffic volume and cargo turnover using three different methods (ARIMA, neural net and auto selection), of which the best was the ARIMA forecast. The best forecast generated by SPSS (ARIMA) was compared with the fact for 2017 and the MTPD forecast generated by the old method described in the Introduction section of this article.

Results

The main results of the research work and the experiment in graphical form are presented below. In Figure 1, we see three lines on the graph that show a comparison of freight traffic for all nomenclatures of goods and all types of cargo: the forecast of experts of the MTPD KTZ (green line), the forecast using ARIMA (blue line) and the actual volume of traffic in 2017 (red line). The Figure 1 clearly shows that the blue line of the ARIMA monthly forecast for the volume of freight transportation and the red line of the actual volume of freight transportation practically coincide starting from the third month of 2017. At the same time, the green line differs significantly from the fact. The value of the MAPE indicator for the forecast of experts of the MTPD KTZ was 9.2%, while for ARIMA — 2.0%, which indicates a significant excess of the quality of the ARIMA forecast over the expert forecast.

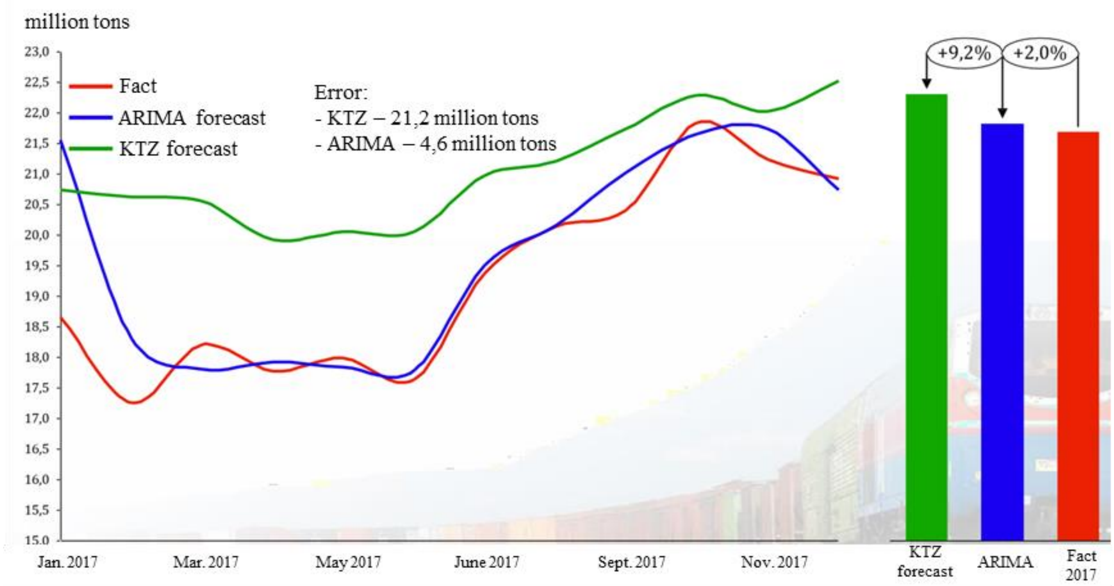

Figure 1: Cumulative traffic forecast for all nomenclature and message types compared to the 2017 fact and MTPD KTZ forecast.

Note – compiled by the author based on data on historical traffic volumes obtained from KTZ internal information systems

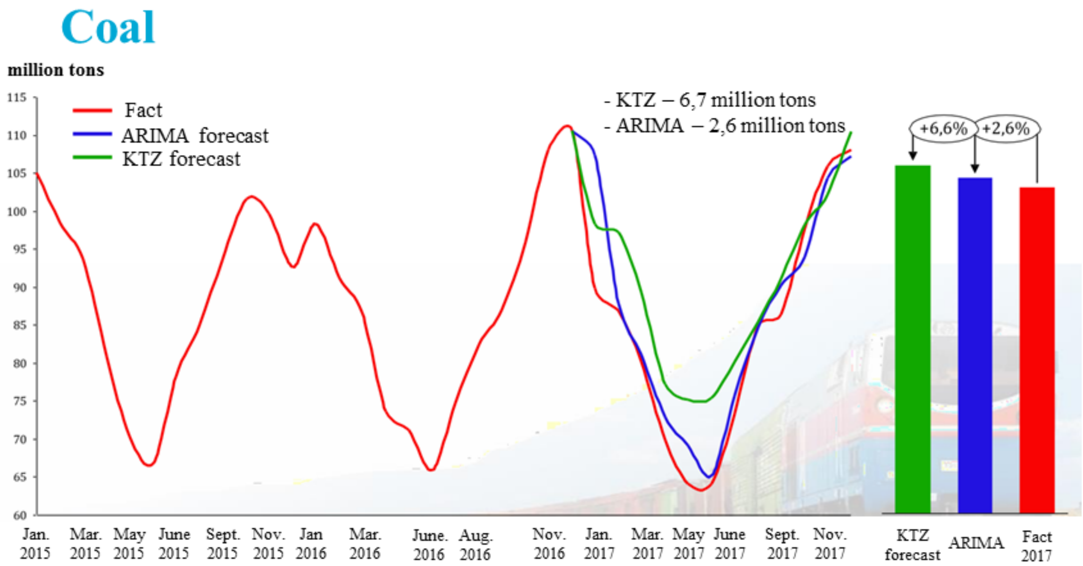

Figure 2: Comparison of fact with MTPD experts' forecast and SPSS simulation result (ARIMA model) on the total coal transportation volume in all modes of communication.

Note – compiled by the author based on data on historical traffic volumes obtained from KTZ internal information systems

As can be seen in Figure 2, the forecast for coal traffic, which is the main nomenclature of freight transported by KTZ (the share of coal in traffic exceeds 40 %), was much better predicted by the ARIMA model. One of the reasons the ARIMA model predicted future traffic volumes so accurately is the high correlation of traffic volumes with the macro indicators found in the study, as well as the high seasonality of coal traffic. The "predictor screening" feature in IBM SPSS Modeler allows you to select characteristics, helping you to identify the fields that will be most important in predicting certain outputs. From a set of hundreds or even thousands of predictors, the feature selection node screens, ranks and selects the predictors that may be most important. You can end up with a faster and more efficient model that uses fewer predictors, runs faster, and is easier to understand.

With data on the correlation between specific predictors and traffic volume and freight turnover, using forecasts from leading global and national agencies, you can greatly improve the quality and accuracy of the forecast.

Discussions

The advantages of using a planning system using the methods and models described above.

1. The speed of making forecasts and plan is reduced from the current 3 months to a maximum of 3–5 days, which will save more than 1,000 man-days or 8,000 man-hours of work.

2. With such a speed of processing historical data and generation of forecasts, there is an opportunity to develop many more forecasting scenarios (earlier MTPD experts generated only three scenarios — basic, optimistic and pessimistic; now the number of scenarios is unlimited), considering various scenarios of economic sectors' development.

3. There is a real opportunity to reduce the average monthly error in forecasts from the current 36%, to a potentially ambitious 10% or less. Achieving a MAPE of less than 10% would allow for much more accurate forecasting of both KTJ freight revenues and variable costs, which are dependent on freight performance. Forming a more accurate forecast of revenue on a monthly basis for the next year will allow for optimization of the costs of credit lines and other borrowing instruments used by KTZ.

4. With more accurate freight turnover forecasts, KTZ can more accurately calculate the volume of demand and the timing of purchases and deliveries of diesel fuel for diesel locomotives and electricity for electric locomotives. Expecting peaks or increased demand for transportation of this or that range of cargo during certain periods during the next year, KTZ can optimally plan the operating fleet of both locomotives and wagons and, if necessary, timely plan a request for wagon assistance from neighboring railway administrations.

5. When the advantages of automation and MTPD experts' knowledge are combined, serious progress can be made in the speed and quality of demand forecasts, and, consequently, in the overall business planning process at KTZ.

Conclusions

The essence of the study was to compare the quality of the two forecasts with the actual performance of KTZ in the field of freight transportation. For this purpose, a five-year period (from 2012 to 2016 inclusive) was selected and actual historical data on the volume of transportation and freight turnover were loaded into a specialized software product for data analysis and forecasting IBM SPSS Modeler. Various macroeconomic indicators for the Republic of Kazakhstan and other trading partner countries of Kazakhstan were also loaded into the system. SPSS generated a forecast of traffic volume and cargo turnover for all nomenclatures of goods and types of communication for 2017 and the forecast data were compared with the official data of KTZ for 2017 and with the forecast data that were generated by MTPD experts in 2016 for 2017. Thus, forecasts were compared with actual data for all cargo types and all types of services in terms of tonnes of traffic and tonne-kilometres of freight turnover. The comparison revealed that forecasts using modern mathematical and statistical models, showed quite comparable results with the results of three months of work carried out by MTPD experts. Especially good results using SPSS were obtained for those nomenclatures of goods and types of communication, for which there were complete, uninterrupted data, the volume of historical transportation for the previous five years was non-zero, and for which it was possible to find macro indicators correlating with the volume of transportation and cargo turnover in the past.

Brief conclusions from the study are as follows:

1. Modern mathematical and statistical models and software should be introduced into the practice of the largest enterprises in Kazakhstan, including the transport industry.

2. The experiment has shown the potential of using the above methods in practice for data analysis, forecasting and allows saving up to 8,000 man-hours of work of MTPD experts. It will allow experts to concentrate not on manual processing of data, but on their analysis. It will allow to increase the reliability of forecasts, because the system will show based on influence of what predictors the forecast is formed.

3. The experiment was conducted on real data; a comparative analysis of the results was performed for all cargo types and types of messages used in KTZ practice together with the MTPD experts and presented to the KTZ management. The results of the pilot experiment on the use of specialized forecasting software served as the basis for launching the “Integrated Planning System” project.

Thus, the methodology discussed in this article, the results of the scientific experiment and recommendations based on the results of the experiment have been put into practice at KTZ.

Complementary Data

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Магистральдық теміржол көлігінде жүк тасымалдауға сұранысты жоспарлау жүйесін жетілдіру

Аңдатпа

Мақсаты: Сұранысты болжау ұйымның ресурстарын оңтайлы жоспарлау үшін маңызды қадам болып табылады. Теміржол жүк тасымалының болашақ көлемі мен жүк айналымына көптеген факторлар әсер етуі мүмкін. Сараптамалық әдістермен жасалған болжамдардың сапасы енді уақыт талаптарына сәйкес келмейді. Мақаланың мақсаты — болжамдардың дәлдігін фактімен, яғни екі түрлі әдіспен салыстыру.

Әдісі: Мақалада авторегрессиялық интеграцияланған жылжымалы орташа (ARIMA) және пайыздық орташа абсолютті қатені (MAPE) және орташа абсолютті қатені (MAE) қолдана отырып, нәтижелерді болжау мен салыстырудың сараптамалық әдістері сияқты теориялық зерттеу әдістері қолданылған.

Қорытынды: Салыстыру нәтижелері Қазақстандағы жүк теміржол тасымалдарына сұраныс болжамдарының сапасын арттыру үшін уақыттық қатарларды талдауды пайдаланудың үлкен перспективаларын көрсетеді.

Тұжырымдама: Уақыттық қатарларды талдау Қазақстанның ірі кәсіпорындарының, соның ішінде көлік саласының тәжірибесіне енгізілуі мүмкін. Бұл әдістер кәсіпорындардың жұмысын жақсы жоспарлау арқылы олардың тиімділігін айтарлықтай арттыра алады.

Кілт сөздер: сұранысты жоспарлау, сұранысты болжау, теміржол жүк тасымалы, регрессиялық талдау, болжамдардың сапасын бағалау.

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Совершенствование системы планирования спроса на грузовые перевозки на магистральном железнодорожном транспорте

Аннотация

Цель: Прогнозирование спроса является жизненно важным шагом для оптимального планирования ресурсов организации. На будущий объем и грузооборот железнодорожных грузовых перевозок могут влиять многие факторы. Качество прогнозов, сделанных экспертными методами, уже не отвечает требованиям времени. Целью данной статьи является сравнение точности прогнозов двумя разными методами с фактом.

Методы: В настоящей статье использованы теоретические методы исследования, такие как авторегрессионное интегрированное скользящее среднее (ARIMA) и экспертные методы прогнозирования и сравнения результатов с использованием процентной средней абсолютной ошибки (MAPE) и средней абсолютной ошибки (MAE).

Результаты: Результаты сравнения показывают большие перспективы использования анализа временных рядов для повышения качества прогнозов спроса на грузовые железнодорожные перевозки в Казахстане.

Выводы: Анализ временных рядов может быть внедрен в практику крупнейших предприятий Казахстана, в том числе и в транспортной отрасли. Эти методы могут значительно повысить эффективность предприятий за счет лучшего планирования их операций.

Ключевые слова: планирование спроса, прогнозирование спроса, грузовые железнодорожные перевозки, регрессионный анализ, оценка качества прогнозов.

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