Adv Syst Sci Appl 2020; **02**; 44-55
Published online at https://ijassa.ipu.ru.

Influence Assessment of Intelligent Unmanned Ground Vehicles on the Transport Network State

Andranik Akopov[1,2], Nerses Khachatryan[1,2], Fedor Belousov[1,2*]

[1)] *National Research University Higher School of Economics, Moscow, Russia*

E-mail: aakopov@hse.ru, nkhachatryan@hse.ru, fbelousov@hse.ru

[2)] *Central Economics and Mathematics Institute RAS, Moscow, Russia*

E-mail: nerses@cemi.rssi.ru

Abstract: This article is devoted to econometric analysis of the results of experiments conducted with two agent-based models, which describe the movement of ground vehicles. There are two types of road users in these models: manned ground vehicles (MGV) and unmanned ground vehicles (UGV). In the first model, the main difference between UGV and MGV is an ability to exchange massages between UGV for transmitting information about extreme situations, which allows them to adjust speed and direction of movement. In the second model, in addition to the above differences, UGV have an additional advantage, namely, the ability to intelligently assess density of traffic flow for efficient maneuvering. In these models, at a given roundabout, traffic characteristics such as output stream traffic and the number of traffic accidents are analyzed. The main task of the econometric analysis is to study dependence of these traffic characteristics on the model parameters such as average vehicle speed, input flow rate, message exchange rate between UGV, and the impact of the effect obtained from the implementation into UGV ability of intelligent estimation of traffic flow density.

Keywords: unmanned ground vehicles, manned ground vehicles, agent-based model, experimental results, econometric analysis

1. INTRODUCTION

Currently, the task of developing new intelligent control systems for an ensemble of ground-based UGV is being actualized in order to ensure high-speed and safe traffic, maximize the capacity of the transport system and minimize the number of factors (for example, emerging traffic accidents) that threaten other road users.

Works [1-7] are devoted to development of UGV control systems. In particular, the paper [1] proposes an algorithm based on predictive tracking control, designed to reduce time for decision-making. A very promising direction in the design of UGV control systems is an approach based on the use of machine learning methods, in particular, reinforced learning [2]. Such methods make it possible to ensure an effective response of UGV to the occurrence of certain situations on the road (for example, the sudden appearance of a pedestrian). At the same time, even the use of multilayer neural networks with a large number of neurons and synoptic connections (deep learning) [8, 9], the use of ultraprecise neural networks [10], etc. does not allow for zero learning error in pattern recognition and classification of moving objects with complex characteristics. Therefore, the task of developing UGV control systems based on simple rules that take into account the most common road situations for making effective decisions about maneuvering, changing lanes [4, 7], adjusting the speed and direction of traffic, etc. is urgent. Such a task can be solved using agent-based simulation methods [6, 7, 11, 12], fuzzy clustering [7, 13, 14, 15] and genetic optimization algorithms [16].

So, earlier we developed and implemented two agent-based models of MGV and UGV motion in AnyLogic simulation system [6, 7].

[*] Corresponding author: fbelousov@hse.ru

The first model, using the previously proposed phenomenological approach [11], is designed to assess the influence of various parameters (such as average initial speeds, input flow intensity, data exchange rate between UGV, etc.) on the behavior and condition of unmanned and manned ground vehicles in a dense flow [6]. The spatial dynamics of MGV and UGV is defined by a system of difference equations with a variable structure. The model takes into account the effects of "turbulence" and "traffic congestion" caused mainly by high vehicle density and occurrence of road accidents. At the same time, effective interaction is carried out between the UGV, in particular, periodic exchange of messages about the traffic situation (for example, about the places where accidents occur), in order to timely adjust speed and direction of movement. An important feature of this model is the proposed concept of the agent's personal space. The behavior of agents (MGV and UGV) in flow depends on density of the surrounding space. As the flow density increases, the radius of the agent's personal space is compressed (i.e., the transport flow is compacted). However, after reaching a certain threshold value of density, the radius of the agent's personal space increases significantly in manned ground vehicles, due to the occurrence of panic, and partially increases in UGV, due to a predetermined desire to avoid collision in dense traffic flow.

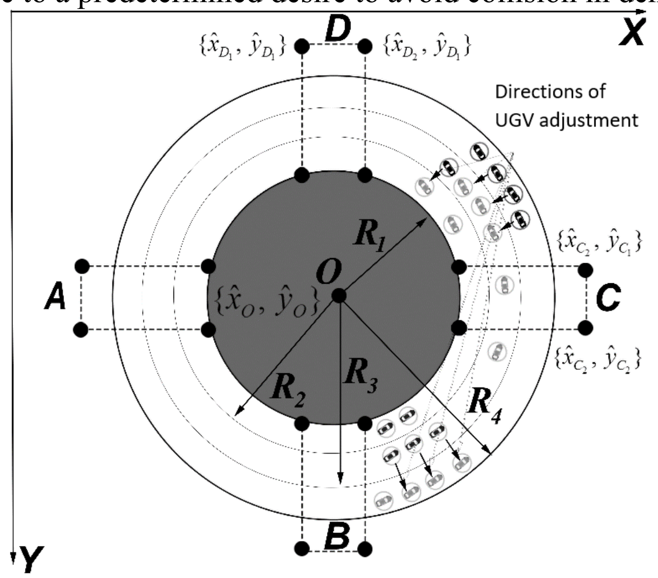

Fig. 1.1. Configuration of road space for MGV and UGV

The second model is designed for effective management of UGV, in particular, by maneuvering when changing lanes, the algorithm of which is based on the proposed fuzzy clustering algorithm [7]. The movement of the MGV and UGV ensemble in a certain two-dimensional space is considered. The space consists of combination of circular motion, two entrances and two exits from the circle (Fig. 1.1). At the same time, UGV makes individual decisions about trajectory adjustment based on simple rules. If there is less dense traffic in one of the adjacent lanes, this UGV is tuning to the corresponding lane. In this case, the flow density is estimated using fuzzy clustering methods for each of the available alternatives (lanes) across the entire ensemble of vehicles (both UGV and manned ground vehicles that do not have all the information about the density of the surrounding space). As a result, adaptive UGV management is supported, which minimizes the risks of accidents (accidents involving UGV) and maximizes traffic (total output stream) in conditions of heavy traffic flow. Software implementation in AnyLogic of the developed simulation model was performed and numerical experiments were carried out. Modes that ensure safe and high-speed movement of vehicles in dense traffic flow are found (Fig. 1.2). The developed system (Fig. 1.2) allows us to evaluate influence of multiple control parameters (for example, average speeds of MGV and UGV, intensities of input flows of MGV and UGV, etc.) on the total number of accidents and traffic of the output stream.

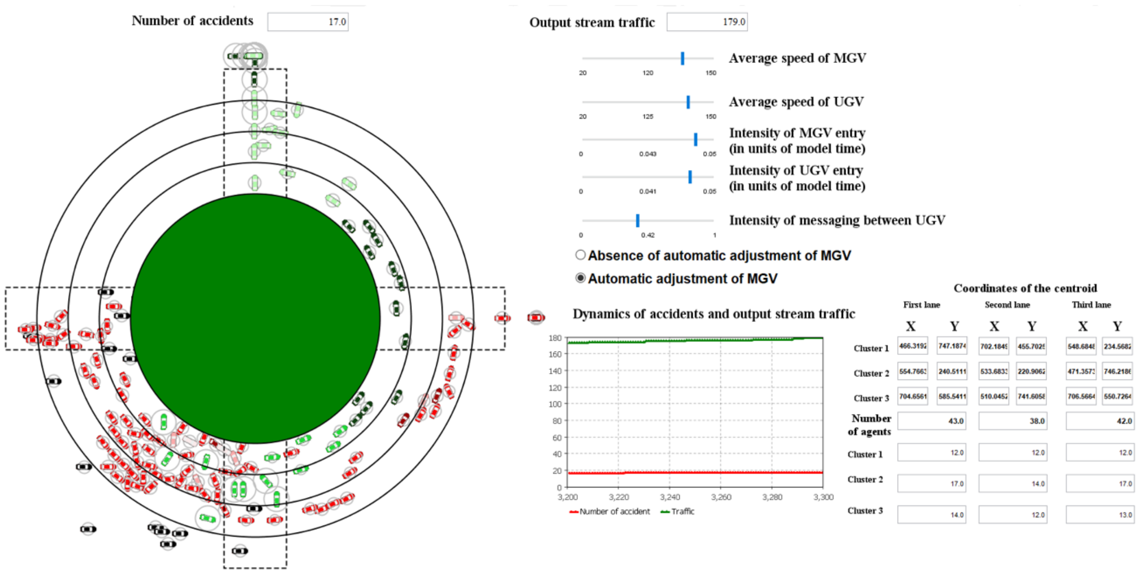

Fig. 1.2. Software implementation of the model in AnyLogic simulation system

This work is devoted to the analysis of the results of experiments conducted with these models. The main task of this analysis is to study dependence of the output stream traffic and the number of accidents on model parameters such as average vehicle speed, input stream intensity, message exchange frequency between UGV, and the impact of the effect obtained from the implementation into UGV ability of intelligent estimation of traffic flow density. To do this, a pool of identical experiments was conducted within each model. A set of experiments is formed as a result of multiple runs of the model, in each of which the specified model parameters take values in a given range with a given step. Finally, a database consisting of the results of more than one hundred thousand experiments is formed for each model.

Based on these results, an econometric analysis was carried out: the dependence of the output stream traffic and the number accidents on the parameters in both the first and second models was studied. Also the effect obtained as a result of the introduction of UGV with the ability to intelligently assess the density of road traffic, consisting in increasing the output stream traffic and reducing the number of accidents, was estimated.

2. SOURCE DATA, PRIMARY DATA ANALYSIS

This paper uses data obtained from a pool of experiments with each of the two agent-based models [6, 7] that describe the movement of vehicles, both manned and unmanned, in a given section of circular motion. In these experiments, such traffic characteristics as the output stream traffic and the number of traffic accidents over a certain period of time, which act as dependent variables, were calculated. The following parameters of agent-based models are explanatory variables:

- IntensityOfUncrewedVehicles – intensity of entry of UGV to the specified section of circular motion (in units of model time);
- IntensityOfUsualAgents – intensity of entry of MGV to the specified section of circular motion (in units of model time);
- SpeedOfUncrewedVehicles – average UGV speed (km/h);
- SpeedOfUsualAgents – average MGV speed (km/h);
- IntensityOfConnections – intensity of messaging between UGV (in units of model time).

As noted in the introduction, lot of experiments are formed as a result of multiple runs of the model implemented in AnyLogic using the special option “Sensitivity Analysis”. In this case, the specified model parameters take values in the specified range with the specified step (Table 2.1).

Table 2.1. Variation of model parameters

№	*Name of parameter*	*Range of variation*	*Variation step*	*Number of variations*
1	IntensityOfUncrewedVehicles	0.005 – 0.05	0.005	10
2	IntensityOfUsualAgents	0.005 – 0.05	0.005	10
3	SpeedOfUncrewedVehicles	40 – 140	10	11
4	SpeedOfUsualAgents	40 – 140	10	11
5	IntensityOfConnections	0 – 1	0.1	11

It is easy to see that the total number of experiments in each pool is 133100. The Table 2.2 shows the main descriptive statistics of dependent variables.

Table 2.2. Descriptive statistics

	Average	*Median*	*Standart deviation*	*Minimum*	*Maximum*
Output stream traffic (model 1)	56.5	56	25.4	3	149
Output stream traffic (model 2)	67.8	65	35.3	3	207
Number of accidents (model 1)	16	10	18.6	0	148
Number of accidents (model 2)	5.7	1	12.7	0	145

According to Table 2.2, introduction of intelligent UGV leads to an increase in output traffic by 20% and a decrease in the average number of accidents by 2.8 times. It is also worth noting that the median number of accidents is reduced from 10 to 1, i.e. in model with the ability to intelligently estimate the traffic density, approximately half of the experiments do not have an accident. In Fig. 2.1 and Fig. 2.2 histograms of the output stream traffic distribution are presented, and in Fig. 2.3 and Fig. 2.4 – histograms of the distribution of the number of accidents in model 1 and model 2, respectively.

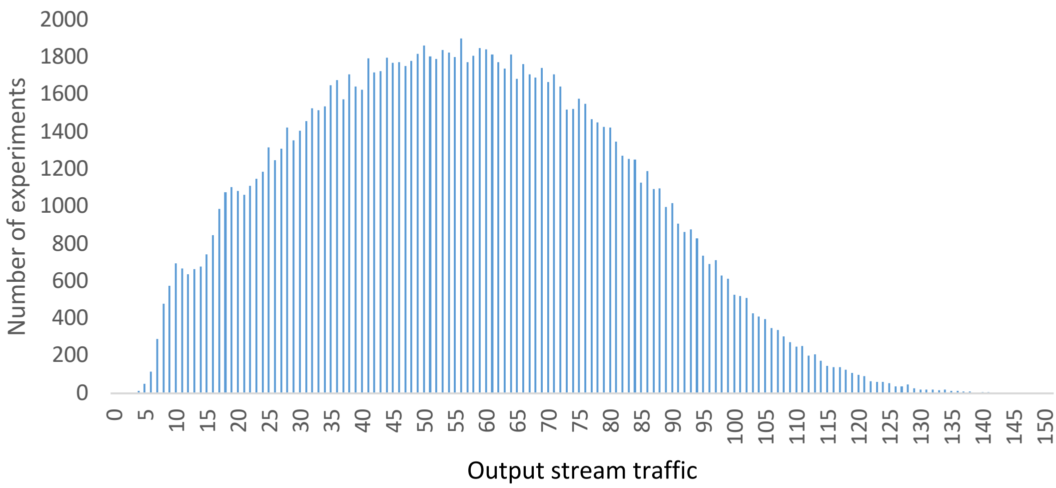

Fig. 2.1. Histogram of the output stream traffic distribution in model 1

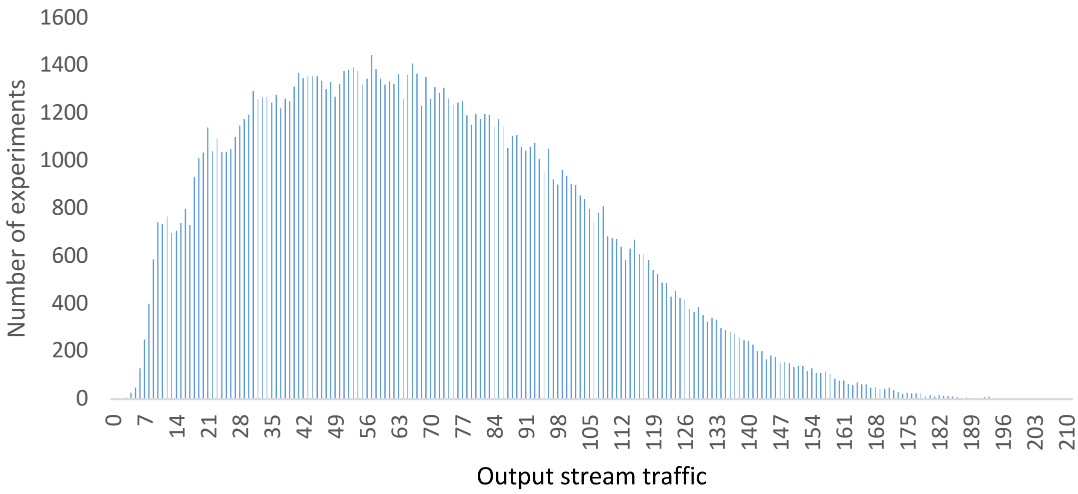

Fig. 2.2. Histogram of the output stream traffic distribution in model 2

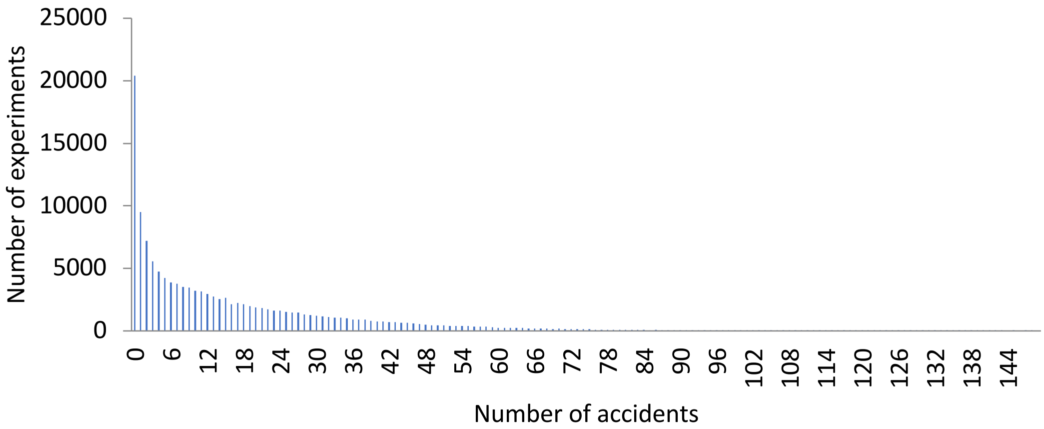

Fig. 2.3. Histogram of the number of accident distribution in model 1

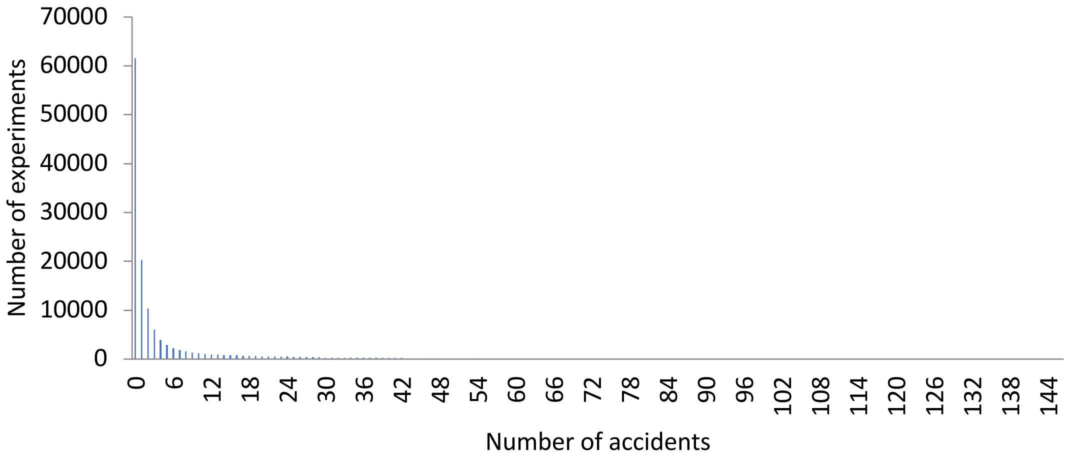

Fig. 2.4. Histogram of the number of accident distribution in model 2

From Fig. 2.3 and Fig. 2.4 it follows that the number of experiments without an accident in model 2 is three times less than in model 1. We finish the initial data analysis with the graph below (Fig. 2.5). It shows how the number of experiments in which the number of accidents is not less than the specified number (between the minimum and maximum number) decreases in both the first and second models.

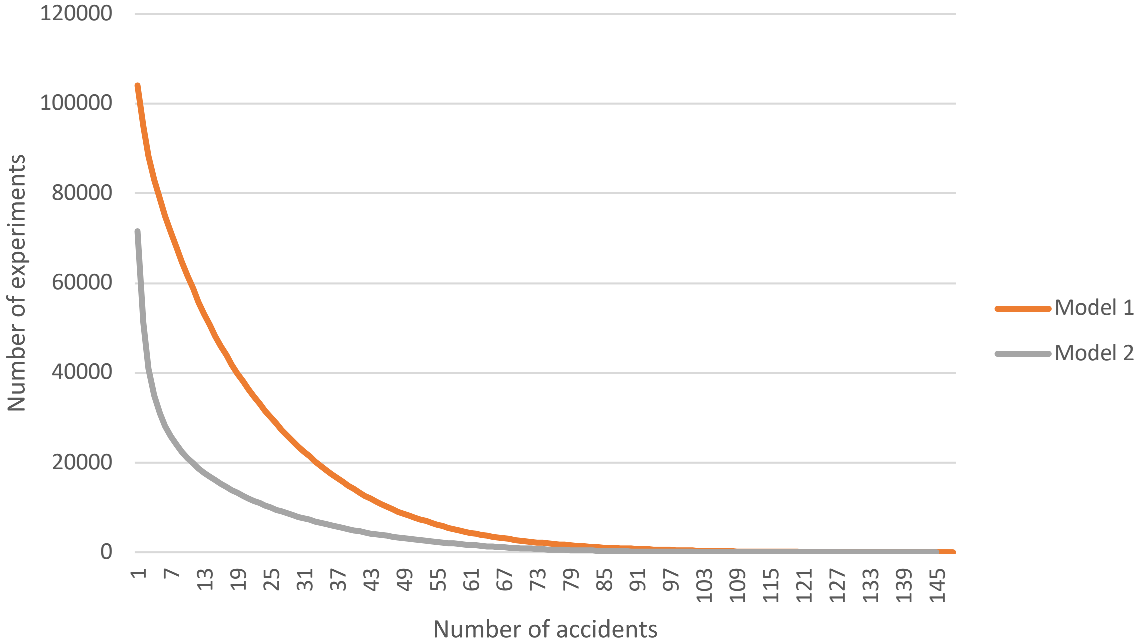

Fig. 2.5. Number of experiments with number of accidents not less than a given value

3. ECONOMETRIC MODEL SPECIFICATION SELECTION

Let's proceed to the study of the influence of the model parameters specified in Table 2.1 on the output stream traffic and the number of accidents, i.e., to construct and evaluate the corresponding regression equations. At the initial stage of this study, we will try to determine the model specification. Since the set of explanatory variables is defined in advance in the framework of building the above agent-based models, we are trying to determine the type of assumed dependency. We restrict ourselves to two types of functions that are most often encountered in econometric studies: linear and power-law. In this regard, we present matrices of pairwise correlations of all variables (both explanatory and dependent), as well as their logarithms for both models (Tables 3.1, 3.2, 3.3, 3.4). The following notation is used in these tables:

- X1 – IntensityOfUncrewedVehicles;
- X2 – IntensityOfUsualAgents;
- X3 – SpeedOfUncrewedVehicles;
- X4 – SpeedOfUsualAgents;
- X5 – IntensityOfConnections;
- Y1 – Output stream traffic;
- Y2 – Number of accidents.

Thus – X1, X2, X3, X4, X5 – explaining variables, a Y1, Y2 – dependent.

Table 3.1. Correlation matrix of variables in model 1

	X1	*X2*	*X3*	*X4*	*X5*	*Y1*	*Y2*
X1	1.00	-0.20	-0.008	0.03	-0.0002	0.07	0.47
X2	-0.20	1.00	0.002	0.03	0.0005	0.15	0.46
X3	-0.008	0.002	1.00	-0.02	-0.0006	0.40	0.11
X4	0.03	0.03	-0.02	1.00	0.002	0.74	-0.21
X5	-0.0002	0.0005	-0.0006	0.002	1.00	0.0003	-0.003
Y1	0.07	0.15	0.40	0.74	0.0003	1.00	-0.16
Y2	0.47	0.46	0.11	-0.21	-0.003	-0.16	1.00

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Table 3.2. Correlation matrix of logarithms of variables in model 1

	LOG(X1)	*LOG(X2)*	*LOG(X3)*	*LOG(X4)*	*LOG(X5)*	*LOG(Y1)*	*LOG(Y2)*
LOG(X1)	1.00	-0.22	-0.008	0.02	-0.0007	0.09	0.47
LOG(X2)	-0.22	1.00	0.001	0.03	0.0005	0.08	0.44
LOG(X3)	-0.008	0.001	1.00	-0.015	-0.0003	0.37	0.10
LOG(X4)	0.02	0.03	-0.015	1.00	0.002	0.75	-0.17
LOG(X5)	-0.0007	0.0005	-0.0003	0.002	1.00	-0.0003	-0.001
LOG(Y1)	0.09	0.08	0.37	0.75	-0.0003	1.00	-0.10
LOG(Y2)	0.47	0.44	0.10	-0.17	-0.001	-0.10	1.00

Table 3.3. Correlation matrix of variables in model 2

	X1	*X2*	*X3*	*X4*	*X5*	*Y1*	*Y2*
X1	1.00	-0.26	-0.02	0.12	-0.001	0.23	0.19
X2	-0.26	1.00	0.04	-0.008	-0.002	0.13	0.39
X3	-0.02	0.04	1.00	-0.05	-0.001	0.37	0.12
X4	0.12	-0.008	-0.05	1.00	-0.0009	0.74	-0.41
X5	-0.001	-0.002	-0.001	-0.0009	1.00	-0.003	0.001
Y1	0.23	0.13	0.37	0.74	-0.003	1.00	-0.37
Y2	0.19	0.39	0.12	-0.41	0.001	-0.37	1.00

Table 3.4. Correlation matrix of logarithms of variables in model 2

	LOG(X1)	*LOG(X2)*	*LOG(X3)*	*LOG(X4)*	*LOG(X5)*	*LOG(Y1)*	*LOG(Y2)*
LOG(X1)	1.00	-0.23	-0.02	0.10	-0.002	0.20	0.14
LOG(X2)	-0.23	1.00	0.04	-0.03	-0.0006	0.07	0.45
LOG(X3)	-0.02	0.04	1.00	-0.05	-0.001	0.35	0.10
LOG(X4)	0.10	-0.03	-0.05	1.00	-0.0006	0.77	-0.47
LOG(X5)	-0.002	-0.0006	-0.001	-0.0006	1.00	-0.001	0.001
LOG(Y1)	0.20	0.07	0.35	0.77	-0.001	1.00	-0.40
LOG(Y2)	0.14	0.45	0.10	-0.47	0.001	-0.40	1.00

Based on the data from these tables, we can draw the following conclusions:

1. The pairwise correlation both between explanatory variables and between their logarithms is low in both models, which, when evaluating the corresponding regression equations, cannot become a source of multicollinearity. This is important given that we are interested in the contribution of each explanatory variable to changes in dependent variables.
2. Comparing pairwise correlations between dependent and explanatory variables does not allow us to determine which of the functions (linear or power-law) most adequately describes the dependence of output stream traffic and the number of accidents on the model parameters. Therefore, in the future we will conduct econometric analysis using both types of functions.

In connection with the use of power functions, which will be logarithmized before estimation, we discard the results of experiments in which a variable assumes a zero value. Thus, to construct the regression equations for the output stream traffic, the data of 102448 observations were used, and for the number of accidents – the data of 65134 observations.

4. ECONOMETRIC ANALYSIS OF TRAFFIC CHARACTERISTICS IN THE FRAMEWORK OF LINEAR REGRESSION EQUATIONS

We proceed to evaluate the dependences of the output stream traffic and the number of accidents in both models on the indicated parameters of the model in the framework of linear regression equations. So, we will build and study linear regression equations with the following dependent variables:

- output stream traffic in model 1;
- output stream traffic in model 2;
- number of accidents in model 1;
- number of accidents in model 2.

The coefficients were estimated in the framework of the classical multiple regression model using the least squares method. Since the White test confidently rejects the null hypothesis of homoskedasticity of regression residues, standard errors are estimated by using the White procedure.

4.1. Results of an econometric analysis of the output stream traffic in the framework of linear regression equations

Here are the results of evaluating the dependence of the output stream traffic (Table 4.1) on the above set of explanatory variables.

Table 4.1. Dependent variable – output stream traffic, linear regression

Explanatory variables	*Model 1*	*Model 2*
Constant	-37.76*** (0.27)	-79.16*** (0.40)
IntensityOfUncrewedVehicles	147.22*** (3.72)	499.05*** (5.29)
IntensityOfUsualAgents	284.38*** (4.56)	446.01*** (6.70)
SpeedOfUncrewedVehicles	0.34*** (0.002)	0.48*** (0.002)
SpeedOfUsualAgents	0.60*** (0.002)	0.88*** (0.003)
IntensityOfConnections	0.40 (0.28)	-0.12 (0.25)
R^2	0.73	0.76

Note. In parentheses are the values of standard errors. ***, **, * – significance at the 1, 5 and 10% level, respectively.

As follows from Table 4.1, all explanatory variables in both models except IntensityOfConnections, which describe the output stream traffic, are significant at a 1% level. We also note that in both models the values of the determination coefficients are quite high.

Comparing the coefficients for significant variables in both models, we can draw the following conclusions:

1. An increase in the UGV input stream intensity by 0.005 units of model time (variation step, Table 2.1) leads to an increase in model 2 output stream traffic compared to model 1 output stream traffic by about 1.76 units. For MGV, the indicated difference is 0.81 units.
2. An increase in the average UGV speed by 10 km / h (variation step, Table 2.1) leads to an increase in the output stream traffic of model 2 compared with the output stream traffic of model 1 by 1.4 units. For MGV, the indicated difference is 2.8 units.

4.2. Results of an econometric analysis of the number of accidents in the framework of linear regression equations

Here are the results of evaluating the dependence of the number of accidents on the above set of explanatory variables (Table 4.2).

Table 4.2. Dependent variable – number of accidents, linear regression

Explanatory variables	*Model 1*	*Model 2*
Constant	-22.46*** (0.20)	-6.34** (0.24)
IntensityOfUncrewedVehicles	797.77*** (2.98)	414.23*** (3.96)
IntensityOfUsualAgents	810.13*** (3.14)	546.11*** (4.00)
SpeedOfUncrewedVehicles	0.07*** (0.001)	0.04*** (0.001)
SpeedOfUsualAgents	-0.15*** (0.001)	-0.22*** (0.002)
IntensityOfConnections	-0.16 (0.13)	0.12 (0.16)
R^2	0.62	0.45

Note. In parentheses are the values of standard errors. ***, **, * – significance at the 1, 5 and 10% level, respectively.

From Table 4.2 it follows that, as in the previous case, the IntensityOfConnections variable is not significant. All other explanatory variables describing the number of accidents in both models are significant at a 1% level. The positive values of the coefficients in the variables IntensityOfUncrewedVehicles and IntensityOfUsualAgents are quite natural. The average speed of UGV has a positive effect on the number of accidents, and the average speed of MGV is negative. This is explained as follows: an increase in the speed of MGV, in contrast to an increase in the speed of UGV, is a result of enough free traffic and leads to a decrease in road congestion, and an increase in the speed of UGV can lead to unpredictable actions by MGV. Comparing coefficients for explanatory variables in both models, we can draw the following conclusions:

1. An increase in UGV input stream intensity by 0.005 units of model time (variation step, Table 2.1) leads to a decrease in the number of accidents in model 2 compared to the number of accidents in model 1 by about 1.92 units. For MGV, the indicated difference is about 1.6 units.
2. An increase in the average UGV speed by 10 km / h (variation step, Table 2.1) leads to a decrease in the number of accidents in model 2 compared with the number of accidents in model 1 by 0.3 units. For MGV, the indicated difference is 0.7 units.

In conclusion, we note that evaluating the dependence of the output stream traffic and the number of accidents on the specified model parameters using the linear function gives generally good results. Only an assessment of the dependence of the number of accidents on the studied parameters in model 2 can be called not very successful due to the rather low value of the determination coefficient equal to 0.45. We proceed to the estimation of these dependences using a nonlinear function.

5. ECONOMETRIC ANALYSIS OF TRAFFIC CHARACTERISTICS IN THE FRAMEWORK OF NONLINEAR REGRESSION EQUATIONS

Let's proceed to estimate the dependences of the output stream traffic and the number of accidents in both models on the indicated parameters of the model in the framework of nonlinear regression equations. So, we will build and study power regression equations with the following dependent variables:

- output stream traffic in model 1;
- output stream traffic in model 2;
- number of accidents in model 1;
- number of accidents in model 2.

After logarithming of the equation, the coefficients were estimated in the framework of the classical multiple regression model using the least squares method, and standard errors were estimated using the White procedure. Here are the results of evaluating the dependence of the output stream traffic (Table 5.1) and the number of accidents (Table 5.2) on the indicated set of explanatory variables.

Table 5.1. Dependent variable –. output stream traffic, nonlinear regression

Explanatory variables	*Model 1*	*Model 2*
Constant	-2.65*** (0.03)	-3.79*** (0.02)
IntensityOfUncrewedVehicles	0.08*** (0.002)	0.17*** (0.002)
IntensityOfUsualAgents	0.08*** (0.002)	0.13*** (0.002)
SpeedOfUncrewedVehicles	0.55*** (0.003)	0.68*** (0.003)
SpeedOfUsualAgents	1.07*** (0.004)	1.35*** (0.003)
IntensityOfConnections	0.002 (0.002)	-0.0000013 (0.002)
R^2	0.72	0.77

Table 5.2. Dependent variable – number of accidents, nonlinear regression

Explanatory variables	*Model 1*	*Model 2*
Constant	11.77*** (0.06)	13.86*** (0.07)
IntensityOfUncrewedVehicles	1.11*** 0.005	0.66*** (0.006)
IntensityOfUsualAgents	1.10*** (0.004)	1.12*** (0.006)
SpeedOfUncrewedVehicles	0.30*** (0.008)	0.20*** (0.009)
SpeedOfUsualAgents	-0.61*** (0.008)	-1.61*** (0.009)
IntensityOfConnections	-0.07*** (0.005)	0.004 (0.005)
R^2	0.58	0.52

Note. In parentheses are the values of standard errors. ***, **, * – significance at the 1, 5 and 10% level, respectively.

Comparing Table 5.1 and Table 5.2 with Table 4.1 and Table 4.2, respectively, we can conclude that power regressions give qualitatively the same conclusions as linear ones. This is especially true for the description of these dependencies for output stream traffic. As for the description of the dependence for the number of accidents, here we can identify some advantage of power regression. Firstly, the value of the determination coefficient for model 2 increases from 0.45 to 0.52, and secondly, in contrast to the linear dependence, the IntensityOfConnections variable is statistically significant in the first model at a 1% level. The corresponding coefficient value in Table 5.2 (-0.07) allows us to state that an increase in message intensity between UGV by 14% allows reducing the number of accidents by 1%. Moreover, in the second model, this variable is insignificant. This is explained by the fact that in the second model, UGV have ability to estimate density of traffic flow, which allows them to maneuver effectively. In such a situation, the exchange of messages about the presence of an accident becomes irrelevant for the UGV.

6. CONCLUSION

In [6, 7] two agent-based models of movement of UGV and MGV, which were developed and implemented in AnyLogic simulation system, are described. The main difference between the second model and the first is that UGV is endowed with an additional capability - the ability to intelligently assess the density of traffic flow. The main purpose of this article is to evaluate the effect obtained from the implementation of these UGV, which is to increase output stream traffic and reduce the number of accidents. For this purpose a pool of identical experiments was carried out within each model, the results of which became the initial basis for conducting an econometric analysis. For both the first and second models, the dependence of the output stream traffic and the number of accidents on a given road section in a given period of time on a number of model parameters such as the average vehicle speed, input stream intensity, and the frequency of exchanges between UGV was studied. The study of these dependencies was carried out both in the framework of linear and power regressions. Evaluation of these dependencies made it possible to determine an increase in the output stream traffic and a decrease in the number of accidents in the second model relative to the indicated characteristics in the first model depending on the model parameters.

ACKNOWLEDGEMENTS

The reported study was funded by RFBR, project number 19-29-06003.

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