Досліджується рух автомобіля в магістральному транспортному потоці на міжміських маршрутах. Рух має бути енергоощадним, безпечним і уможливлювати дотримання бажаного розкладу. Розроблена методика аналізу вхідного потоку даних на основі імітаційної моделі. Запропонований алгоритм імітаційного моделювання базується на використанні доступних інформаційних ресурсів керування автомобілем. Керування рухом пов'язане з вибором швидкості при відомих дорожніх і транспортних обмеженнях. Представлений алгоритм дає змогу зважити доцільність використання кожної з можливостей збільшення швидкості, впродовж прогнозованого горизонту. Зміст алгоритму полягає в оптимальному перерозподілі ресурсів часу. Показниками якості контролю є абсолютні відхилення від оптимальної енергоощадної програми вільного руху і від запланованого розкладу руху. Виконано моделювання руху вантажного автопоїзда на міжміській магістралі Е-371. Виявлено, що загальний обсяг інформації зростає при збільшенні дистанції сканованого трафіку. Однак частка достовірної інформації при цьому зменшується. З'ясовано, що залежність показників якості контролю руху транспортного засобу від розміру горизонту прогнозування є кусково-неперервною. На кожній неперервній ділянці залежність має екстремальне значення горизонту, при якому відхилення від оптимальної програми є мінімальним. Отримані результати можна застосувати в сучасних інтелектуальних транспортних системах. Результати досліджень дають змогу розробляти і дотримуватись оптимальних довготермінових програм руху на магістральних дорогах. При цьому розв'язується проблема керування великими потоками даних. Користуючись розробленою методикою, великі об'єми інформації для прогнозування можна подавати частинами, з обґрунтованою періодичністю

Ключові слова: інтелектуальні транспортні системи, прогнозування швидкості, аналіз потоку даних, оптимальна програма руху, магістральні перевезення

OPTIMIZATION OF VEHICLE SPEED FORECASTING HORIZONT ON THE INTERCITY HIGHWAY

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1. Introduction

Modern means of telecommunications used in intelligent transport systems (ITS) provide information on the movement of cars in both cities and on intercity roads. This service is considered as one of the most popular today [1]. The ability to accurately plan the route, determine the travel time, predict traffic delays and make necessary administrative orders regarding fleet interaction in the network is implemented through telemetry means. The necessary criterion for evaluating the planned actions and the probability of achieving its level is laid down in decisions-making. Accuracy and reliability of the provided information are the main indicators of high efficiency of ITS. On the other hand, modern information support is of high cost. For example, the cost of installing video detectors on highways (the most popular tools in ITS) was from $ 45 thousand to $ 75 thousand per km of road in 2012–2016 in different countries [2]. In addition, the maintenance of their supporting information systems is expensive.

The accuracy of the information currently provided depends not only on the error of the received signals. For example, a GPS navigator error of 2–3 % is quite satisfactory and acceptable in order to decide on the choice of traffic program. Here the term *traffic program* means the speed change depending on the forecast road and traffic conditions. As for the long-distance travel of vehicles on the highway network, the traffic program here can last several hours and of course, traffic conditions change during this time quite dynamically. There is a lack of operative information on traffic and road

conditions when it comes to long-term planning. As a result, optimal driving programs are performed rarely. Instead, the planned schedules are broken, the terms of delivery of goods and passengers far exceed the objectively achievable.

Currently, the idea of intelligent transport systems implementation is considered very promising in Europe and America. However, the high level of investment restrains it, moreover, it does not have a guaranteed return. It is a question of uncertainty about the efficiency of the received information on highways. Therefore, substantiation of the power of information streams perceived by the driver, or an automated on-board vehicle control system is a task, which helps to solve the current scientific and applied problem of ITS implementation.

2. Literature review and problem statement

The publication [1] presents analytical models and methods for estimating the flow of information based on the technology of perception of mobile data coming from the motor transport vehicle (MTV). The aim of the study was to obtain a solution with low costs of ITS implementation. The proposed analytical models are used to analyze the relationship between traffic information (traffic, density and traffic speed) and the number of cellular signals. Traffic information can be estimated on the basis of the proposed analytical models of Cellular Floating Vehicle Data (CFVD). In addition, a method of MTV speed predicting based on the algorithm of Back Propagation Neural Network (BPNN) is proposed. The proposed models allow to carefully analyze the input data and predict the future speed of the car for road users. However, the presented studies concern to short-term forecasting only. Besides, MTV and other road users, as well as transport infrastructure facilities, must be equipped with forecasting tools. Research results and methods may be useful within urban ITS.

Means of traffic information collecting differ in principles of signal generation. However, no application of known tools without an integrated system meets the requirements of accuracy and spatio-temporal capacity of the information flow. For example, the data of video cameras (as distance sensors) are quite satisfactory for estimating the traffic density [2]. However, video sensors are usually not available where they are needed. The formation of "dead zones" eliminates all previously made forecasts. In addition, most existing motion detection sensors are point sensors. Such sensors can generate only the number of MTV that are in one monitoring area (circuit). Using more circuits enables to reveal the acceleration/deceleration of objects, and sensors on observation cars allow you to describe road and traffic conditions over long distances.

In [3], it is indicated that the control of average speed and density of traffic for large spatial and temporal coverage is required for high efficiency of traffic management. However, the field of the average flow rate is estimated by the harmonic average value based on the sample point measurements at present. This does not provide the required forecasting accuracy. Estimation of density should take into account the dynamics of the traffic flow state in time and space. This means that a model approach should be used. Updated information based on the flow model at fixed stages of the transportation cycle and information from probing MTV should be taken into account. In [4], a review of methods, tools and appropriate analytical models for short-term prediction of MTV speed was performed. The large variability

of the input data flow was called the main problem of using the vast majority of known models. It was pointed out that forecasting based on model-oriented programming is inferior in efficiency compared to data-based programming. However, it is proposed to use standard statistical flow estimates calculated over a fixed period of time as input values. Such online forecasting is contradictory. After all, the higher the amount of data, the more accurate the statistical estimate. On the other hand, the longer the data collection period, the less time is left to make management decisions. Also, this paper does not substantiate the choice of forecasting horizon.

The study [5] showed that the restrictions imposed on the choice of MTV speed depend on traffic conditions. Classification of conditions is performed. An analysis of traffic objects that can be sources of reports and traffic restrictions is also performed. However, the research material does not cover the tasks related to substantiating the effectiveness of the information obtained.

For the most part, all new information technologies in transport are based on mutual "communication" between road users, as well as with stationary road objects. After all, the opportunity to improve the reliability and accuracy of forecasting is obtained through the exchange of information. In [6], there are examples, where the method of estimating the speed of MTV in the flow was developed for a "mixed" movement scenario. The traffic consists of both "independent" and "linked" MTV. However, the author used only those results of average speed measurement, which could be obtained from the sensors of cars connected to the ITS. The data of a microscopic Next Generation Simulation (NGSIM) model for the case of single unconnected data streams were used in this work. A test of the ability to assess the traffic state was performed on the basis of aggregate information received from the MTV. Different speeds of connected vehicles are taken into account.

The study [7] proposes an Eco-Approach and Departure (EAD) system based on real-time forecasting, which allows the driver to drive through a signal intersection in a safe and environmentally friendly way in the urban traffic flow. The EAD algorithm can provide a smooth and energy-efficient speed trajectory, taking into account the previous flow and queues at intersections. The results of numerical simulations show that the EAD is able to save 4 % or more energy. It should be expected that the use of such technology will save no less energy resources also in long-distance routes, taking into account the peculiarities of trunk traffic and speed forecasting technology. However, it is necessary to estimate the desired amount of information required for its use to control the traffic program within the selected forecast horizon.

The study [8] uses a longer section of the highway with internal congestion. The task was to test the ability of the proposed traffic estimation scheme to create appropriate signs for changing traffic conditions on a large section of the highway. In both cases, the results were satisfactory, if we talk about the benefits of MTVs "communication". However, NGSIM-based models are actually characterized by large accelerations/decelerations. These errors were not observed before in the phase trajectories according to NGSIM.

In [9], the application of Continuous Conditional Random Fields (CCRF) for traffic forecasting is considered. CCRF is a probabilistic approach consisting of traffic forecasts. Forecasts, in turn, are based on spatial and temporal correlations of traffic data. The probabilistic approach provides information on the level of forecasting uncertainty in addition to improving forecasting accuracy. Moreover, information on

the relative importance of specific predictive and spatio-temporal correlations can be easily obtained from the model. The CCRF is fault-tolerant and can provide predictions even if some observations are lacking. However, the CCRF model is not suitable for predicting rare events on the highway, such as congestion, accidents, and natural disasters. The accuracy of the model decreases exponentially with the increasing forecasting horizon. The impact of the size of the forecast horizon on the quality of the CCRF forecast remains unknown.

The study [10] presented an online system for predicting the duration of road travelling, which used a system of Vehicle Infrastructure Integration (VII). This is an integrated traffic simulator using the PARAMICS (Paramics Microsimulation Australia) environment. An experimental study was conducted on a highway network in the United States. The efficiency of the evaluated VII system is satisfactory. However, the accuracy of the VII model depends significantly on the proportion of vehicles equipped with data tools. All these benefits of the model are rapidly reduced if the share of MTV with VII support approaches values exceeding 25 %. There is a high probability that the communication network on which the use of the system is based will become congested due to the increase in the data flow.

The advantages of the technology of Connected Vehicles (CV) are generally recognized at present [10, 11]. CVs represent so-called V2I communication, including improved security, increased environmental sustainability, increased mobility, and so on. However, these technologies are not ready for implementation yet, as they require significant investment. The study [10] shows that the investment and management needed to reach the potential of CV technologies are lagging behind. So far, Vehicle-to-Vehicle (V2V) communication technology is considered more realistic [11]. Obviously, automakers do not want to depend on government agencies, although they begin to spend resources on V2V technology. The current transport infrastructure, including international transport corridors, is not ready to interact with the connected vehicles. Investment at the state and local levels is lacking even in developed countries such as the United States.

In [12, 13], attempts were made to estimate the influence of the forecasting horizon on the accuracy of the forecast, but in these works, horizons with a duration of movement from 15 to 60 minutes only were considered. The possibility of communication between MTVs to increase the forecasting horizon is not taken into account in any of the known works. The forecasting horizon in this sense is the time difference from the last observed speed value to the moment at which the forecasting is performed. The spatial forecasting horizon is measured in the range of 12–90 km, taking into account the range of permitted MTV speeds. This is enough to plan many routes. However, the impact of distance on the accuracy of forecasting and the effectiveness of decisions in ITS is not specified in these publications. Forecasting horizons were divided into short-term (up to 15 minutes), medium-term (30–45 minutes), and long-term (up to 60 minutes) in the study [13]. But this classification is relative. These studies are useful for urban traffic conditions. The presented results are of little use in the conditions of long-distance transportations if the performance of the transport task takes up to 10 hours, so traffic and road conditions are not so changeable. In addition, there are no recommendations on the difference in the technology of implementation of these four categories of forecasts.

Studies of modern ITS [14, 15] use the latest car speed control programs, which are often called Intellectual Speed Adaptation (ISA). ISA monitors the current MTV speed, compares the speed with the set external flow rate, and applies adjustments (provides advice to the driver and/or controls the maximum speed). Preferably, the desired speed is set in space, based on road and geographical conditions. The best implementation of ISA is one where the maximum MTV speed never exceeds the speed limit for these conditions. However, it is impossible to systematically choose a traffic program, taking into account the most economical conditions, with the help of ISA. After all, unforeseen flow delays are not compensated by time reserves, which can be detected by long-term forecasting.

It is known that fuel consumption and emissions of vehicles are directly associated with the vehicle moving program [16]. Reliable and accurate preliminary forecasting of the MTV state on the road is important for the effective application of the savings management strategy, especially in the conditions of a congested highway.

It is possible to improve observance of the schedule on the set route by means of car speed control programs, using the latest ITS technologies. Thus, the development of a new algorithm is presented in [17], which uses the existing speed limits and information about road conditions to develop the optimal speed phase trajectory on the forecasting horizon. However, the researchers did not form a clear restriction on the implementation of the traffic schedule. The developed algorithm offers optimal transport cycles, not taking into account that along the highway such cycles can have different lengths and structures [18]. Therefore, the given algorithm is not quite suitable for the highway.

New approaches to MTV speed control lead to the formation of new requirements for cruise control functions. In [19], the main and important aspects of new systems of Cooperative Adaptive Cruise Control (CACC) are considered. Various routing protocols that support data transfer requirements between MTVs are analyzed. To be accessible on highways, the control system must reflect the change in traffic in real time. Thus, the paper also discusses the problems faced by existing CACC control modules when it comes to approximately ideal control. The researchers' tasks were mainly focused on two aspects: vehicle communication and human factors and their impact on the design of the CACC controller. The presented results will contribute to the development of the CACC system. But the proposed ones are not close enough to the real dynamics of traffic. It is necessary to conduct more comprehensive research with integrated communications, human factors and management methods, to understand and analyze more practical situations of MTV management. This can be implemented through simulation.

Suitable for motorways means of vehicle surveillance are described in detail in [20]. These are new smart wireless motion sensors. Together with the sensors, algorithms for speed and distance estimation classification and synchronization of travel time were developed, integrated and tested for effectiveness. Several field studies conducted on highways and city roads for different scenarios and under different traffic conditions resulted in 99.98 % detection accuracy, 97.11 % speed estimation accuracy, and 97 % length-based vehicle classification accuracy. However, there are no data in the paper on the influence of the forecast horizon on the obtained velocity estimates. There are also no recommendations on the possibility of using sensors and appropriate algorithms in the cruise control system on long-distance routes.

The influence of network structure indicators, route direction and road conditions on determining the actual

traffic density in the transport network was studied in [21]. But, the results are presented only for the network in a static state, in which there is no influence of changing traffic and road conditions.

The methods based on the use of neural networks today offer good solutions for on-line predicting of traffic parameters. However, some specific forms of behaviour of highway traffic subjects can be analyzed only by large amounts of input data namely simulators. Thorough analysis requires the introduction of hybrid approaches and the combination of predictors [22]. The analysis of methods presented in the publication [23] gave some understanding of short-term real-time traffic forecasting, which can be used to develop new approaches to MTV speed control.

The problem of combining different data flows in ITS is often encountered in traffic management. This problem was partially solved in [24]. ITS integrates information from a variety of sources and online sensors, detects conflicts, and develops MTV routing solutions. In this way, ITS helps to reduce fuel consumption by vehicles and the associated emissions of harmful substances into the atmosphere. The formation of unstructured data streams into structural formations is used. Thus, a compact model with clustering and deep neuro-fuzzy classification for traffic estimation is proposed. However, it also requires large data sets that are dynamic to set up and train. Modern data collection systems are not able to perceive and process such data sets.

Predicting the speed of MTV significantly affects the efficiency of energy management of hybrid cars. To do this, a new approach to speed prediction has been developed, using the concept of Chaining Neural Network (CNN) [25]. CNN can be used as a basis for an equivalent strategy to minimize energy consumption. The road network model is built in the VISSIM environment (PTV UK Ltd.), assuming that modern V2V (vehicle-to-vehicle) and V2I (vehicle-to-infrastructure) communications are available for each vehicle in real time. However, the limit of communication is 200 meters. This limit was adopted due to the use of DSRC – Dedicated short-range communications, which is available in modern V2I technologies. The technique is designed for the city network, where traffic conditions change abruptly and nonlinearly and cannot be applied to the highway.

In [26], the authors suggest that their proposed model of Multiple Neural Networks (MNN) is better than a single model of Artificial Neural Networks (ANN) for multilevel prediction. MNN combines short-term and long-term neural networks to use a wide range of predictions that differ in the horizon. The proposed MNN model gradually adopts the predictions of its predecessors in the time chain. The speed forecasting horizon increases. However, the prediction error remains permanent.

The dependences of fuel consumption on vehicle speed and road conditions were analyzed and clarified in [27]. The authors showed that for given road conditions there is an optimal value of speed at which fuel consumption is minimal. This statement can also be agreed with, taking into account the known developments of energy-saving transport cycles [18]. However, such statements are accepted for instantaneous speeds in the absence of forced braking/acceleration. In addition, when road conditions change, transient modes objectively occur. Therefore, the average speed of the cycle should be used when planning a movement program.

The problem of increasing the efficiency of forecasting the MTV speed in the traffic flow hinders further development and implementation of intelligent traffic control systems, in particular, on highways, which follows from the analysis of literature data. Most aspects of ITS in forecasting remain unresolved. In particular, the issue of ensuring the accuracy of forecasting large data sets for long-term forecasts is unresolved. The methodology of data flow processing on intercity routes is also imperfect, and the available information is used inefficiently. Vehicle speed control allows you to save at least 4 % of energy costs in urban traffic. The savings can be even greater on long-distance traffic given the duration of traffic and the intensity of traffic flows. This applies to both cars with hydrocarbon engines and electric cars. However, the understanding of the desired MTV speed in the traffic flow under the conditions of compliance with the traffic schedule has not been formed clearly so far. There are also no methods to justify the choice of traffic program under the known road and transport conditions. To improve the accuracy of forecasting, communication systems of road users such as V2V, V2I are used. Methods that control data flow parameters are the most successful for analyzing data flows. Neural networks, as well as their modifications, such as neural network circuits, have been widely used in speed prediction. However, there are no literature sources that would substantiate the forecast horizon and methods of using operational data from this horizon.

3. The aim and objectives of the study

The aim of the study is to determine the influence of the speed forecast horizon on the performance of the savings program.

To achieve this aim, the following research objectives were formulated:

– to substantiate the method and the corresponding algorithm for calculating the savings program of MTV movement on a given long-distance route, subject to compliance with the fastest traffic schedule in a the given road and traffic conditions;

– to perform simulation of MTV movement for different forecasting periods and characteristics of traffic on highways;

– to construct the dependence of quality indicators of observance of saving modes of movement on the forecasting period, and to substantiate optimum values of the MTV speed forecast horizon.

4. Substantiation of the methodology and algorithm for calculating the savings program of MTV movement

The movement of MTV on the roads of the intercity route was considered. The start and end points of the route are set. The length of the route L_{max} is known. The current speed V of the MTV varies depending on road and traffic conditions. It was assumed that the road conditions, i. e. the terrain, plan and profile of the route, the condition of the road surface are known. Such conditions for the given MTV can be described by the program of free motion $V_i(x)$ – speed, which varies along the length of the route $x=[1, L_{max}]$. Optimal is the program of movement, which provides the greatest fuel economy in the absence of obstacles that cause delays, congestion and other forced changes in speed. Given the known studies, it can be argued that any deviation from $V_i(x)$ (increase or decrease in speed) leads to an increase in energy consumption [27]. There is a limit to the maximum absolute speed $V_{a.max}$, such that $V(x) \leq V_{a.max}$

for the MTV of the given class. Motion program was considered, which consists of a relative speed ratio $V_i(x)=V(x)/V_{a.\max}$. So, $0<V_i(x)\leq 1$. By $V_i(x)$ we mean the relative speed taken as a fraction of the maximum speed $V_{a.\max}$ for the given MTV henceforward. Therefore, all values that are included in the following consideration are relative and, accordingly, dimensionless. The route can be divided into arbitrarily small sections x_i such that the speed $V(x)\geq 0$ is considered constant, without a significant deterioration in the accuracy of the calculation. Each section x_i is the smallest unit of distance travelled by the MTV. Thus, the optimal motion program is a set of discrete values $V_i(x)$, for $0<x\leq L_{\max}$. The moments of the optimal schedule of the vehicle $0<t_i<T_x$, where T_x is the optimal time of arrival at the final point of the route are calculated by the program $V_i(x)$. We choose the time of departure from the starting point of the route, focusing on this schedule, to arrive on time at the final destination. A driver, or the on-board automatic control system, reduces the speed to a certain value $V_{\max}(x)$ on section x due to the fact that there are situations on the highway, in which one needs to slow down if the relevant information is available. These situations are increasing traffic density, increased accident hazard due to weather, natural or other conditions. Thus, the speed $V_{\max}(x)$ is a limitation in the application of the optimal motion program and adherence to the appropriate schedule, if $V_{\max}(x)<V_i(x)$. The speed $V_{\max}(x)$ is taken as the main parameter that characterizes the transport conditions on the highway, taking into account the purpose of the study. However, the execution of the schedule on a given route can be ensured by predicting $V_{\max}(x)$ for some distance of the route W, which is called the *forecast horizon*. Since all distances are measured in units of x, then W is also a relative dimensionless variable. If there is information about $V_{\max}(x)$, one can identify those sections of the route where $V_{\max}(x)>V_i(x)$. The speed can be increased from optimal $V_i(x)$ to maximum $V_{\max}(x)$ in such areas. This is a specific time resource that can be used, making deviations from the optimal program, but following the schedule. It is assumed that the larger the forecasting horizon W, the more opportunities there are to follow the optimal program for the speed $V_i(x)$. After all, if you divide the entire route $L_{\max}$ into sections of size W, you can get the total number of sections, on each of which the driver receives one information message:

$$J=\left\lceil\frac{L_{\max}}{W}\right\rceil. \tag{1}$$

It is clear from (1) that the larger the forecasting horizon W, the less operational information messages will be received by the driver, so the decisions made on each j-th section of the route are more difficult to change.

Note that the means of forecasting traffic conditions on highways have not yet reached such a functional level to give quite reliable and accurate information for the long term (at least 60 minutes) [2]. At the same time, the traffic flow density can change rapidly over a period of time Δt. Previous studies have shown that the standard deviation of the predicted traffic flow density is nonlinear depending on the forecast horizon. However, the influence of the size of the prediction horizon W on the ability to perform the optimal movement program $V_i(x)$, with a given schedule $t_x(x)$, has not been studied.

The content of the research task is as follows. One needs to choose the following set of values of average speeds on a given highway with characteristics $V_i(x)$ $V(x)$ on sections $x=1, 2,..., x_{i-1}, x_i, x_{i+1},..., L_{\max}$, for wich:

$$\sum_{x=1}^{L_{\max}}\left(\left|V_i(x)-V(x)\right|\right)\to\min, \tag{2}$$

provided that the MTV arrives at the final destination of the route no later than deadline $T_x=t_x(L_{\max})$.

The choice of speeds is made within one distance W. The choice must be made taking into account the permitted maximum speeds $V_{\max}(x)$, which are known only in the area of the forecast horizon W. However, valid speed limit information may be distorted.

The problem in this formulation cannot be solved by known exact or heuristic methods [28]. The method and an appropriate simulation model (SM) have been developed and applied to solve this problem, as well as to study the influence of the forecasting horizon on the choice of speed. Its content is that the selection of the traffic program within W is performed on the basis of randomly generated arrays of data on road and traffic conditions. The selection is made according to predetermined deterministic rules. Variables in the simulation are the size of the forecast horizon and the number of plots J accordingly.

The initial arrays of SM input data are an array of optimal velocities $V_i(x)$, an array of maximum velocity constraints $V_{\max}(x)$ on each of the sections J. These arrays were previously obtained using a random number generator by expressions:

$$V_i(x)=\left(V_{i.\min}+(V_{i.\max}-V_{i.\min})\cdot Random\right), \tag{3}$$

$$V_{\max}(x)=\left(R_{\min}+(R_{\max}-R_{\min})\cdot Random\right), \tag{4}$$

where $V_{i.\min}$, $V_{i.\max}$ are the minimum and maximum possible MTV speeds, according to the optimum movement program; *Random* is the random number between [0; 1], obtained by a random number generator [29]; $R_{\min}$, $R_{\max}$ are the minimum and, accordingly, the maximum possible values of the MTV speed limit due to traffic parameters.

Additional variables and arrays are used besides $V_i(x)$ and $V_{\max}(x)$, namely $V_{w.\max}(x)$ is an array of maximum speed limits, which is formed as a result of distance W randomization. If the array $V_{\max}(x)$ is considered in the SM as unknown in advance, but the information about this array is uncertain, then the data array $V_{w.\max}(x)$ for a driver is known, but only on the planning horizon W. The array $V_{w.\max}(x)$ is calculated by the expression:

$$V_{w.\max}(x)=V_{\max}(x)\cdot\left(1-random(W)/W\right), \tag{5}$$

where $random(W)$ is a random number in the interval [0; W].

According to the expression (5), the accuracy of determining $V_{w.\max}(x)$ decreases with increasing W.

Additional parameters of the SM are also:
$-\overline{V}$ − average speed on the route according to the program $V_i(x)$:

$$\overline{V}=\frac{\sum_{x=0}^{L_{\max}}V_i(x)}{L_{\max}}; \tag{6}$$

$-T_z(x)$ − planned travel time of section x, which is determined only within the forecast horizon W by the formula:

$$T_z(x)=T_z(x-1)+\frac{1}{\min(\overline{V},V_{\max}(x))}; \tag{7}$$

– $V_z(x)$ – planned velocity in section x, which is determined only within the forecast horizon W;

– $\overline{T}(x)$ – average travel time of section x of the route, determined by the average speed $\overline{V}$:

$$\overline{T}(x) = \frac{x}{\overline{V}}. \tag{8}$$

The content of the simulation technique is that the actual control program $V(x)$ is planned every cycle, if sections x change within $(x_{i+w} - x_i) = W$. The speed $V(x)$ is selected within the programs $V_{w.max}(x)$ and $V_i(x)$ at the length of such a cycle. Deviations $V(x) > V_i(x)$ or $V(x) < V_i(x)$ are allowed if forced by traffic conditions, but the deviation $V(x) > V_{w.max}(x)$ is prohibited. Since $V_{w.max}(x)$ is approximated in content relative to the actual speed limits $V_{max}(x)$, then the correction of the program $V(x)$ is performed on the next cycle, based on the desired speed, which should be achievable at the end of the predicted distance at the end of each cycle. The average desired speed on the distance W is determined by the expression:

$$V_{des} = \frac{W}{T_z(W \cdot x + W) - T_x(W \cdot x)}, \tag{9}$$

where $T_z(W \cdot x + W)$ is the planned travel time of the final section of the forecast horizon W, which is calculated by the expression (7); $T_x(W \cdot x)$ is the actual time of arrival at the beginning of the distance, taking into account deviations from the optimal program $V_i(x)$, and delays in schedule.

Schedule adjustment is performed by finding probable time reserves due to speed deviations:

$$D(x) = V_{w.max}(x) - V(x). \tag{10}$$

The set of $D(x)$ values found is sorted in descending order. Then, using the Johnson principle and algorithm [30], those sections are first selected where the speed increase reserve is minimal and the speed $V(x) := V_{w.max}(x)$ is set higher than planned for them. Next, the reachability of the planned algorithm is checked and, if the time of passing the final section of the distance corresponds to the schedule, the correction is completed. Otherwise, the next available reserve of forced speed increase is selected. In this way, there is a dynamic approach to the optimal solution of the problem of choosing a traffic program. According to research results, Johnson's algorithm provides approximate optimization [31]. The block diagram of the SM algorithm is given in Fig. 1, 2.
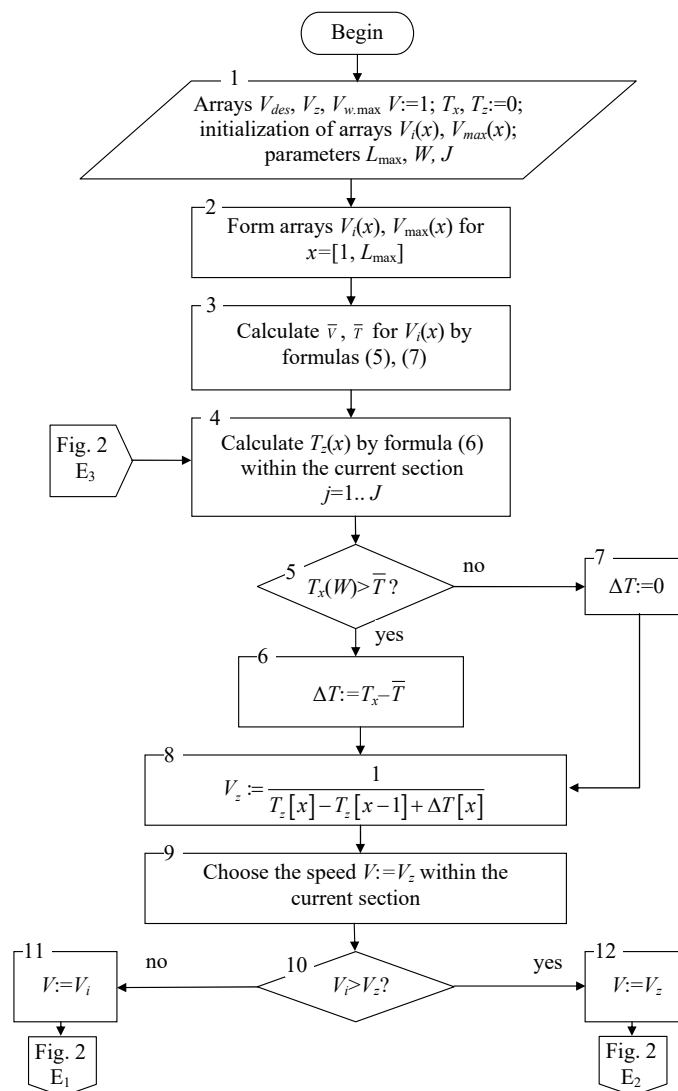

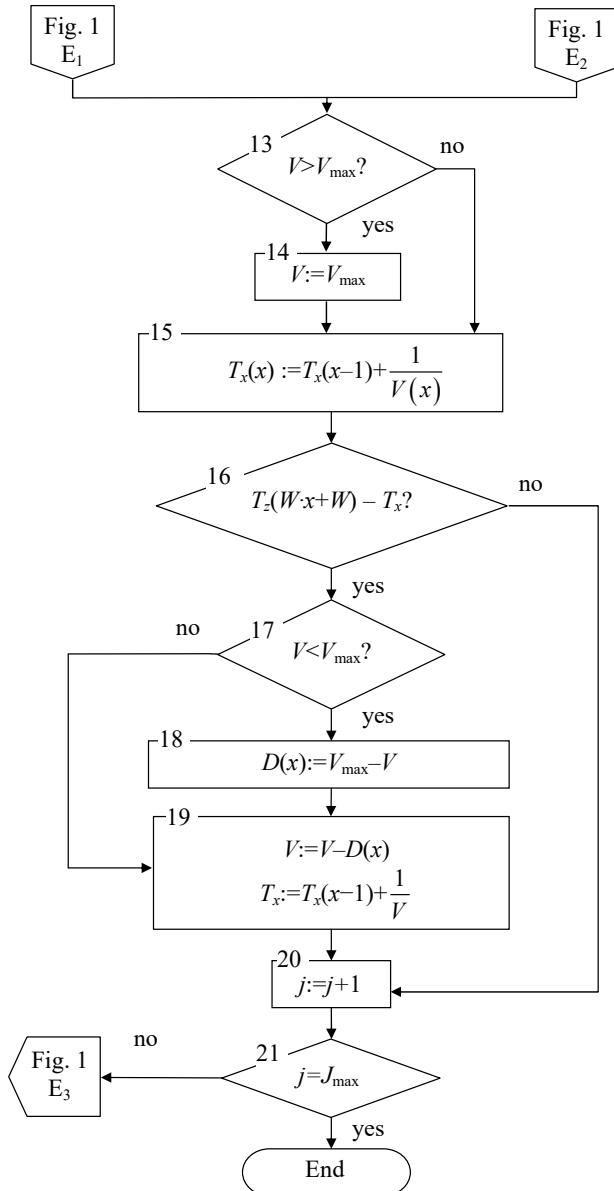Fig. 1. Block diagram of the SM algorithm (beginning)

Fig. 2. Block diagram of the SM algorithm (continued)

5. Preparation of the input data array and simulation

To perform the simulation process, initial data describing the highway with speed limits were prepared. The analogue of initial data concerns European road driving route E−372 on the section of the Ternopil – L'viv route (Ukraine) at the beginning of 2020. Initial data are divided into road and transport conditions. The starting point of the route is a gas station, L'vivska str., 36, Ternopil. The final point of the route is the TIR station in the Malekhiv town, L'viv region. The maximum traffic flow is 32 thousand cars per day. The road has two lanes of 3.75 m wide for most of its length, which do not have a separate lane. There are no traffic intersections. Instead, there are road structures to limit the maximum speed before pedestrian crossings and in populated areas. The maximum speed on the road is limited to 25 m/s. A road train

was considered consisting of a DAF XF 105 truck, an engine capacity of 12.9 liters with a Cogel Cargo SN 24 semi-trailer, and a total train weight of 38.400 kg. Traction-speed characteristics of the road train are calculated for the given road conditions and the saving modes of free steady travelling for characteristic sections of the E−372 route are defined. Data are given for weather conditions: average daily air temperature − +19 °C, wind speed − no more than 10 m/s, no precipitation. The average design speed of free movement for this route is 21.3 m/s. Mathematical expectation $E(V_i)$ and standard deviation of velocity $\sigma(V_i)$ were used to characterize the profile of road conditions. Speed is the most important derivative indicator among traffic and operational indicators of highways. Since the MTV speed is a random variable it is necessary to know the values $E(V_i)$ and $\sigma(V_i)$ to evaluate the method of obtaining information about it. It is obvious that $E(V_i)$ and $\sigma(V_i)$ are also random variables, which, moreover, depend on L_{max}. However, the dispersion of these estimates is much smaller than the dispersion of the process $V_i(t)$, therefore, knowledge of the estimates $E(V_i)$ and $\sigma(V_i)$ is sufficient to characterize road conditions. The relative characteristics of the route, according to the initial data, are given for typical 12 sections. Each section represents one category of the road according to Ukrainian standard DBN V.2.3-4:2015. Thanks to such estimates, it is possible to organize the input data obtained by the random number generator by the expression (3). Initial data were prepared for the highway with a length of L_{max}=12,5000 m. Relative values were taken for research. The length of the route was measured by the number of the smallest sections of the route. The length of the smallest section is taken to be x=25 m. The accepted value follows from the fact that at the maximum acceleration/deceleration of the freight train on the highway in higher gears, which does not exceed 0.4 m/s², its speed varies within 3 %. This means that within the distance x=25 m, the speed of the MTV can be considered constant. This transformation allows you to use a discrete array of input data for the SM. Thus, L_{max}=5,000x. The forecast horizon W varied within $10x$...$5,000x$. The smallest horizon $10x$ can be provided with the information received by operative visual observation of a driver. Road conditions were assumed to be stable if traffic conditions changed. The calculated values of the average energy-saving speeds of free movement, in accordance with road conditions, are given in Table 1.

Table 1

Characteristics of sections of the L'viv − Ternopil route

Section No.	Distance from the starting point, m	Section length, m	Truck average speed, m/s	Relative speed units	
				mathematical expectation	standard deviation
1	0	4,400	21.0	0.837	0.019796
2	4,400	12,400	22.5	0.876	0.019357
3	16,800	2,600	12.5	0.534	0.043717
4	19,400	9,500	22.5	0.901	0.028936
5	28,900	5,400	14.0	0.526	0.029262
6	34,300	8,000	22.3	0.892	0.028927
7	42,300	3,700	12.1	0.484	0.040526
8	46,000	11,500	22.5	0.893	0.030205
9	57,500	44,500	23.2	0.922	0.020113
10	102,000	10,000	19.5	0.782	0.022139
11	112,000	9,000	24.8	0.992	0.022753
12	121,000	4,000	19.5	0.782	0.019596

14 sets of initial data on different traffic conditions observed on the Ternopil – L'viv route were used. The characteristics are given in Table 2. The data are selected from the tachographs of trucks that performed this route. The velocity profiles V_{max} do not have characteristic sections.

Table 2

Characteristics of the initial traffic data

Indicator	1	2	3	4	5	6	7
$E(V_{max})$	0.8	0.8	0.8	0.8	0.8	0.7	0.7
$\sigma(V_{max})$	0.0032	0.0024	0.0016	0.0008	0.0004	0.0041	0.0031
Indicator	8	9	10	11	12	13	14
$E(V_{max})$	0.70	0.7	0.7	0.6	0.6	0.6	0.6
$\sigma(V_{max})$	0.0024	0.0016	0.0008	0.0032	0.0024	0.0016	0.0008

An example of the velocity trajectory for the initial traffic data set No. 1 is given in Fig. 3.
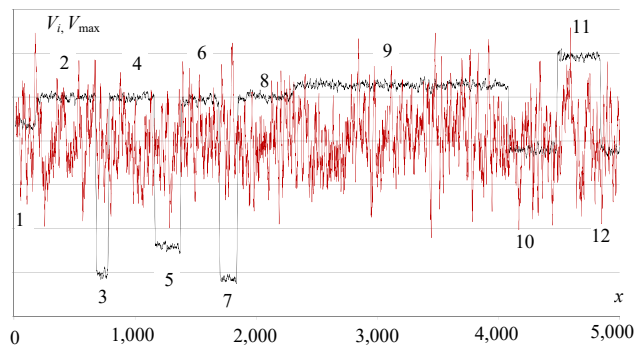

Fig. 3. Oscillograms of the speed profile on the Ternopil — L'viv route limited by road and traffic conditions: black color — restriction on road conditions V_i; red color — restrictions on traffic conditions V_{max} (rows linearly filtered on 10 points); 1—12 — section No.

It is evident from the given fragment of input data that the speed of MTV can change, taking into account road and traffic conditions within $V \in [0,45; 1.0]$ from $V_{a.max}$. The absolute maximum speed of the MTV is accepted $V_{a.max}=25$ m/s. The graph shows that there are sections where the speed V_i is a speed limit of the freight road train V. These are, for example, sections 3, 5, 7. The average energy-saving speed of the freight vehicle $V_i=0.54$ (13.5 m/s) for section No. 3 and restriction on traffic conditions is $V_{max}=0.896$. This speed ratio is due to poor road conditions. There are also areas where V_{max} is a constraint for V. For example, these are sections $x=2$, 4, 8 and others. This means that selecting and adjusting the driving program, a driver must be guided by three values: V_i, V_{max}, V_z.

The simulation was two-stage. The arrays of initial data $V_i(x)$ and $V_{max}(x)$ were generated by expressions (3) and (4) in the first stage. The arrays were checked for erroneously generated data that do not correspond to practical data taken from the analogue of the route. In the second stage, the developed SM was used to simulate the choice of MTV speed when using the initial data and applying prediction for the distance W. The forecast horizon in each set of input data changed cyclically. SM was performed in the environment of the algorithmic programming language Delphi based on the proposed algorithm.

6. Evaluation of quality indicators of the movement program on a given highway route

Indicators such as the absolute total speed deviation from the optimal DV program (11) and the time deviation from the planned travel schedule ΔT were used to assess the quality of vehicle control in the presence of a dynamic speed forecast (12):

$$DV = \sum_{x=1}^{L_{max}} \sqrt{\left(V(x) - V_i(x)\right)^2}, \qquad (11)$$

$$\Delta T = t\left(L_{max}\right) - T_{max}, \qquad (12)$$

where $t(L_{max})$ is the duration of the last section of the route.

Dependences $DV(W)$, $\Delta T(W)$ (Fig. 4, 5) were obtained as a result of the simulation. Dependences $DV(W)$ of Fig. 4 are given for the data set No. 1 (Table 1).
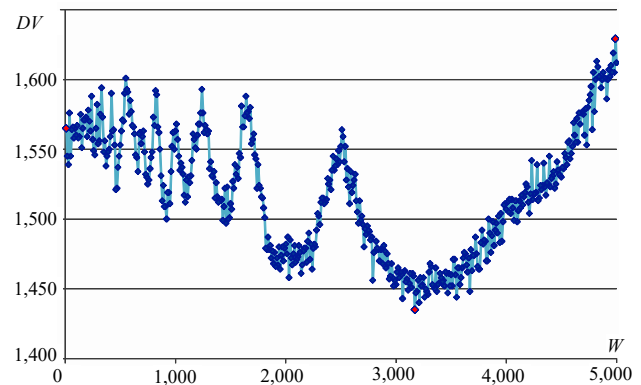

Fig. 4. Dependence of the total deviation of the DV program from the forecast horizon W for $E(V_{max})=0.8$ and $\sigma(V_{max})=0.0032$

The set No. 1 is characterized by a high value of the average velocity level ($V_{max}=0.8$) and a relatively low variance ($\sigma=0.0032$). The dependences $DV(W)$ for data sets No. 2–14 have similar characteristics. The type of dependences $DV(W)$ of sets No. 1–14 does not differ fundamentally. Simulation results are time series. Trend lines of all dependencies $DV(W)$ are piecewise continuous. The intervals between the jumps in the dependences increase with increasing W. At $W<1,000$, the monotony of the trend line is absent. The boundaries of each continuous section correspond to the numerical values of the argument W, which are multiples of the route length L_{max}. Each section of the dependence $DV(W)$ can be described by a parabolic dependence and has a minimum DV_{min}.

The dependence $\Delta T(W)$ (Fig. 5), as well as all dependences for the input data sets No. 2–14 are also time series.

The same features as of $DV(W)$ are characteristic of any dependence $\Delta T(W)$, according to the input data set. Minimums of the function $\Delta T(W)$ are displayed at approximately the same values of W as for the function $DV(W)$. The same applies to the global optimal values of W for $\Delta T(W)$ and for $DV(W)$ for any $\sigma(V_{max})$ and $E(V_{max})$. For example, the smallest total deviation from the planned schedule $\Delta T_{min}=4,735$ s for $\sigma(V_{max})=0.0033$ and $E(V_{max})=0.8$ (No. 1) is observed at $W=3,430$. And the smallest value of $DV_{min}=1,435$ – at $W=3,480$.
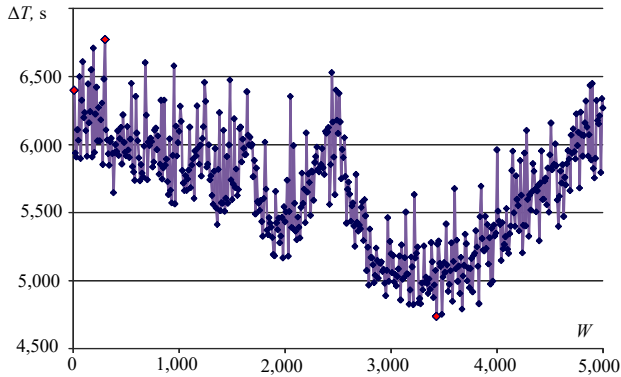
Fig. 5. Dependence of the total deviation of the optimal schedule from the forecast horizon W for $\sigma(V_{max})=0.0012$ and $E(V_{max})=0.85$

The following characteristic points (red dots) can be noted on each of the obtained dependences $DV(W)$ and $\Delta T(W)$: global minimum values of indicators DV_{min}, ΔT_{min}; global maximum values of DV_{max}, ΔT_{max}; numerical value of the indicator, which corresponds to the minimum forecast horizon $W_{min}=10$ (250 m). The time series element at W_{min} concerns the case when the driver, performing the transport task, is not guided by any external forecast regarding speed limits, but selects the speed that is as close as possible to the limit on traffic conditions V_{max}. In this case, the driver does not meet either the criterion of maximum savings or the criterion of accurate execution of the schedule. The numerical values of the estimates DV and ΔT at W_{min} are a significant difference from the minimum estimates as can be seen from Fig. 4, 5.

The travel schedule, which is based on the selected speed from the alternatives V_i and V_z, with the constraint $V<V_{max}$ was obtained for each simulated value of W. A fragment of the optimal schedule for the input data set No. 1 is given in Fig. 6.

```
Current time = 10779 s
Scheduled time = 5957 s
The average actual relative speed is 0.46
The average relative speed on road restrictions is 0.84
The average relative speed for traffic restrictions is (
The total deviation from the program of movement 1450
The total deviation from the schedule is 4822 s
Number of sections 2
Forecasting horizon 3170
 St_dev_Vi =0.0017 Stdev_Vmax = 0.0041
 Vi_aver =0.865 Vmax_aver = 0.805
****************************************************
    x    Vi      Vmax     Vz      V       Vdev      Tx
    1   0.83    0.94     0.84    0.84    -0.01      1.19
    2   0.85    1.01     0.84    0.85     0.00      2.37
    3   0.82    0.52     0.52    0.52     0.30      4.30
    4   0.81    0.66     0.66    0.66     0.15      5.82
    5   0.84    1.04     0.84    0.84     0.00      7.01
    6   0.83    1.14     0.84    0.84    -0.01      8.20
    7   0.86    1.25     0.84    0.86     0.00      9.36
    8   0.82    1.02     0.84    0.84    -0.02     10.55
    9   0.83    0.78     0.78    0.78     0.06     11.84
   10   0.84    0.65     0.65    0.65     0.19     13.38
                            ...
 4995   0.75    0.83     0.45    0.45     0.30  10769.30
 4996   0.80    0.91     0.75    0.75     0.06  10770.64
 4997   0.81    0.94     0.62    0.62     0.19  10772.25
 4998   0.80    0.48     0.29    0.29     0.51  10775.72
 4999   0.80    1.01     0.84    0.84    -0.04  10776.92
 5000   0.80    0.54     0.39    0.39     0.41  10779.45
```

Fig. 6. Fragment of the printout of the optimal schedule

Transport conditions varied in the SM according to the mathematical expectation and standard of velocity devi-

ation. The input data sequences given in Table 2 were obtained thanks to the random number generator for this case. Arrays of input data differ in the mathematical expectation, which acquired numerical values of $E(V_{max})$: 0.8, 0.7, 0.6. The standard deviation of the numerical values of the arrays $\sigma(V_{max})$ is: 0.0041, 0.0032, 0.0024, 0.0016, 0.0008, 0.0004. The numerical value of $\sigma(V_{max})<0.0004$ is practically impossible, as transport conditions on the route do not change, which was not observed on this route. The numerical value of $\sigma(V_{max})>0.0041$ according to the tachograph data on this highway was not detected. Within the obtained data ranges, histograms of the dependences $DV_{min}(\sigma, E)$ (Fig. 7) and $\Delta T_{min}(\sigma, E)$ were constructed (Fig. 8).
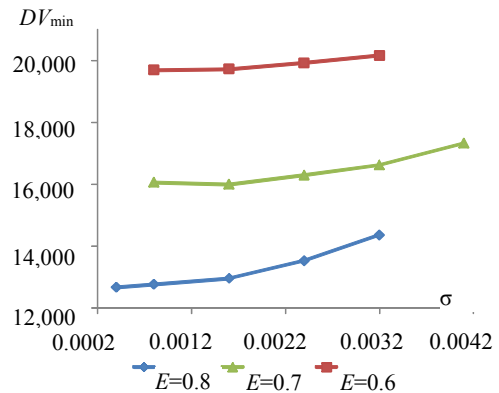

Fig. 7. Empirical plots of the minimum total deviation from the optimal traffic program under different traffic restrictions
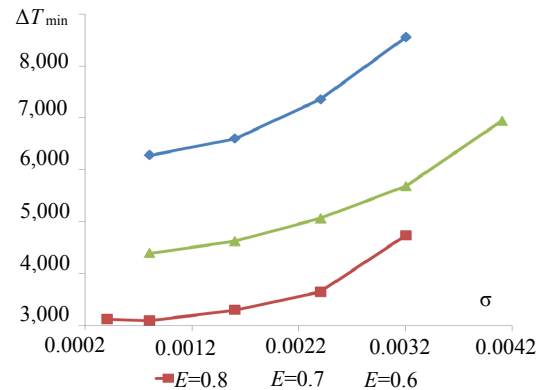

Fig. 8. Empirical plots of the minimum total deviation from the optimal schedule under different traffic restrictions

All empirical dependencies are increasing in the given interval. Fig. 8 shows a more rapid increase in the dependences $\Delta T_{min}(\sigma)$ than $DV_{min}(\sigma)$. More significant effect of the mathematical expectation $E(V_{max})$ on the control quality parameters than the standard deviation $\sigma(V_{max})$ is also noticeable.

7. Discussion of the results of modelling the process of forecasting and speed selection

The main result of SM application is the identification of patterns of the process of optimal control of MTV using long-term speed forecasts in terms of long-distance traffic. The SM algorithm, which is shown in the block diagram

in Fig. 1, 2, is based on the use of information resources of vehicle control, which are available to a driver. Thus, a driver is faced with the choice of speed V_i, V_z and V_{max} according to blocks 9–12 of the algorithm at each discrete step of the control process. One needs to choose the lowest speed from these three values. There are conditions where the optimal movement program and schedule are not met due to road or traffic restrictions according to Fig. 3, 6, for a particular vehicle. For example, at the beginning of the forecast horizon x=10 there is information that at step x=8 (Fig. 6) due to traffic, the current speed of the MTV should be increased by 0.02 units. This increase will lead to the realization of the desired schedule in general, which is expressed by the time of arrival exactly on schedule, or with minimal deviations from the schedule at the end of the route. However, it will deviate from the optimal energy saving program by 0.02 units. Therefore, under normal conditions, the driver is unlikely to increase speed if he applies the criterion of saving movement. The presented algorithm allows to consider the expediency of the specified possibility of speed increase, considering all possible situations during the forecasted horizon W. Fig. 6 shows that there are enough such situations on the route. The content of the algorithm, in fact, is the optimal redistribution of known resources to change the speed in order to obtain the minimum values of criteria (11), (12). In contrast to the known distribution algorithms, this SM uses the heuristic principle of Johnson's optimization: the optimal solution is achieved by using initially the smallest resources – to the largest. In addition, the algorithm uses a speed adjustment procedure relative to the planned schedule as additional information is obtained. Thus, it was possible to reduce deviations from both the optimal energy saving program and the planned schedule, compared to the traditional operational control of MTV without a long-term forecast. The red dot on the left top side of Fig. 4, 5 shows the case when W=10, i. e. the driver uses information about road and transport conditions within the visual inspection (approximately 250 m). This causes delays in the execution of the transport task for 6,400 s and a total deviation from the optimal speed of 1565 units for the input data set No. 1. As the forecast horizon increases to 80 km, the total deviation from the schedule decreases to 4,735 s, i. e. decreases by approximately 1,665 s, which is 27.9 % of the duration of the planned cycle. The deviation from the optimum speed is reduced by 121 units, i. e. 7.2 % of the case W=10. However, this result can be obtained under the most favourable circumstances, i. e. when the driver has chosen the right decision regarding speed. Adverse circumstances may occur in the absence of information. There is a point in Fig. 4, 5, which reflects the maximum deviation from traffic conditions due to the random nature of traffic. In this case, the total deviations from the optimal program can reach 1,629 units, and from the optimal schedule – 6,771 s, which is, respectively, 118 units of speed and 2,036 s more than the expected control quality. The difference between long-term forecast control and control based on visual operational information will be even greater with a decrease in the mathematical expectation of the average traffic speed, and an increase in its standard deviation, according to the dependences in Fig. 7, 8. After all, the driver of the vehicle intends to move on the route with an average speed $V_{z.2}>V_{z.1}$, where the indices 1 and 2

correspond to traffic conditions, for which, respectively, $E_2(V_{max})<E_1(V_{max})$. However, the variability of transport conditions leads to greater delays, which, according to the algorithm in Fig. 1, 2, will increase DV and ΔT.

However, the application of the optimal traffic planning algorithm has limitations on the amount of information that it is advisable to use for the driver when performing a planned trip. Given the forecast deviations, reflected in the value of $\sigma(V_{max})$, the speed of the MTV may differ significantly from the planned one. Thus, when the input data set No. 1 $E(V_{max})$=0.8, and $\sigma(V_{max})$=0.0032 in one step, the expected speed can vary within 0.8±0.064 units. This is 20±1.6 m/s in absolute units. If the forecast horizon increases, for example to W=2,500 (62.5 km), then at the end of the forecast period the expected speed varies within 0.8±0.132 units of 20±3.3 m/s. This deviation introduces uncertainty into the traffic program, so the driver will not be able to provide the optimal traffic program. Therefore, the program should be adjusted based on the receipt of regular information. This can explain the extreme nature of the time series of quality indicators of MTV control when changing the forecast horizon. The extreme of each obtained time series is explained by the contradiction of such factors. On the one hand, the longer the traffic forecast is performed, the more rational decisions can be made. On the other hand, the blurring of the input data increases with increasing W. Thus, it is possible to note those values of the forecast horizon in Fig. 4, 5, which correspond to the fullest use of information in long-term forecasting. These are the minimum distances relative to DV and ΔT in the figures. If we take into account the dependence in Fig. 7, 8, the forecast horizon also needs to be adjusted relative to the statistical estimation of traffic parameters. As the mathematical expectation of the average speed of cars in the intercity transport flow increases, the requirements for the forecasting accuracy increase, the standard deviation should be smaller.

The results of the simulation of the choice of MTV speed open new opportunities for the implementation of ITS on highways. This is manifested in the identified phenomena of reception and use of information flows. In contrast to the known technologies of road transport navigation, as well as ITS, the application of the proposed methodology and algorithm allows to develop and adhere to optimal traffic programs not only quickly but also in the long run. This solves the problem of managing large data streams. Using the developed methodology, information for forecasting can be submitted in parts, with reasonable frequency.

The results obtained apply only to long-distance highways and can be recommended for traffic flows where the average speed of cars with a standard deviation is not more than 8 % of the expected one.

At the same time, some aspects of the obtained regularities are not investigated, which need to be continued in future researches. First, it is necessary to find out the mechanism of compliance of the MTV control program with dynamic indicators, which means acceleration/deceleration on the route. After all, the errors of optimal control will be significant with small lengths of the route, and the size of section x, where the average speed was assumed to be constant. Second, future research on cruise control systems will require an integrated approach to the technologies of data reception and transmission, communication of traffic actors and choice of control actions.

8. Conclusions

1. The proposed method and algorithm for MTV control on the long-distance highway shows the ability to adhere to the optimal energy-saving traffic through the use of long-term forecasting of speed limits. One can reduce the total deviations from the optimal speed by 7.2 % compared to the operational traffic control within the driver's sight when forecasting the parameters of the traffic flow at a distance of more than 75 km on a given route. Time delays can be reduced by more than 27 %.

2. One needs to choose the optimal distance of the route, which is associated with the scattering of the expected speed, as well as the total length of the route, when substantiating the forecast horizon of the car speed in the traffic. On the studied section on the E−372 route Ternopil – L'viv, the appropriate forecast horizon can be one of three values: 35.5, 50, or 79 km at an expected speed of 20 m/s and its standard deviation of 0.0825 m/s. Smaller forecast horizons are not feasible to maintain the optimum speed under given conditions, as small horizons do not provide a higher quality of decision than when they can be taken by the driver when visually observing the operational situation. If the mathematical expectation of speed increases and the standard deviation decreases, the corresponding forecast horizons need to be increased.

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