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FORECASTING THE VOLUME OF URBAN FREIGHT TRAFFIC

Abstract

The efficient development of transportation vehicles in conditions of stiff competition and global digitalization depends on the correct methodology and forecasting of freight transportation. A review of scientific literature showed that all studies are directed towards the railway mode of transportation. The research conducted in this work focuses on freight transportation by road transport in the city of Almaty, where trucks remain the sole means of delivering goods from one point to another at the local transportation level. The main goal of the research presented in this article is to analyze statistical indicators of transportation volumes and freight turnover by road transport and develop software aimed at forecasting the expected volume of freight transportation. In logistics planning and management, the moving average method is employed to predict truckload volumes and freight turnover for the next year. This method works by averaging data points to smooth out random fluctuations, thereby providing a more stable forecast. This phenomenon arises from replacing the original levels of the time series with arithmetic means calculated for certain time intervals. To facilitate transportation volume planning and substantiate the optimality of freight transportation, it is necessary to have up-to-date statistical data. These statistic data serve as the basis for constructing a dynamic representation of automobile traffic volumes and freight turnover in the city of Almaty. The growth rates of indicators are calculated to assess dynamics. The forecasting aspect of freight transportation volume is addressed by developing an algorithm based on the moving average method.

Key words: road transport, forecasting, moving average method, freight traffic, freight turnover, software, algorithm.

Introduction

The urban transportation framework of major cities encompasses a sophisticated network of transportation infrastructures, intricate equipment configurations, and complex methodologies for urban traffic management, all of which collectively facilitate the flow of goods within the urban environment [1–6].

The foundation of the transportation system comprises transport and logistics firms that offer their services. In tandem with the evolution of logistics within the nation, a considerable number of manufacturers and transport logistics enterprises have developed a primary focus on the efficient sale of goods and the optimization of cargo movements. This shift has led to a significant reduction in transportation expenditures, decreased warehousing costs, expedited delivery times, and an overall enhancement of the goods movement process.

In the Republic of Kazakhstan, competition among transport and logistics companies intensifies progressively each year. Road transportation emerges as the most advantageous mode for freight transport due to its cost-efficiency, rapid "door-to-door" cargo delivery devoid of additional transshipments, and time-saving attributes. In light of these circumstances, transport and logistics firms are compelled to meticulously forecast and strategize their operations to satisfy the escalating populace's increasing demand for timely goods delivery. The careful selection of forecasting methods ensures an increase in demand and meets the needs of transport and logistics companies [1, 2, 3, 7].

This work promotes the adoption of a forecasting method specifically designed for road transportation, along with the development of a software application to calculate predictive values for the coming year.

The primary objective of this study is to design a software application capable of generating predictive estimates for the anticipated volume of cargo transportation across diverse modes of transport.

Research in the domain of forecasting methods for freight transportation volumes and turnover has garnered significant attention from scholars worldwide, including those hailing from countries such as Kazakhstan, Russia, and beyond. Noteworthy contributions in this field have been made by a multitude of authors, among whom Krakovsky Y.M., Popova N.N., Izotov O.A., Gulamov A.A., Gozbenko V.E., Bedrin D.S., Zdorova A.Ch., Shirov A.N.N. stand out prominently [7, 8, 9, 10].

A focal point of interest in these scholarly endeavors revolves around the methodologies and models employed for forecasting railway freight transportation. Of particular significance are the works of Bedrin D.S., whose research sheds light on a comprehensive system of approaches and methodologies for planning and forecasting, encompassing the utilization of cutting-edge big data collection and analysis technologies. Bedrin's contributions underscore the critical role played by robust forecasting methodologies in navigating the complexities of modern transportation systems, especially amidst intense competition and the relentless wave of global digitalization [11].

Indeed, the effective development and optimization of transportation systems in the face of stiff competition and evolving technological landscapes hinge crucially upon the adept application of methodologies for planning and forecasting freight transportation dynamics. Bedrin's work serves as a poignant reminder of the pivotal role played by scholarly research in shaping and refining these methodologies, thereby facilitating the seamless integration of innovative technologies and data-driven insights into the fabric of contemporary transportation planning and management practices. Additionally, current research methods in the practice of forecasting freight flows include input-output methods, correlation and regression analyses, as asserted in Zdorova A.Ch.'s work [12]. Studying the development of international transport corridor (ITC) infrastructure requires the comprehensive use of modern research methods, including various heuristic approaches and statistical modeling, as indicated in a referenced work [13].

A comprehensive review of existing research reveals a predominant focus on the analysis of railway freight transportation dynamics. Scholars have predominantly adopted methodologies and models such as the "cost-output" approach, particularly leveraging static models, alongside correlation and regression analysis methods, as elucidated by Shirov A.N. [14].

While railway freight transportation garners significant scholarly attention, it's imperative not to overlook the pivotal role played by road transport, especially at the local level, where trucks serve as the primary mode of goods delivery between points. In this regard, a notable work [15] delves into the analysis of the KAMAZ-55102 dump truck's characteristics through graph-analytical calculations. Such analysis facilitates the determination of total calculated acceleration time and total calculated distance, shedding light on the operational efficiency of road transport vehicles.

Furthermore, attention is drawn to the development of regional freight transportation markets, exemplified by research conducted in the Kherson region [16]. This study employs a diverse array of research methodologies, including problem-oriented analysis, logical generalization, structuralfactual analysis, and the index method, to evaluate market concentration and explore the implications of advanced transport technologies on regional freight dynamics.

In a departure from conventional methodologies, the work of Tomasz Grzejszczak and colleagues [17] introduces a novel approach centered around the use of Long Short-Term Memory (LSTM) neural networks for predicting transport orders. Termed as "freight taxi," this innovative approach mirrors the organizational principles of taxi services, aiming to minimize empty return routes by strategically matching new orders with completed ones. Leveraging LSTM networks, the proposed model predicts the carrier's next cities of visit based on its historical routes, thus optimizing route planning and enhancing operational efficiency.

Moreover, researchers have increasingly focused on enhancing freight utilization efficiency through the integration of intelligent systems, as evidenced by ongoing studies in the field. This burgeoning research area holds promise for revolutionizing freight transportation practices, driving efficiency gains and sustainability improvements across the supply chain.A scientific article [18] analyzed the demand for urban goods movement, revealing the scale of the urban freight transport problem and its impact on the population's quality of life, as well as identifying trends in the balance between urban and intercity freight movement. Sultanbek's work [19] presents research aimed at accurately forecasting demand in the field of railway freight transportation, which is shaped by a complex set of dynamic variables.

In a seminal research paper [20], paramount attention is directed towards the augmentation of freight utilization efficiency through the integration of intelligent systems into logistics management practices. The core thrust of this research endeavor revolves around the development of a sophisticated system that leverages computer vision algorithms and intelligent technologies. This system is meticulously designed to detect and implement a myriad of functions aimed at optimizing the utilization of freight transport within vehicles. Additionally, it encompasses advanced cargo monitoring capabilities aimed at mitigating losses and enhancing operational efficiency throughout the transportation process.

This pioneering research represents a paradigm shift in contemporary logistics management, as it underscores the transformative potential of intelligent systems in revolutionizing freight transportation practices. By harnessing the power of cutting-edge technologies, such as computer vision algorithms, this system promises to unlock new avenues for improving resource utilization, streamlining operations, and enhancing overall supply chain performance.

Furthermore, the research paper delves into the realm of demand and tariff forecasting methodologies within the context of freight truck transportation. Notably, the study elucidates significant findings pertaining to the efficacy of econometric models, particularly Autoregressive Integrated Moving Average (ARIMA) models [21]. Through meticulous analysis and empirical validation, the research demonstrates the remarkable predictive capabilities of ARIMA models in forecasting demand dynamics and tariff fluctuations within the freight truck transportation domain.

This empirical evidence underscores the importance of leveraging sophisticated analytical tools and methodologies in navigating the complexities of modern freight transportation logistics. By embracing econometric models like ARIMA, transportation stakeholders can gain invaluable insights into future demand trends and tariff dynamics, thus enabling them to make informed decisions and devise strategic interventions to optimize operational performance and enhance overall competitiveness in the marketplace.

Materials and methods

The aggregated scheme of the simulation-analytical transportation management system, depicted in figure 1, should ensure the execution of the following stages:

1) Selection of mathematical model types corresponding to the problem being solved.
2) Formation of initial data for the problem in the form of cost or time matrices for transportation, production and consumption volumes, and throughput capacities.
3) Forecasting various parameters of transportation management.
4) Modeling unstable parameters of the chosen mathematical model.
5) Implementation of the algorithm selected for determining the optimal transportation plan according to the chosen model.

6) Returning to the first stage to consider alternative or modified options for transportation routes.

7) Comparative analysis of the obtained results and, if necessary, formation of additional initial data for the problem.

8) Formulation of final recommendations regarding the selection of efficient transportation routes.

One of the initial stages of operation of the developed simulation-analytical transportation management system is the forecasting of various system parameters, which is discussed in the following section.

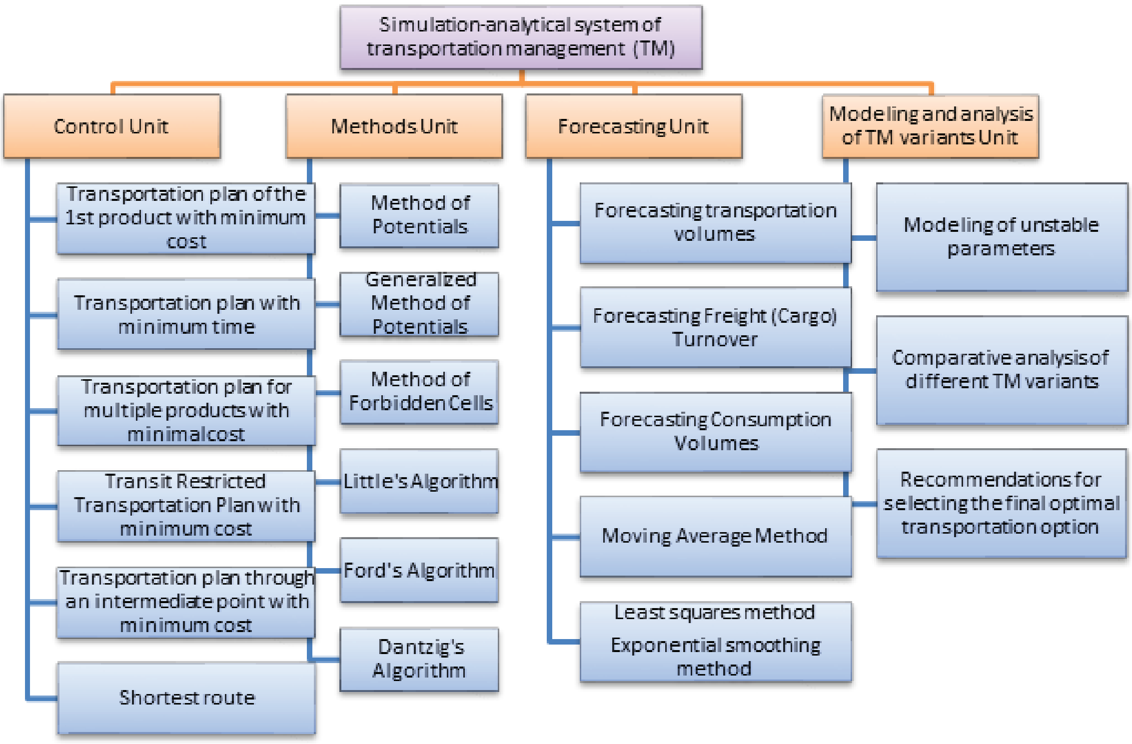

Figure 1 – Scheme of the simulation-analytical transportation management system

Note: Compiled by authors.

Within the multifaceted domain of logistics planning and management, a plethora of forecasting methods and models are consistently deployed to ascertain the optimal orchestration of freight movement within urban landscapes. Forecasting emerges as an indispensable tool, serving as a linchpin for scientifically validating plans, wherein the forecast encapsulates crucial data essential for facilitating the seamless flow of goods.

Achieving a comprehensive understanding of cargo transportation volumes over a designated timeframe is pivotal for making informed decisions regarding the composition of vehicle fleets within transportation enterprises. Among the myriad methodologies employed to meet this exigency, the moving average method stands out as a prominent choice [22–25], offering a systematic approach to forecast cargo transportation volumes accurately.

To illustrate the efficacy of such forecasting methodologies, we present comprehensive statistical data and the trajectory of cargo transportation volume and turnover by road within the urban landscape of Almaty over the preceding decade. This data, meticulously compiled by the authors, is derived from a specified source, serving as the cornerstone for our analysis [26]. Table 1 elucidates the numerical insights, while figure 2 visually encapsulates the trends observed, providing a holistic perspective on the dynamics of cargo transportation within the specified locale.

Table 1 – The quantities pertaining to the transportation of goods and the associated cargo turnover via road-based logistics within the urban confines of Almaty

№	Years	Transportation volumes, million tons	Traffic volume growth rate, %	Cargo turnover of road transport, million tons km	Cargo turnover growth rate, %
1	2012	168,3		17 899,7	
2	2013	194,4	1,16	18 867,3	1,05
3	2014	216,8	1,12	21 732,8	1,15
4	2015	232,1	1,07	21 494,5	0,99
5	2016	252,2	1,09	23 704,6	1,10
6	2017	254,5	1,01	27 482,8	1,16
7	2018	247,0	0,97	37 703,3	1,37
8	2019	257,4	1,04	20725,4	0,55
9	2020	252,3	0,98	23567,0	1,14
10	2021	270,1	1,07	24360,2	1,03
11	2022	278,3	1,03	27381,3	1,12
Mean			0,86		0,97
Note: Compiled by the authors based on reference [22].					

By the culmination of the year 2022, the cumulative volume of road-based cargo transportation had surged to 278.3 million tons, denoting a modest yet discernible uptick of 1.03% in comparison to the recorded figures of the preceding year, 2021. In parallel, the cargo turnover attributed to road transport operations in 2022 attained a significant milestone, registering a total of 27,381.3 million ton-kilometers traversed, indicative of a comparable 1.12% escalation relative to the analogous period.

Upon undertaking a meticulous examination of the dataset, it becomes increasingly apparent that a degree of fluctuation permeates the trends associated with both transportation volume and cargo turnover. This fluctuation is palpable in the computed average growth rates for these parameters, standing at 0.86% and 0.97%, correspondingly. Such nuances in growth trajectories underscore the complexity inherent in forecasting and managing road-based cargo transportation dynamics.

In an endeavor to furnish a more nuanced understanding of these evolving trends, a deeper analytical approach was undertaken. This involved the construction of a trend line predicated on a logarithmic approximation, aimed at delineating the underlying patterns governing the observed fluctuations.

The resultant equation, $Y= 43{,}583\ln(x)+169{,}15$ serving as a mathematical representation of the trend line, provides a platform for discerning the underlying dynamics influencing road-based cargo transportation volumes and turnover over the specified timeframe.

The coefficient of determination, a fundamental metric in assessing the efficacy of predictive models, has been meticulously computed for the presented model, yielding a noteworthy value of 0.9558. This translates to an impressive 95% accuracy rate, thereby accentuating the robustness and reliability of the trend line in encapsulating the observed variations within the dataset. Such a high coefficient of determination serves as a testament to the fidelity of the model in accurately representing the underlying dynamics governing the fluctuations in road-based cargo transportation volumes and turnover. This metric underscores the efficacy of the employed methodology in providing insights into the intricate patterns and trends prevalent within the domain of logistics and transportation management.

The moving averages method, esteemed within the realm of statistical analysis, emerges as a widely acknowledged approach for smoothing time series data. This methodological framework facilitates the generation of short-term forecasts, leveraging the inherent stability ingrained within the progression of indicators. Central to its efficacy is the principle that future values tend not to deviate significantly from their preceding counterparts.

One of the primary advantages offered by the moving averages method lies in its capacity for data smoothing, achieved through the reciprocal attenuation of random fluctuations inherent within the averages. This attenuation is achieved by replacing the original data points in the time series with their arithmetic mean over a specified time interval. The resulting value represents the midpoint of this defined interval. The period is then incrementally shifted by one observation, and the averaging process is repeated. It is important to emphasize that the time intervals used for computing the averages remain consistent throughout the analysis.

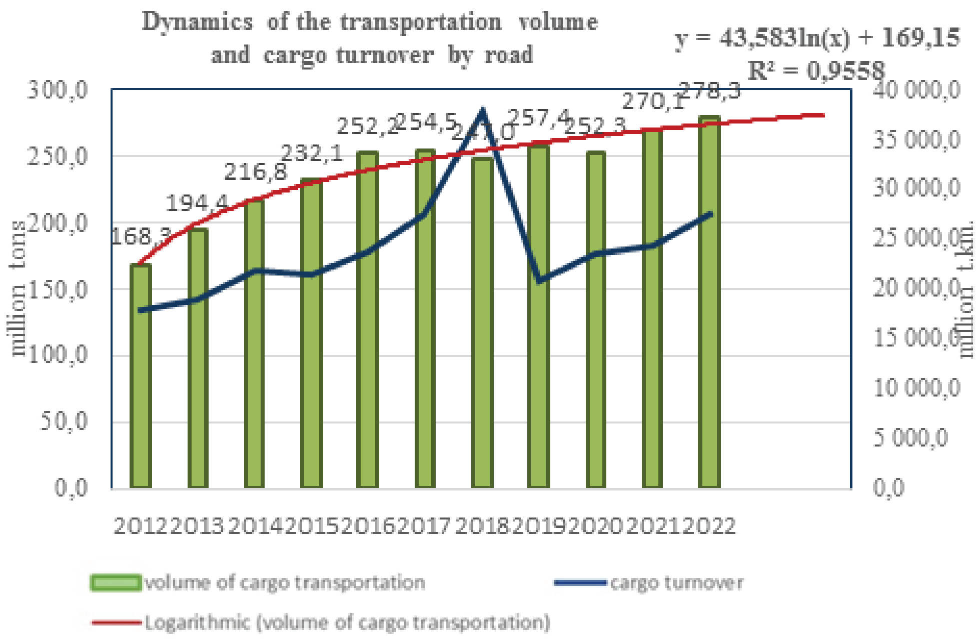

Figure 2 – The dynamics of cargo transportation volume and road cargo turnover

Note: Compiled by the authors based on reference [22].

As a consequence of this methodological framework, each computed average assumes a centered position within the analyzed data. This centrality implies that the average is attributed to the midpoint of the smoothing interval, thereby serving as a representative level for that specific point in time [22–28]. This methodological rigor ensures consistency and accuracy in the analysis, enhancing the reliability of forecasts and insights derived from the moving averages method.

The moving average is computed using the following formula:

$$y_{t+1} = m_{t-1} + \frac{1}{n}\left(y_t - y_{t-1}\right), \text{ if } n = 3,$$

where $(t+1)$ – the forecast period;

t – the period preceding the forecast period (year, month, etc.);

y_{t+1} – the predicted indicator;

m_{t-1} – the moving average for two periods before the forecast;

n – the number of levels included in the smoothing interval;

y_t – the actual value of the phenomenon under study for the previous period;

y_{t-1} – the actual value of the phenomenon under study for two periods preceding the forecast

The average relative error is calculated by the formula:

$$\varepsilon = \frac{1}{k-2}\sum_{i=2}^{k-1}\left[\frac{|y_a - y_c|}{y_a}\cdot 100\right]$$

where y_a – the actual value of the indicator;

y_c – calculated indicator value;

k – number of observations.

Figure 2 presents the flowchart of the algorithm used for forecasting traffic volumes using the moving average method. Let's outline the operation of the algorithm. Operator 1 inputs the initial data:

k – the number of observations;

n – the number of levels included in the smoothing interval;

l – the number of forecast periods;

v – an array containing information about traffic volumes.

Operator 2 initiates a loop to calculate arrays of moving averages m and errors ε .

Operators 3 and 4 compute element-wise moving averages $m[i]$ and errors $\varepsilon[i]$

Operator 5 begins another loop to calculate an array of forecast values for cargo transportation volumes, moving averages m, and an array of errors ϵ for the obtained forecast values.

Operators 6-8 sequentially compute forecast values for cargo transportation volumes $v[k+i]$, moving averages $m[k+i-1]$, and errors $\varepsilon[k+i-1]$.

Finally, operator 9 manages the presentation of the calculated values (v, m, ε) .

Results and discussion

One of the paramount challenges in the realm of transportation development revolves around the persistent issue of congestion within transport networks. With the likelihood of transformations in urban transport infrastructure on the rise, the prevalence of traffic congestions, irregular routes, and related complexities becomes increasingly pronounced. In light of these challenges, it becomes imperative to devise effective strategies for alleviating the congestion plaguing transport networks.

Central to addressing the issue of transport network congestion is the need to accurately forecast the volume of transportation and freight movement via road transport within urban settings, particularly in cities like Almaty. Such forecasts serve as crucial inputs for informed decision-making and strategic planning aimed at optimizing the flow of freight transportation amidst urban traffic dynamics. In this context, employing statistical forecasting methods emerges as a key approach to anticipate future transportation demands and proactively address routing challenges.

One promising solution to this multifaceted problem entails the application of the moving average method to forecast cargo demand and preemptively resolve routing tasks within the transportation flow. By leveraging the predictive capabilities of the moving average method, transportation planners and stakeholders can gain valuable insights into anticipated cargo demands and strategize accordingly to mitigate congestion and optimize resource allocation.

Recognizing the significance of forecasting as a scientific tool for justifying plans and interventions, it becomes imperative to ensure that the forecasts generated contain comprehensive and pertinent information requisite for planning the optimal movement of freight transportation within urban landscapes. In light of this imperative, extensive research efforts have been undertaken, culminating in the development of an automated program designed to derive forecast values utilizing the C# programming language. This automated tool not only streamlines the forecasting process but also enhances accuracy and efficiency, thereby empowering decision-makers with timely and reliable insights to navigate the complexities of urban transportation planning and management.

In the realm of smoothing methods, the judicious utilization of the most recent data within the series is paramount, as information tends to lose relevance over time. Moreover, prioritizing data points closer to the forecast interval is essential, as they inherently carry more weight in predicting future trends.

To forecast cargo transportation volume employing the moving average method, a dedicated program was meticulously crafted utilizing the robust capabilities of the C# programming language within the Visual Studio 2019 integrated development environment, as depicted in figures 3-4 [29]. This program serves as a sophisticated tool for leveraging historical data on cargo transportation volume in Almaty, spanning back to the year 2012, as its foundational dataset (Refer to table 1).

An integral aspect of evaluating the effectiveness of any forecasting methodology lies in quantifying the discrepancy between predicted and actual values. In this context, the average relative forecast error, symbolized as ϵ, assumes pivotal significance. Notably, the calculated average relative forecast error stands at a mere 1.632%, comfortably below the predefined threshold of 10%. This minimal margin of error signifies a commendable level of forecast accuracy, attesting to the efficacy of the moving average method in capturing and extrapolating trends within the dataset.

Furthermore, a comprehensive numerical analysis underscores the stability and reliability inherent in forecasting methodologies facilitated by the moving average method. This analytical rigor not only validates the robustness of the employed forecasting approach but also instills confidence in the forecasted values derived through the program. As such, the program serves as a valuable asset in the arsenal of tools available to transportation planners and stakeholders, empowering them to make informed decisions and navigate the complexities of urban transportation management with precision and efficacy.

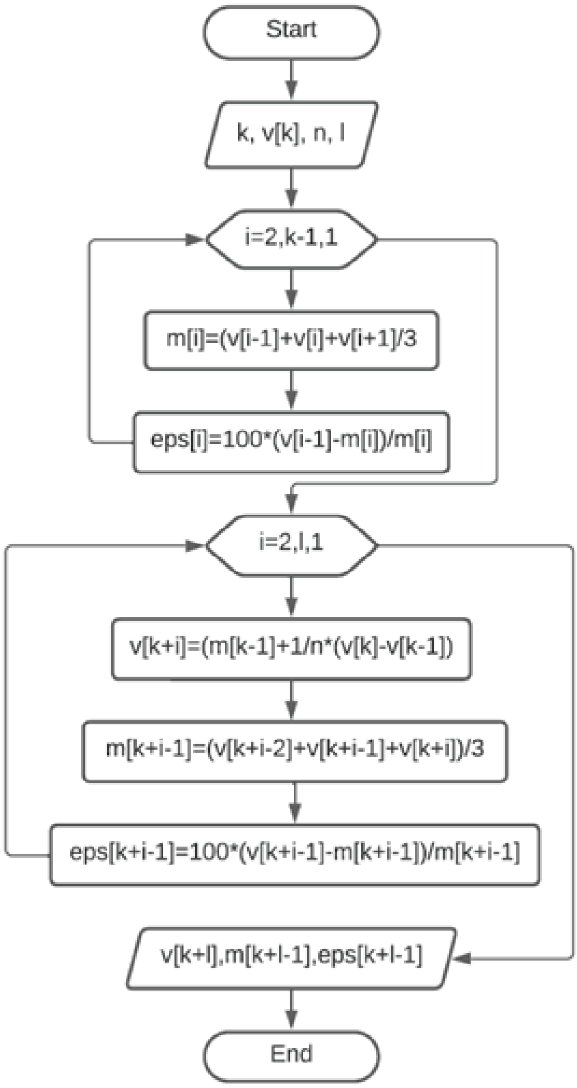

Figure 3 – Algorithm of the moving average method

Note: Compiled by authors.

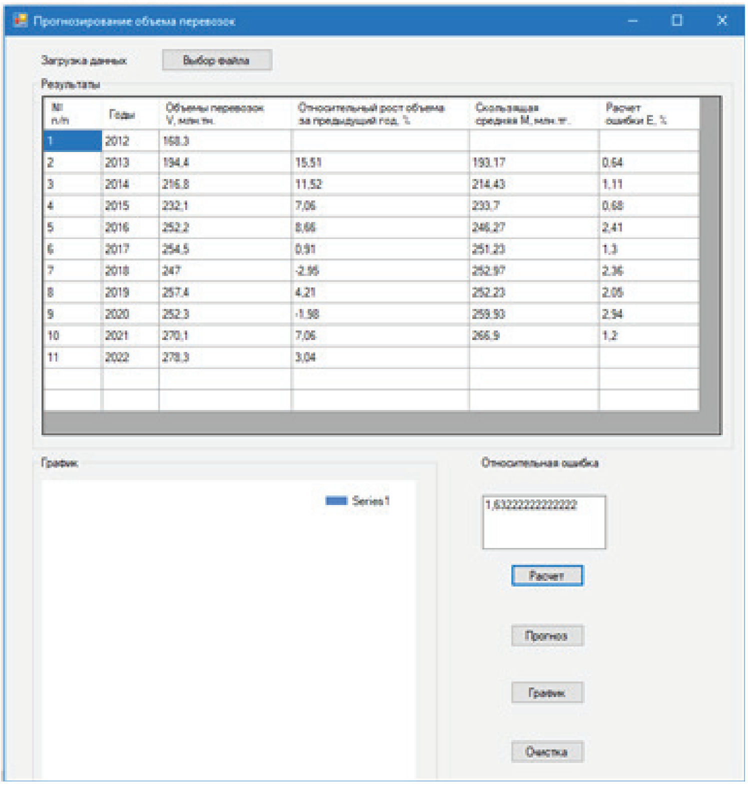

Figure 4 – The software application designed for predicting cargo transportation volumes, including the input of initial data

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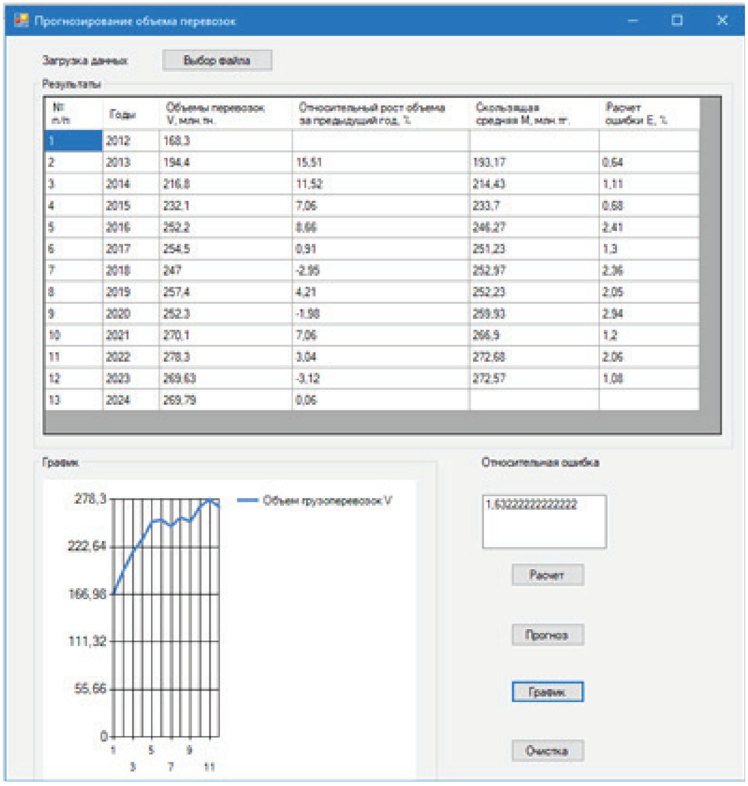

Figure 5 – The software application for predicting cargo transportation volumes, including forecasts for 2023 and 2024 traffic volumes.

Note: Compiled by authors.

To further improve the accuracy and adaptability of the freight volume forecast, the following areas of program development can be considered:

1. Integration of additional data. Including additional variables in the analysis, such as weather conditions, economic indicators and seasonal factors, which can significantly affect the volume of cargo transportation.
2. Development of hybrid models. Combining the moving average method with other forecasting methods, such as machine learning-based models (e.g., regression analysis, neural networks), can improve the accuracy and adaptability of forecasts.
3. Automation and optimization of parameters. Implementation of algorithms to automatically tune model parameters, such as moving average window length, to optimize forecasts in real time.
4. User interface development. Creation of a convenient and intuitive user interface for easier interaction with the program and interpretation of forecasting results.
5. Regular data updates. Ensuring that the data used is regularly updated to keep forecasts current and accurate, which is especially important in the face of dynamic changes in the cargo transportation industry.

The program, based on the moving average method, has proven its effectiveness and accuracy in forecasting freight volumes in Almaty. However, to maintain and improve its performance, it is necessary to constantly improve analysis methods and incorporate new data and technologies into the forecasting process.

Conclusion

The chosen moving average method presents a versatile toolset capable of generating short-term forecasts, thereby enabling transport and logistics firms to strategize their operations effectively. By leveraging these forecasts, companies can make informed decisions regarding route planning and resource allocation, ultimately enhancing the quality of customer service provided.

Additionally, the developed program enables forecasting on an annual scale as well as on a more detailed monthly basis. This expanded temporal resolution empowers transportation and logistics enterprises with a finer-grained understanding of demand fluctuations and seasonal trends, thereby enabling more agile and responsive decision-making.

By embracing the capabilities afforded by the developed program and the moving average method, transport and logistics companies stand to elevate their performance metrics significantly. Through accurate and timely forecasts, coupled with agile operational strategies, firms can optimize their routes, minimize inefficiencies, and deliver superior service to their customers. In doing so, they not only enhance their competitive position within the industry but also contribute to the overall efficiency and reliability of the transportation and logistics ecosystem.

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ҚАЛАЛЫҚ ЖҮК ТАСЫМАЛЫ КӨЛЕМІН БОЛЖАУ

Андатпа

Қатаң бәсекелестік пен жаһандық цифрландыру жағдайында көлік құралдарының тиімді дамуы жүк тасымалының дұрыс әдіснамасы мен болжамына байланысты. Ғылыми әдебиеттерге жүргізілген шолу барлық зерттеулердің теміржол көлігіне бағытталғанын көрсетті. Жұмыс барысында Алматы қ. автомобиль көлігімен жүк тасымалдауды зерттеу жүргізілді, мұнда жергілікті тасымалдау деңгейінде жүк көліктері жүктерді бір нүктеден екінші нүктеге жеткізудің жалғыз жолы болып қала береді. Осы мақалада ұсынылған зерттеудің негізгі мақсаты – жүк тасымалы көлемінің және автомобиль көлігімен жүк айналымының статистикалық көрсеткіштерін талдау және жүк тасымалының күтілетін көлемін болжауға арналған бағдарламалық қосымшаны әзірлеу. Жоспарлау және логистика менеджменті саласында алдағы жылға автомобиль көлігі мен жүк айналымының көлемін болжау үшін жылжымалы орташалар әдісі қолданылды. Жылжымалы орташалар әдісінің принципі есептелген орташа мәндер шеңберіндегі кездейсоқ ауытқуларды өзара компенсациялау болып табылады. Бұл құбылыс уақыт қатарының бастапқы деңгейлерін белгілі бір уақыт аралығында есептелген орташа арифметикалық мәндермен ауыстыру нәтижесінде пайда болады. Тасымалдау көлемін жоспарлауды жеңілдету және жүктерді тасымалдаудың оңтайлылығын негіздеу үшін өзекті статистикалық деректер болуы қажет. Статистикалық деректер Алматы қ. жол қозғалысы мен жүк айналымы көлемінің динамикалық көрінісін құруға негіз болды. Динамиканы бағалау үшін көрсеткіштердің өсу қарқыны есептелді. Жүк тасымалдау көлемінің болжамдық жағы жылжымалы орташалар әдісіне негізделген алгоритмді жасау арқылы шешілді.

Тірек сөздер: автомобиль көлігі, болжау әдістері, жылжымалы орташалар әдісі, жүк тасымалдау, жүк айналымы, бағдарламалық қамтамасыз ету, алгоритм.

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ПРОГНОЗИРОВАНИЕ ОБЪЕМА ГОРОДСКИХ ГРУЗОВЫХ ПЕРЕВОЗОК

Аннотация

Эффективное развитие транспортных средств в условиях жесткой конкуренции и глобальной цифровизации зависит от правильной методологии и прогнозирования грузовых перевозок. Проведенный обзор научной литературы показал, что все исследования направлены на железнодорожный вид транспорта. В работе проведено исследование грузоперевозок автомобильным транспортом в г. Алматы, где на уровне местных перевозок грузовики остаются единственным способом доставки грузов из одной точки в другую. Основной целью исследования, представленного в данной статье, является анализ статистических показателей объемов перевозок и грузооборота автомобильным транспортом и разработка программного приложения, предназначенного для прогнозирования ожидаемого объема грузоперевозок. В сфере планирования и управления логистикой для прогнозирования объемов автомобильных перевозок и грузооборота на предстоящий год используется метод скользящего среднего. Принцип метода скользящего среднего заключается во взаимной компенсации случайных отклонений в рамках рассчитанных средних. Это явление возникает в результате замены исходных уровней временного ряда средними арифметическими значениями, рассчитанными за определенные временные интервалы. Для облегчения планирования объемов перевозок и обоснования оптимальности грузоперевозок необходимо располагать актуальными статистическими данными. Статистические данные служат основой для построения динамического представления объемов автомобильного движения и грузооборота в г. Алматы. Для оценки динамики рассчитываются темпы роста показателей. Прогностическая сторона объема грузоперевозок решается путем разработки алгоритма, основанного на методе скользящего среднего.

Ключевые слова: автомобильный транспорт, прогнозирование, метод скользящего среднего, грузоперевозки, грузооборот, программное обеспечение, алгоритм.

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