Traffic Modeling Approaches

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Abstract

Assessing the quality of traffic management and design solutions in the field of traffic management, especially for complex objects, complex traffic management schemes for cities with a population of over 500 thousand inhabitants, temporary traffic management schemes for the period of closure of significant sections of the street network, involves the need to consider a fairly large number data to resolve contradictions of uncertainty of an objective and subjective nature. These difficulties are mainly due to the lack of reliable methods for predicting the distribution of traffic flows within the area covered by the traffic light network of the automated traffic control system, under various options for management decisions. This, in turn, is due to the presence of a significant number of factors influencing the intensity of road transport traffic and the distribution of traffic flows along sections of the street network.

Keywords

Traffic, modeling, integral risk, green wave, objective function, objective function parameters

1. Introduction

Assessing the quality of traffic management and design solutions in the field of traffic management, especially for complex objects, complex traffic management schemes for cities with a population of over 500 thousand inhabitants, temporary traffic management schemes for the period of closure of significant sections of the street network, involves the need to consider a fairly large number data to resolve contradictions of uncertainty of an objective and subjective nature. These difficulties are mainly due to the lack of reliable methods for predicting the distribution of traffic flows within the area covered by the traffic light network of the automated traffic control system, under various options for management decisions. This, in turn, is due to the presence of a significant number of factors influencing the intensity of road transport traffic and the distribution of traffic flows along sections of the street network.

These factors include:

- topological characteristics, reflecting the geometric structure of the road network and the parameters of its individual elements (for example, the width of the roadway, the configuration of intersections, traffic junctions);
- factors related to the organization of traffic itself (one-way traffic, bans on maneuvers at intersections, bans on the movement of freight transport);
- factors determined by the presence of traffic light regulation (phase-by-phase traffic flow diagrams and parameters of traffic light regulation, characteristics of regulated directions, the presence of coordinated control of traffic light objects);
- characteristics of the road surface, reflecting its condition and affecting the conditions and speed of traffic;

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- factors related to the presence of pedestrian flows and the organization of pedestrian traffic (location of unregulated and regulated pedestrian crossings, the presence of pedestrian barriers);
- factors associated with the movement of route public transport (traffic intensity of route buses and trolleybuses, the location of tram stops when the tram track is located at the same level as the roadway and the frequency of tram traffic);
- factors associated with parking vehicles on the roadway, which interferes with traffic flow.

Obviously, it is possible to consider all the diversity of these factors by expert means to construct predictive flow distributions only for small sections of the road network. Optimization of automated control in complex traffic patterns requires the creation and use of computer models.

In addition to the listed factors, the intensity of traffic flows on the road network is decisively influenced by the demand for movement by road transport, the nature of which has changed significantly over the past decade, both in quantitative and qualitative terms. The changes that have taken place in the world recently have led not only to a manifold increase in the level of motorization, but also to a sharp increase in the share of business movements, which currently determine peak loads on city highways.

The traffic flow models that have existed to date are focused more on urban planning than on traffic management problems [1]. There is also no experience in determining the demand for business travel by road. In addition, there is no consensus on how to evaluate the effectiveness of traffic control.

2. Justification and selection of the target function of traffic control

The effectiveness of traffic control can be assessed by many criteria depending on the control. The following values can be used as a target function for traffic management: the volume of harmful atmospheric emissions, the total travel time along the route, the number of stops per trip, the skip rate, the average delay of the crew per cycle, the average downtime due to delays [2], the speed of communication , number of accidents, traffic intensity [3], total time of vehicle delays at intersections. Most of the listed characteristics of road traffic are interrelated [4].

The target function can be determined from the results of field measurements or from mathematical modeling data. A mathematical model is a simplified representation of a real system and, regardless of its detail and complexity, it can claim to be the only correct reflection of the processes being studied. One of the conditions for the significance of the developed models is the display of the parameters that make up the objective function.

For example, the objective function for determining the time required to move a car from one point to another through signalized intersections can be represented by the operator

$$F_1 = f(S, Vcp, \tau) \tag{1}$$

where

S is the distance that the car must travel;

V_{cp} is the average speed of the vehicle;

τ is the total vehicle delay time at signalized intersections.

In a similar way, we can describe the function for determining the fuel consumption of a car when driving through signalized intersections from one point to another:

$$F_2 = f(S, Vcp, \mathrm{O}, \tau) \tag{2}$$

where

O is the engine volume of the car.

Generally averaged data on atmospheric air pollution reflect the unfavourable environmental situation in almost all areas of the city [6, 5].

Air pollution is one of the biggest problems in the city, leading to high rates of disease and premature mortality among the population. According to WHO, PM2.5 concentration levels in Almaty in winter are 17 times higher than the maximum permissible values. Health risks, in turn, come with high economic costs. According to a 2022 World Bank report, more than 10,000 premature deaths due to air pollution are projected annually in Kazakhstan, with an economic cost of more than US$10.5 billion per year [7].

In Almaty in 2022, emissions of pollutants into the atmosphere amounted to 127 thousand tons. More than half of them are from motor transport - 70 thousand tons, stationary sources - 46 thousand tons, the private sector - 11 thousand tons (9%). The average annual level of fine dust PM2.5 in Almaty has increased by 20% over the past three years, including due to an increase in the number of vehicles entering the city by 230 thousand units. The content of nitrogen dioxide NO2 in the atmospheric air (from transport, boiler houses, thermal power plants and other enterprises) is twice the maximum permissible concentration (MPC) [8]. The average concentration of carbon monoxide is 2.5 MPC, the concentration of nitrogen oxides is 2.1 MPC, ozone - 1.4 MPC

According to the stationary observation network, the level of atmospheric air pollution in the city of Almaty was generally assessed as high, it was determined by an SI value of 6.7 (high level) in the area of post No. 30 (Shanyrak, school No. 26, Zhankozha Batyr St., 202 ;) and the value of NP = 26% (high level) in the area of post No. 28 (aerological station (Airport area) Akhmetov St., 50) for ozone concentration [8].

Over the past five years, the level of air pollution in the 2nd quarter changed as follows:

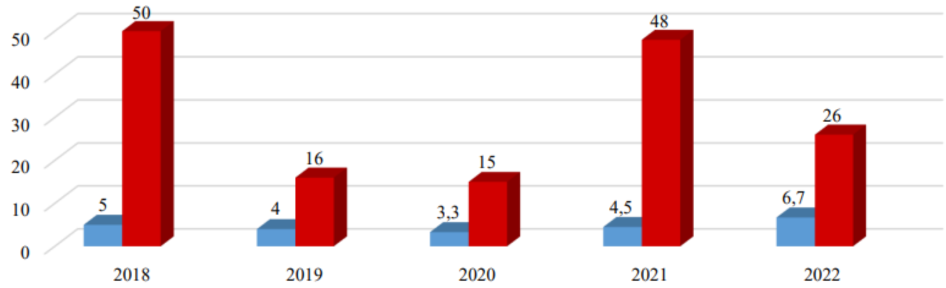

Figure 1: Results of monitoring of atmospheric air quality in Almaty (2018-2022 years) [8]

The analysis allows us to conclude that the existing level of air pollution in Almaty poses a threat to the population and the environment. In this regard, it seems necessary to assess the possibility of using the value of environmental risk as an objective function, which is determined depending on the level of atmospheric air pollution from vehicle exhaust gases.

3. Methodology for calculating environmental risk

As is known, to characterize and assess the quality of the environment, a regulatory approach is used, focused on the concept of maximum permissible concentrations [9, 10].

The regulatory approach [11, 12], while creating the appearance of the existence of environmental standards, does not allow assessing the damage and losses to society due to the deterioration of the quality of the living environment in comparison with acceptable sanitary and hygienic standards. The only conclusion that follows from a comparison of the actual state of the environment with regulatory data is the following: if there is an excess of environmental parameters above the standards, then this is dangerous. To numerically assess risk, it is necessary to turn to statistical data on the state of public health, which record an already accomplished fact, when the consequences cannot be changed, much less prevented [13].

In the published works of various authors, empirical approaches predominate, based on studying the influence, most often, of individual harmful factors or certain groups of factors [14, 15]. As a rule, when assessing the quality of the environment, the most significant factors that have the greatest impact on the biosphere are identified. And considering only these factors, environmental safety assessments are made.

The presence of harmful substances of any concentration in the environment creates a danger to human health. At the same time, there is always a risk of a reduction in average life expectancy due to diseases or other health problems.

In general, when atmospheric air is polluted in accordance with the Weber-Fechner law, there is a certain functional relationship between the level of pollution and risk:

$$r = a \cdot \lg \frac{C}{C_0} \tag{3}$$

where

r is the risk level;

C is the concentration of harmful substances in the air.

Acceptable risk, as the probability of death within a year for an individual from dangers associated with the technosphere, is considered equal to 10^{-6} [16]. It can be accepted that the acceptable level of risk corresponds to the content of impurities in the air with a concentration equal to the MPC.s. If the concentration of harmful substances in the air is equal to the average lethal C = LC50, then the risk level will be r = 0.5. Thus, based on standard indicators determined experimentally [17], two fixed points of dependence can be established (4)

$$\begin{cases} 10^{-6} = a \cdot lg \frac{MPC_{da}}{C_0} \\ 0.5 = a \cdot lg \frac{LC_{50}}{C_0} \end{cases} \tag{4}$$

The function of the magnitude of potential environmental risk from the concentration of xenobiotics in the atmospheric air will take the following form

$$r = 0,5 \cdot \frac{lg \frac{\mathrm{C}}{MPC_{da}}}{lg \frac{LC_{50}}{MPC_{da}}} \tag{5}$$

This equation allows us to determine the reduction in average life expectancy (ALE) at a known concentration (C) of harmful substances in the air. Using an assessment in the form of a ratio of two quantities is equivalent to a transition from an intensive to an extensive characteristic of the impact - the dose, which, as is known, is an integral quantity and is determined considering the time of exposure [18].

The expected individual risk is calculated taking into account the time spent in these conditions [19]

$$r_{per} = r \quad \cdot \eta \tag{6}$$

where

r_{per} is the ratio of the time an individual spends in the contaminated zone to the length of the day.

The expected probable reduction in average life expectancy per year will be:

$$ALE_{per} = 365 \cdot r_{per} \tag{7}$$

Calculation of the total environmental risk R under the independent action of several substances is performed in the following sequence. First, the risk value r_i is calculated for each substance, and then the total risk is determined as

$$R = 1 - \prod_{i=1}^{m} (1 - r_i) \tag{8}$$

where

m is the number of factors.

The proposed methodology for calculating the value of the total risk and reduction in life expectancy, using regulatory data as a base, allows us to provide a quantitative assessment of the danger of air pollution. In this regard, it is possible to apply the value of environmental risk as an objective function of traffic management [20].

4. Calculation of emissions of exhaust gas components

When calculating the emissions of the harmful substances contained in the exhaust gases of vehicles, carbon (CO), hydrocarbons (CMHN) and nitrogen oxides (in terms of nitrogen dioxide NO_2) are considered for carburetor engines. For cars with diesel engines, soot content is additionally determined [21, 22]. It should be noted that more stringent European standards take into account emissions of CO, as well as the amount of C_mH_n and NO_x [23].

Primary mixing of exhaust gases occurs in a certain volume above the road surface Vo = L*b*h, where L is the path length (m), b is the width of the roadway, h is the height of the volume where the primary mixing occurs. The value h = 2 m is taken to be equal to the average height of cars in the flow since when they move, air is completely displaced and mixed with exhaust gases.

The road enters the road and removes from it depending on the speed and direction of the wind in the general case the next volume of air Q, M3/s:

$$Q = h*u*(L*Sin\alpha + b*Cos\alpha) \tag{9}$$

where

u - the speed of wind, m/s;

α - the angle between the direction of the wind and the axial line of the road (hereinafter we will consider according [23] scattering of impurities for the direction of the wind of the perpendicular road, when α = 90).

$$\boldsymbol{Q} * \boldsymbol{C_f} + \mathrm{M}_{\boldsymbol{i}} - \boldsymbol{Q} * \boldsymbol{C_i} = \boldsymbol{V_i}\frac{\boldsymbol{dC_i}}{\boldsymbol{dt}} \tag{10}$$

where

$Q*C_f$ is the amount of harmful substances supplied taking into account background concentrations $C_f = 0.4*MPC_{mr}$ on the road, mg/s;

$Q*C_i$ is the amount of substances carried off the road after initial mixing, mg/s;

C_i is the concentration of the substance above the road surface, mg/m^3;

M_i - emission of substances with exhaust gases, mg/s;

t - time, s;

Q is the volume of air entering the cell above the road surface, m^3/s.

In the stationary state $dCi / dt = 0$, so after transformations we find as

$$\mathrm{C}_i = C_f + \frac{\mathrm{M}_i}{Q} \tag{11}$$

The obtained dependence allows us to solve two problems: to find the concentration of harmful substances above and near the road surface at a given wind speed and to calculate the wind speed at which the maximum permissible concentration limit.r. value will be reached.

In this study, for the convenience of performing calculations, the concept of a conditional (reduced) car is used. A truck is equal to two, a minibus is equal to one, and a bus is equal to three cars.

Assessment of the level of impact of vehicle exhaust gases on the atmospheric air is carried out on elements of the road network - on streets and intersections. Obviously, the largest amount of exhaust gases is emitted at intersections. To take into account the peculiarities of vehicle exhaust gas emissions at intersections, we introduce additional coefficients:

$$M_i = k_u * k_T * k_i * k_p * k_s * k_v * M_{0i}, \quad (12)$$

where

k_u is the increase in emissions due to traffic lights interrupting the traffic flow;

k_T – increase in emissions due to unsatisfactory fuel quality;

k_i – characterizes the serviceability and regulation of vehicle power systems;

k_p – characterizes the features of the layout and organization of intersections, the presence of public transport stops, pedestrian crossings, underground passages, etc.;

k_s – coefficient of relief complexity of the intersection;

k_v – coefficient characterizing the average «age» of cars in the stream;

M_{0i} and M_i – ideal and real release of components, g/s.

We find the value of M_{0i} for a conventional car using the data [24] on emissions of toxic components P_i per unit of travel according to the formula:

$$M_{0i} = \frac{1000 \cdot n \cdot L \cdot P_i}{3600} \quad (13)$$

where n is the intensity of vehicle traffic, vehicles/hour;

L – length of route, km;

P_i – emission standards for components of a conventional car: carbon monoxide – 24.3 g/km, nitrogen oxides – 0.3 g/km, hydrocarbons – 4.2 g/km.

5. Influence of traffic light control characteristics on the value of integral risk

A significant increase in emissions is associated with unsatisfactory fuel quality and malfunctioning vehicle power systems. About 10% of control analyzes of the fuel used show non-compliance with GOST, so we can accept k_T = 1.1. Control checks of cars carried out by the city showed that every third car needs adjustment of the power system. This corresponds to k_i = 1.33.

Due to the lack of reliable data on the terrain complexity and visibility at all intersections of the city, the value of the coefficient *ks* will be taken as a first approximation equal to 1.05. The value of *kv* = 1.2, since more than 20% of the vehicles in use in the given flow are older than 10 years.

The value *ku*= 1 corresponds to movement on a section of the street without stopping. With traffic light regulation, approximately half of the regulation cycle (20-30 s) is spent accumulating a group of cars and waiting for the permitting traffic light signal. When driving, a conventional car emits P_i = 24.3 g/km or 1.215 g of carbon monoxide over a 50 m section of road that makes up the intersection. And when stopping, the same car emits 4.5*30/60 = 2.25 g of carbon monoxide in 30 seconds in idling mode [24]. When the delay time at the traffic light is 10, 20 and 30 s, the value k_u takes values of 1.75, 2.2 and 2.8, respectively. When waiting for 40 seconds, k_u = 3.47. In the absence of traffic light regulation, the value of k_u increases to k_u = 10...12.

In Fig. 2 presents calculated data on the reduction in life expectancy depending on the characteristics of traffic light regulation and the intensity of traffic flow during rush hours [8]. Calculations were performed according to the methodology outlined above for an average annual wind speed of 4.7 m/s based on the assumption that the time of greatest peak traffic intensity is 2 hours a day.

With ideal traffic organization, and this is only possible if an automated control system is used, when groups of cars move in the “green wave” mode, an intensity below 1700 vehicles/h is safe

[25, 26]. However, the "green wave" regime can only be created on one-way streets. Therefore, always in one of the directions of movement, strict traffic light control will interrupt the traffic flow, thereby creating the preconditions for an increase in exhaust emissions. Curves 2...5 correspond to different values of the average delay time t_z of cars before the intersection.

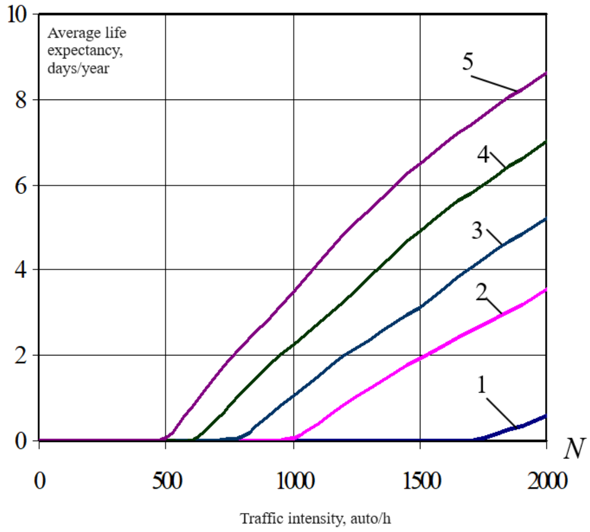

Figure 2: Reduction in average life expectancy for different delay times at traffic lights: 1 – t_{gr}=0 s; 2 – t_{gr}=10 s; 3 – t_{gr}=20 s; 4 – t_{gr}=30 s; 5 – t_{gr}=40 s

The proposed methodology for calculating environmental risk and the magnitude of the reduction in average life expectancy makes it possible to use these characteristics as a target function for traffic management. At the same time, it should be noted that the magnitude of environmental risk and the reduction in average life expectancy, as follows from the results shown in Fig. 2, change slightly at low traffic flow intensities. Therefore, the use of the value of environmental risk and the reduction of average life expectancy as a target function for controlling automated traffic control systems will be effective at significant intensities of traffic flows.

Considering the above, in the future, as an objective function when optimizing traffic control, we will use the total delay time of vehicles in front of intersections of the city street network for one regulation cycle.

At the same time, the effectiveness of control of traffic light objects should be assessed by the values of the total delays of vehicles for all stages in all directions of movement. Therefore, the functional can be taken as the objective function of the traffic light control optimization problem

$$F = \sum_{(i,j)\in M} Z_{ij}\{\Delta t_{0,i}, \Delta t_{0,j}, (T, t_{\text{жс}}, t_{\text{з}})_i, (T, t_{\text{жс}}, t_{\text{з}})_j, l_{ij}, V_{ij}, P_{ij}\} +$$

$$+ \sum_{(k,j)\in M} R_{kj}\{\Delta t_{0,j}, \Delta t_{0,i}, (T, t_{\text{жс}}, t_{\text{з}})_j, (T, t_{\text{жс}}, t_{\text{з}})_i, l_{kj}, V_{kj}, P_{kj}\},$$

where Z_{ij} and R_{kj} are the total delays of vehicles on a stretch with a distance l_{ij} in the forward direction, and l_{kj} in the reverse direction, s;

T — control cycle time, s;

T_{gr} is the duration of the green signal phase, s;

t_{yel}— duration of the yellow signal phase, s;

t_{0m} is the shift of the beginning of the regulation cycle of each traffic light, relative to the selected zero one, while t_{0m} < T.

V — speed limit or recommended speed, km/h;
P is the number of rows for traffic;
M is the set of numbers of traffic light objects on the highway.

6. Conclusions

The influence of traffic light control on the objective function, expressed in the form of the value of environmental risk, has been studied, and it has been shown that environmental risk is mainly determined by the delay time of vehicles in front of controlled intersections. This makes it possible to select an objective function for optimizing the control of traffic light objects as the value of the total delays of vehicles for the entire city street network.

7. References

[1] Bhatia, V.; Jaglan, V.; Kumawat, S.; Siwach, V.; Sehrawat, H. (2022). Intellıgent Transportatıon System Applıcatıons: A Traffıc Management Perspectıve. In Intelligent Sustainable Systems; Springer: Singapore, pp. 419–433.

[2] Oskarbski, J., Gumińska, L., Marcinkowski, T. (2018). Methodology of research on the impact of ITS services on the safety and efficiency of road traffic using transport models. MATEC Web of Conferences.

[3] Péter, T., Bokor, J. (2010). Modeling road traffic networks for control. In: Prof the Hon Dr Stephen Martin (eds) Annual international conference on network technologies & communications (NTC 2010), Thailand, 30th November 2010, pp. 18-22.

[4] K Turner-Fairbank: Traffic Flow Theory and Characteristics. http://www.tfhrc.gov/its/tft/tft.htm.

[5] Toutouh, J., Lebrusán, I., Nesmachnow, S. (2020). Computational Intelligence for Evaluating the Air Quality in the Center of Madrid, Spain. In: Dorronsoro, B., Ruiz, P., de la Torre, J., Urda, D., Talbi, EG. (eds) Optimization and Learning. OLA 2020. Communications in Computer and Information Science, vol 1173. Springer, Cham. https://doi.org/10.1007/978-3-030-41913-4_10.

[6] T. A. Várkonyi, J. K. Tar and I. J. Rudas. (2012). Adaptive emission control of freeway traffic via compensation of modeling inconsistences. 2012 IEEE 10th International Symposium on Applied Machine Intelligence and Informatics (SAMI), Herl'any, Slovakia, pp. 79-84, doi: 10.1109/SAMI.2012.6208933.

[7] Solving the problem of air pollution and improving the health of the population of Almaty through air quality monitoring. URL: https://www.undp.org/ru/kazakhstan/blog/reshenie-problemy-zagryazneniya-vozdukha-i-uluchsheniya-zdorovya-naseleniya-goroda-almaty-s-pomoschyu-monitoringa-kachestva-vozdukha.

[8] Assessment of atmospheric air quality in Almaty and Almaty region. URL: https://kazhydromet.kz/uploads/calendar/114/kvartal_2_file/62ecf3a18f9d92-kv-almaty-i-almatinskaya-oblast-rus-2022-byulleten.pdf.

[9] A. Alsheikhy, Y. Said and T. Shawly. (2023). An intelligent adaptive dynamic algorithm for a smart traffic system. Computer Systems Science and Engineering, vol. 46, no.1, pp. 1109–1126.

[10] Jelínek, J.; Čejka, J.; Šedivý, J. (2021). Importance of the Static Infrastructure for Dissemination of Information within Intelligent Transportation Systems. Commun.–Sci. Lett. Univ. Zilina. 24, E63–E73.

[11] Canadian society of civil engineering annual conference, CSCE, 2021.

[12] Gartner, Nathan H., and Gennaro Improta, eds. Urban traffic networks: dynamic flow modeling and control. Springer Science & Business Media, 2012.

[13] A. Stanovsky, K. Kolesnikova, E. Lebedeva, and I. Kheblov. (2015). Dynamic models in the method of project management, *EEJET, vol. 6, iss. 3(78),* pp. 46–52.

[14] Anat Meir, Hagai Tapiro, Tal Oron-Gilad. (2023). Towards safer, more walkable urban environments for child-pedestrians - application of the theory of Planned behavior, Safety Science, Volume 164. https://doi.org/10.1016/j.ssci.2023.106148.

[15] Jain Neetika and Mittal Sangeeta. (2022). A Computational Model for Driver Risk Evaluation and Crash Prediction Using Contextual Data from On-board Telematics. Recent Advances in Computer Science and Communications, volume 15 (4). https://dx.doi.org/10.2174/2666255813999200930164555.

[16] Georgios Kapousizis, Anna Goodman, Rachel Aldred, Cycling injury risk in Britain: A case-crossover study of infrastructural and route environment correlates, Accident Analysis & Prevention, Volume 154, 2021, https://doi.org/10.1016/j.aap.2021.106063.

[17] Abdollahzadeh Nasiri, A.S.; Rahmani, O.; Abdi Kordani, A.; Karballaeezadeh, N.; Mosavi, A. (2020). Evaluation of Safety in Horizontal Curves of Roads Using a Multi-Body Dynamic Simulation Process. *Int. J. Environ. Res. Public Health*, vol. *17*, 5975. https://doi.org/10.3390/ijerph17165975.

[18] Shabanda, I.S., Koki, I.B., Low, K.H. et al. (2019). Daily exposure to toxic metals through urban road dust from industrial, commercial, heavy traffic, and residential areas in Petaling Jaya, Malaysia: a health risk assessment. Environ Sci Pollut Res, vol.26, 37193–37211. https://doi.org/10.1007/s11356-019-06718-2.

[19] Buchanan C. Traffic in the towns, Crown Edit. – 1963.

[20] A. Gómez-Corral, M.J. Lopez-Herrero, D. Taipe. (2023). A Markovian epidemic model in a resource-limited environment", *Applied Mathematics and Computation*, Vol. 458. https://doi.org/10.1016/j.amc.2023.128252.

[21] P-N. Hossein, "Introduction to Probability, Statistics, and Random Processes", *Kappa Research LLC*, 2014.

[22] K. Kolesnikova, O. Mezentseva and O. Savielieva. (2019). Modeling of Decision Making Strategies In Management of Steelmaking Processes. *2019 IEEE International Conference on Advanced Trends in Information Theory (ATIT)*, Kyiv, Ukraine, pp. 455-460. doi: 10.1109/ATIT49449.2019.9030524.

[23] R. Mian, S.H. Khan, "Markov Chain: An Approach for Analyzing Repeated Ordinal Data", *VDM Verlag Dr. Müller*, 2010.

[24] de Bellis E, Schulte-Mecklenbeck M, Brucks W, Herrmann A, Hertwig R. (2018). Blind haste: As light decreases, speeding increases. PLoS ONE 13(1): e0188951. https://doi.org/10.1371/journal.pone.0188951.

[25] Mohamed M. Naser, Adnan Zulkiple, Walid A. Al bargi, Nasradeen A. Khalifa, Basil David Daniel. (2017). Modeling pedestrian gap crossing index under mixed traffic condition, Journal of Safety Research, Volume 63: 91-98, https://doi.org/10.1016/j.jsr.2017.08.005.

[26] A. Kolomiiets, O. Mezentseva, K. Kolesnikova. (2021). Customer churn prediction in the software by subscription models it business using machine learning methods. *CEUR Workshop Proceedings,* vol.3039, pp. 119-128.