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Predicting the Traffic Capacity of an Intersection Using Fuzzy Logic and Computer Vision

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Abstract: This paper presents the application of simulation to assess and predict the influence of random factors of pedestrian flow and its continuity on the traffic capacity of a signal-controlled intersection during a right turn. The data were collected from the surveillance cameras of 25 signal-controlled intersections in the city of Chelyabinsk, Russia, and interpreted by a neural network. We considered the influence of both the intensity of the pedestrian flow and its continuity on the traffic capacity of a signal-controlled intersection in the stochastic approach, provided that the flow of vehicles is redundant. We used a reasonably minimized regression model as the basis for our intersection models. At the first stage, we obtained and tested a simulated continuous-stochastic intersection model that accounts for the dynamics of traffic flow. The second approach, due to the unpredictability of pedestrian flow, used a relevant method for analysing traffic flows based on the fuzzy logic theory. The second was also used as the foundation to build and graphically demonstrate a computer model in the fuzzy TECH suite for predictive visualization of the values of a traffic flow crossing a signal-controlled intersection. The results of this study can contribute to understanding the real conditions at a signal-controlled intersection and making grounded decisions on its focused control.

Keywords: traffic capacity of an intersection; pedestrian flow; traffic simulation; fuzzy logic method; predictive visualization of a vehicle flow

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1. Introduction

The increasing number of vehicles in urban areas is leading to increased road congestions, accidents, unwanted delays, and environmental pollution. In the conditions of infrastructural urban constraints, traditional traffic management and control systems fail to cope with this problem. Traffic lights at intersections are often non-adaptive and have fixed time delays. There is a need for an optimized and intelligent control system that would improve traffic efficiency.

The management of road network objects with traffic light signalling involves determining the number and sequence of control phases, drawing up basic diagrams of the vehicles and pedestrian movement at each phase, and calculating the duration of steps and phases that form a control cycle. Justified management decisions in this area are generally grounded on computer simulations according to models based on real-time monitoring of transport network objects by road cameras [1–3]. Intelligent transport systems estimate traffic density and modify traffic lights according to the traffic rate.

Many previous studies have focused on quantifying the variations in the total volume of the traffic flow attributed to several random parameters such as weather factors and pedestrian flow and its continuity [4–7].

Related Works

Currently, the traffic capacity of the road transport network is optimized based on an analysis of traffic flows and its categorical content. Traffic monitoring and computer vision cameras are built into automated systems to analyse traffic flows with various parameters [8–10] and diagnose pedestrian crossings [3,11,12].

Echab and Ez-Zahraouy [8] studied the throughput and built phase diagrams and space–time and density profiles to identify various traffic states and the phase transition features. Jingxin and Mei [9] studied the separation of the phases of continuous traffic flow and determined that the flow density, rather than speed, has the predominant influence on the cluster groups of the flow. Their proposed method of clustering flow phases is based on continuous traffic data from the detectors.

Jeon et al. [10] proposed an automated intelligent method for controlling traffic flows at an intersection based on their sequential video images. The simulated RL model of an intersection considered by the authors is not of less quality than the actual traffic flow accounting based on fixed video signals.

Modern computer vision tools contribute to some proactive measures, such as the detection of traffic conflicts and some violations.

Zaki et al. [3] offered a fully automated approach to the detection in continuous video of conflict indicators that lead to violations in the traffic flow.

Munder and Gavrila [11] studied the classification of pedestrian flow at transportation hubs using several classifiers, determined by the performance and efficiency of recorder receivers.

Zhang et al. [12] created a model that can predict pedestrians' red-light crossing intentions. Their model uses computer vision detection and tracking methods and some characteristics of pedestrians are generated, including information on their location. The authors developed a short-term and long-term neural network to predict the pedestrians' intentions on traffic violations.

Primary information is generally obtained from real-time video cameras. The ultimate purpose of this form of monitoring is to create intelligent traffic controllers and regulators able to record the presence of vehicles, pedestrians, and specific situations in a wide transport network, determined by their trajectories [13–16].

Hamdani et al. [13] considered a new model of autonomous intersection control with existing effective approaches to ensure safety on it, giving priority to pedestrian flows. The results of model experiments showed the effectiveness of the autonomous crosswalk control system proposed by the authors, even at unlit intersections, which is revealed in the reduction of traffic flow delays in relation to the conventional systems of traffic light control at intersections.

Xu et al. [14] applied the mathematical programming method to optimize the signal timing of the urban traffic network with traffic light control. In the models of traffic synchronization at intersections, a multiagent approach is used, which is based on the system of signal coordination of various agents interacting with each other to control urban traffic junctions.

Lv et al. [15] developed a methodology to derive vehicle profiles given macroscopic inputs so that Motor Vehicle Emission Simulation can be applied to estimating emissions. Then an optimization methodology of signal timing was developed and solved through the use of a genetic algorithm.

Missing traffic flow data are one of the most critical issues in the application of intelligent transportation systems. Tang et al. [17] proposed a more efficient method for reading the traffic flow data with respect to the traditional approaches of fixing data with different temporal skip coefficients in the observations. They proposed a hybrid method to fill in missing traffic flow data based on fuzzy logic methods, combining both fuzzy discontinuous traffic flow and a fuzzy neural modelling network. Experimental studies have confirmed the validity and effectiveness of the proposed method.

A fuzzy logic controller was used by [18–21] to solve the problem of dynamic uncertainty at intersections. The green-light time of each phase is dynamically decided according to the real-time traffic information to achieve the smallest average vehicle delay to enhance traffic efficiency in the intersection. The excellent performance of the design was confirmed through simulation experiments under different conditions.

Castano et al. [22] developed and implemented a set of measures using both SCANeR and MATLAB/Simulink, which identify obstacles (vehicles, pedestrians, etc.) in the transport system.

New methods are recommended for the control of signal-controlled intersections, such as fuzzy logic, artificial intelligence, cuckoo search algorithms, and differential evolution [23–27], which determine the time of traffic light signals and their phase changes.

Zhang and Ye [23] used the fuzzy logic system methods to forecast traffic flow.

Modelling experiments in a fuzzy logic system produced more accurate and stable traffic forecasts. The effectiveness of this approach is confirmed by obtaining predictions of various traffic flows and different operating conditions of the recording sensors.

Murat and Gedizlioglu [24,25] developed a fuzzy logic multiphased signal control model for isolated signalized intersections. A comparison showed that the performance of the FLMuSiC is better than that of both the traffic-actuated simulation and the aaSIDRA models.

Wu et al. [26] also apply fuzzy logic control methods in their modelling approaches. Their proposed "cuckoo search" algorithm is optimized by fuzzy logic methods to solve actual traffic control problems.

General computer modelling based on the simulation modelling and fuzzy logic methods has also become widespread in the analysis of the traffic situation for various fragmentary flows, from the simulation of transport and logistics systems [28,29] to the public transport policy [30–32].

The purpose of this study is to develop simulation models of intersections that allow us to use mathematical methods and computer programmes to carry out experiments on real-time traffic regulation and predict the traffic capacity of intersections depending on various factors.

Our study will enrich the literature related to traffic modelling and, thus, be useful in many applications of planning and operating a signal-controlled transport network.

2. Materials and Methods

In our study, we focused on analysing the influence of pedestrian traffic on the capacity of an intersection, specifically for when pedestrian and traffic flows are not separated.

2.1. Real-Time Tracking of Vehicle and Pedestrian Movement from Street Surveillance Cameras

To collect traffic and pedestrian flow data, we developed an autonomous tracking system based on neural networks [33]. This system detects the location, trajectory, number, and movement speed of road users. The neural network architecture in our system consists of indicator detection, counting, and calculation modules. The algorithm for obtaining the data on the movement trajectory of vehicles and pedestrians is shown in Figure 1.

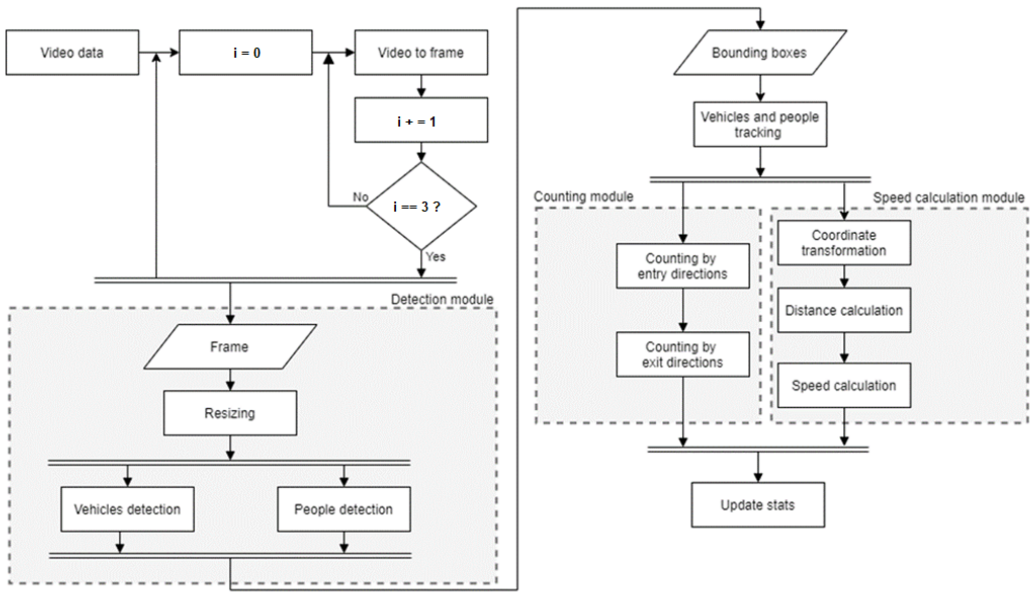


Figure 1. Algorithm for determining the trajectory and speed of pedestrians and vehicles.

We collected data from street video surveillance systems mounted at varying heights and distances from the road. These systems are equipped with video cameras with a fixed frame rate, different resolutions, and resolution power. To collect the data on vehicle and pedestrian flows, we used the streets video surveillance systems with the angle of viewing of the entire functional area of the intersection.

We collected the data at signal-controlled intersections at 25 points using Intersvyaz street [34] surveillance cameras located at an altitude of 14–40 m, with an inclination angle to the horizon of 30–60°. The convolutional neural network provided processing of real-time frames (using the RTSP protocol) with a frame rate of at least 25 frames per second.

In order to detect, classify, and track the trajectory of transport vehicles and pedestrians, we tested the most adapted neural networks for these tasks: RetinaNet, YOLO v4 and SSD, and others. Based on reviews of research and hardware performance requirements for processing video streams in dynamic mode [35,36], we opted for YOLO v4. The testing, the neural network proved to be sufficiently accurate in object recognition and classification, with an image processing speed (608 $\times$ 608) of 19 frames per second.

We developed an algorithm in which the first module processes every third frame of the video stream and recognizes objects using the YOLO v4 neural network. After recognizing and classifying objects, the module of bounding boxes identifies the objects by comparing them with the data from the previous frames to determine trajectory and speed.

We solved the problem of multiple-object tracking using the open-source SORT tracker. The SORT tracker is based on two methods: the Hungarian algorithm [37] and the Kalman filter [38].

In the recognizing, tracking, and continuous matching of predicted objects, we applied the Hungarian algorithm. The Kalman filter was used to check and correct the states of the objects.

The neural network YOLO v4 and the SORT tracker provide a continuous, frame-by-frame data collection about the location of the objects, which allows us to calculate their speed and the exact distance between them.

To train the neural network, we augmented 30,000 processed images, which allowed us to increase the initial data library (DATA SET) up to 500,000 units. This approach allowed us to achieve high accuracy of recognition and to track the objects' movement trajectory and speed within 92–96%.

Figure 2 illustrates the YOLO v4 neural network architecture and a modification of the Darknet-53 neural network, which includes 53 layers [35].

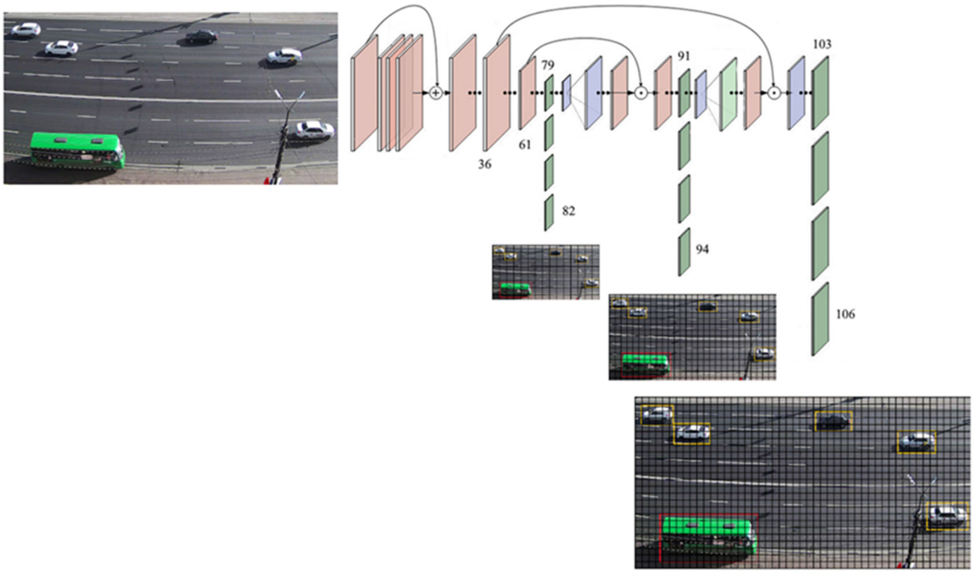


Figure 2. The YOLO v4 network architecture.

In the task of increasing the speed of image processing by the YOLO v4 neural network, we reduced the received image in a three-dimensional tensor of size $h \times w \times 3$, where h, w are the height and length of the input image.

Apart from using ultraprecise layers, the presented YOLO v4 architecture also contains residual layers, layers with increased discretization, and skipped connections.

The neural network processes the video frame from the video flow and produces the tensor with coordinates and classification of objects within their bounding boxes (Figure 3).

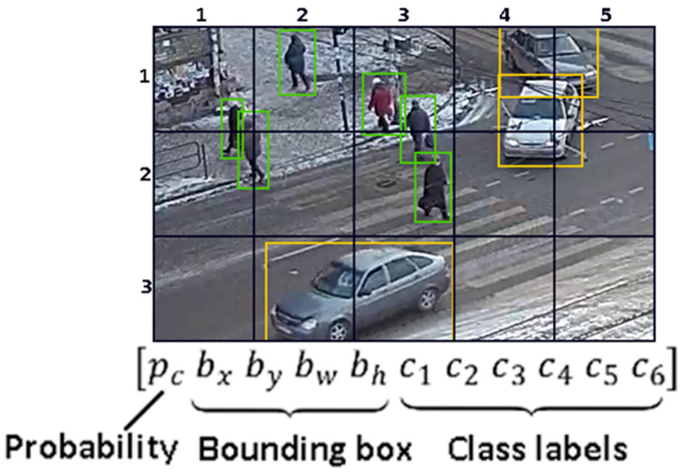


Figure 3. An output tensor.

To train the YOLO v4 neural network, we used the gradient descent backpropagation method. The following method allowed us to define the values of neuron weights in the hidden layers of the neural network. Training of the algorithm is based on the principle of epochs, and the weight changes after some set of training data to the input of the neural network, after which the error is averaged.

Our method of determining the position of pedestrians and vehicles is based on the use of the perspective transformation of mapping coordinates from cameras to a space of geographic coordinates. The developed approach allows us to detect and track the temporal relocation of vehicles and pedestrians.

2.2. *A Conceptual Model of an Intersection, Right Turn*

We propose completing an analysis of the traffic capacity at one signal-controlled object depending on a number of both deterministic (intersection geometry, road quality, etc.) and random influencing factors (pedestrian flow, traffic intensity, weather conditions). The conceptual block diagram of the computer simulation model for this task can be represented as follows (Figure 4).

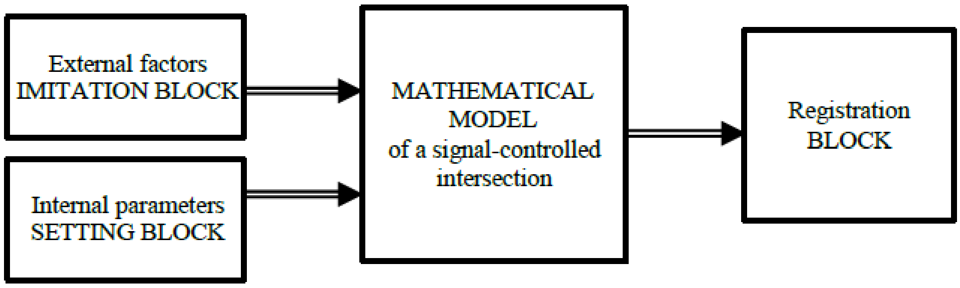


Figure 4. A conceptual block diagram of a signal-controlled intersection model.

This provides for the preliminary development of a mathematical model of the traffic capacity of an urban intersection depending on several influencing factors:

- constant: the geometry of the intersection, the quality of the road surface, line-of-sight interference, and other factors that are invariable over a long period of time; and
- variable or random: weather conditions, light conditions, two-way pedestrian flow, traffic intensity, and more.

This analysis requires the collection of data from many intersections of the urban signal-controlled transport network, as well as several statistical methods to reveal the general tendency of interactions—even going so far as to obtain a mathematical functional dependence.

Further, we consider a specific case of controlling a signal-controlled intersection, which is rather relevant for a densely populated city—a right turn during heavy pedestrian traffic. During a right turn, vehicle traffic is interrupted by the pedestrian flow crossing the road at a pedestrian crossing. The density, duration, and number of interruption intervals of pedestrian flow wherein vehicles can complete their turn are unpredictable. The vehicles themselves also differ in categories, which determines their response time during acceleration, their length, and the difference in the intervals between them.

To study the influence of these factors on traffic capacity, their independent influence should be shown. This can be determined only by computer simulation, since field experiments in real traffic conditions are impossible.

To construct a computer model of a right turn at a signal-controlled intersection (Figure 1), we should first simulate a specific intersection, taking into account all its parameters. Then, we should form a block of the vehicle flow and a block of the disturbing factor—an unpredictable pedestrian flow.

2.2.1. A Complete Regression Model

We will take the complete mathematical model of an intersection from a previous study [7], where it is presented in the form of a regression equation from several factors influencing the capacity:

$$Y_{ps} = f(x_1, x_2, x_3, \ldots, x_n) = k_0 + k_1 \cdot x_1 + k_2 \cdot x_2 + k_3 \cdot x_3 + \ldots + k_n \cdot x_n \tag{1}$$

We obtained this model based on the summary data from video surveillance cameras at 25 intersections in the city of Chelyabinsk, including both the parameters of the intersection itself and the traffic data. The 20 registered factors are reflected in columns 1 and 2 of Table 1, and the coefficients of Model (1)—in column 3.

Table 1. Recorded intersection factors and their interconnection.

	Factors	k_i	$k_{i\ stand}$	r_{xy}
1	**2**	**3**	**4**	**5**
x_1	Duration of the green traffic light, s	0.303	1.275	0.438
x_2	$L1$ (from the stop line to the rounding), m	−0.184	−0.396	0.017
x_3	$L2$ (arc of the turn), m	0.189	0.573	0.296
x_4	$L3$ (approaching the pedestrian crossing), m	0.049	0.062	0.278
x_5	Number of pedestrians in the direction of vehicle movement (to the right), people	−0.117	−0.159	−0.390
x_6	Number of pedestrians in the direction of vehicle movement (to the left), people	−0.280	−0.417	−0.529
x_7	Duration of the 1st free window, s	−0.099	−0.268	0.188
x_8	Number of vehicles passing through the 1st window, pcs.	0.272	0.232	0.267
x_9	Duration of the 2nd free window, s	0.102	0.166	0.146
x_{10}	Number of vehicles passing through the 2nd window, pcs.	0.461	0.426	0.373
x_{11}	Duration of the 3rd free window, s	−0.392	−0.210	−0.109
x_{12}	Number of vehicles passing through the 3rd window, pcs.	0.531	0.106	−0.016
x_{13}	Time to pass through a free window, s	0.056	0.098	−0.062
x_{14}	Number of vehicles in the queue, pcs.	0.099	0.098	0.282
x_{15}	t_1—travel time of the 1st vehicle along $L1$, s	−0.068	−0.046	−0.054
x_{16}	t_2—travel time of the 2nd vehicle along $L2$, s	0.242	0.250	0.009
x_{17}	t_3—travel time of the 3rd vehicle along $L3$, s	0.110	0.041	0.115
x_{18}	t_4—time for the 1st vehicle to leave the pedestrian crossing, s	0.358	0.522	−0.185
x_{19}	Number of vehicles completing their passage at the red traffic light, pcs.	0.013	0.005	−0.220
x_{20}	Sampling for the maximum possible number of vehicles passing without pedestrians, pcs.	−0.360	−0.752	0.358
Y_{ps}	Actual number of passing cars, pcs.			

The quality of the model, as noted earlier, is estimated by the value R^2 = 0.902. This means that 92% of the dispersion in the original data is explained by this model. This is a very high value, confirming the high quality of the complete model constructed for many different intersections.

Additional calculations in the professional SPSS suite also revealed standardized coefficients for the complete model (1) characterizing the relative power of influence of each factor on the dependent variable (column 4 in Table 1). These calculations will be important when selecting the essential influencing factors to further predict vehicle flow.

An additional correlation analysis (Pearson's parametric correlation coefficients) revealed the degree of influence of the factors on the traffic capacity of an intersection. Its results are shown in column 5 of Table 1. Here, paired connections are highlighted in dark grey. They are not statistically significant at the generally accepted error level of 5%. As expected, the main influence on the traffic capacity is the duration of the green traffic light (x_1) and the number of pedestrians (x_5, x_6). Notably, the geometry of the intersection determines its individuality (x_2, x_3, x_4) and must be considered for the subsequent minimization of the intersection model.

2.2.2. Minimization of the Regression Model

For the practical application of the model, we advise that the model be reduced by discarding several factors that are secondary in terms of their influence on the traffic capacity and do not correspond to the problem statement. Ultimately, we advise leaving the physically necessary factors—the intersection geometry, pedestrian flow, and its instability factors.

The mathematical regression model takes the following final form:

$$Y_{ps} = k_0 + k_1 \cdot x_1 + k_2 \cdot x_2 + k_3 \cdot x_3 + k_5 \cdot x_5 + k_6 \cdot x_6 + k_{16} \cdot x_{16} + k_{18} \cdot x_{18} + k_{20} \cdot x_{20} \quad (2)$$

where x_1 is the duration of the green traffic light; x_2, x_3 is the intersection geometry; x_5, x_6 is the number of pedestrians to the right and to the left; x_{16} is the time of vehicle movement along the intersection arc; x_{18} is the time required for the vehicle to leave the pedestrian crossing; x_{20} is the maximum number of vehicles that pass without pedestrians.

The quality of such a reduced model, as expected, is somewhat lower at R^2 = 0.747. The statistical significance of the model is 0.1%, which, despite the reduction of the model, confirms an acceptable level of quality and a high level of statistical confidence. This minimized model will be used further as a static basis for computer simulation.

2.3. Simulation Modelling

Simulation models are a generally accepted approach to obtaining clear results quickly in a time-based sweep. Such models are presented in the form of a diagram consisting of typical blocks of the MATLAB software suite for the Simulink application.

2.3.1. A Static Intersection Model

According to the minimized regression model, the enlarged simulation model for the static version of the problem can be represented as the following diagram (Figure 5). This model implies vehicle arrival flow, but it is not further simulated. Flow is determined by other parameters and assumed to be unlimited, which corresponds to a practical road congestion situation.

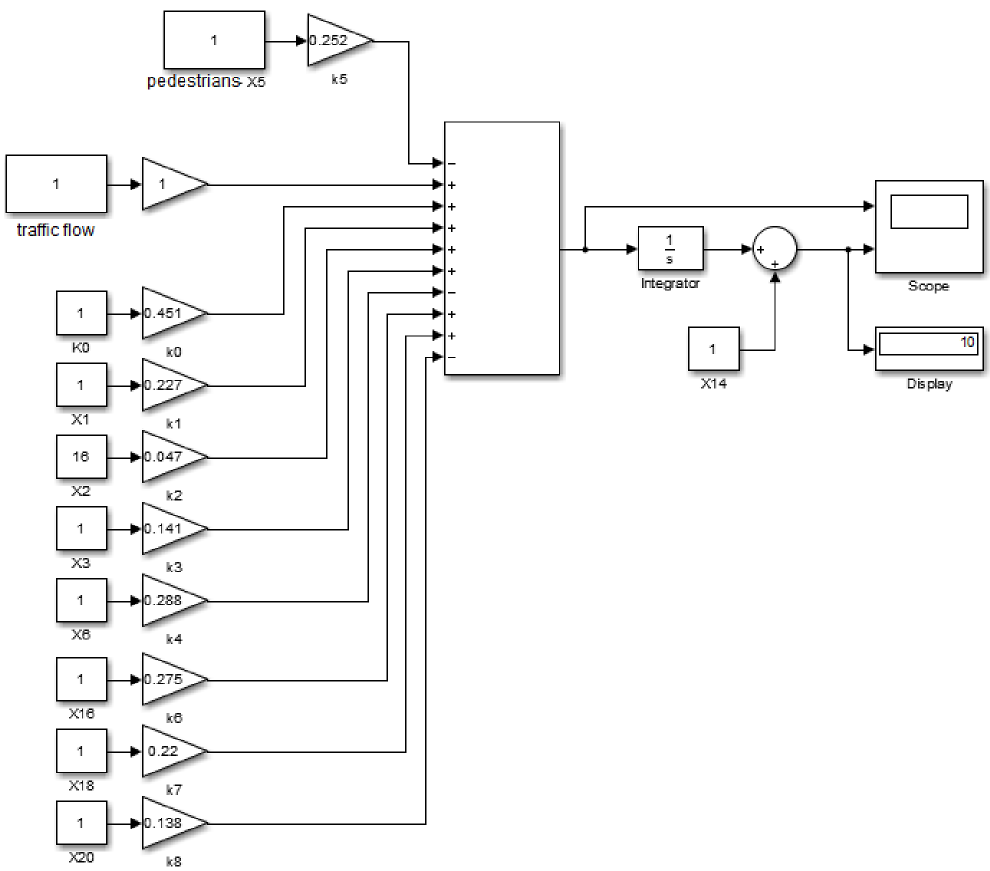


Figure 5. A static simulation model of a signal-controlled intersection.

In the centre of the diagram, the adder block implements a static regression model according to Equation (2); pedestrians (x_5) and vehicle flow simulate external factors, and the right side of the model integrally accumulates the vehicle flow under the initial conditions (x_{14}). Numerical values characterizing one specific intersection are set as the initial data (x_i).

2.3.2. A Continuous-Stochastic Pedestrian Flow Model

We apply a continuous-stochastic model (Q-scheme), setting the uncertainty in the pedestrian arrival flow, to closely approximate real-world conditions. To this end, we supplement the model with a block for generating a random pedestrian flow with a uniform distribution law, which provides for a preset probability value (constant x_5 block). A complete model of a random pedestrian flow is shown in Figure 6.

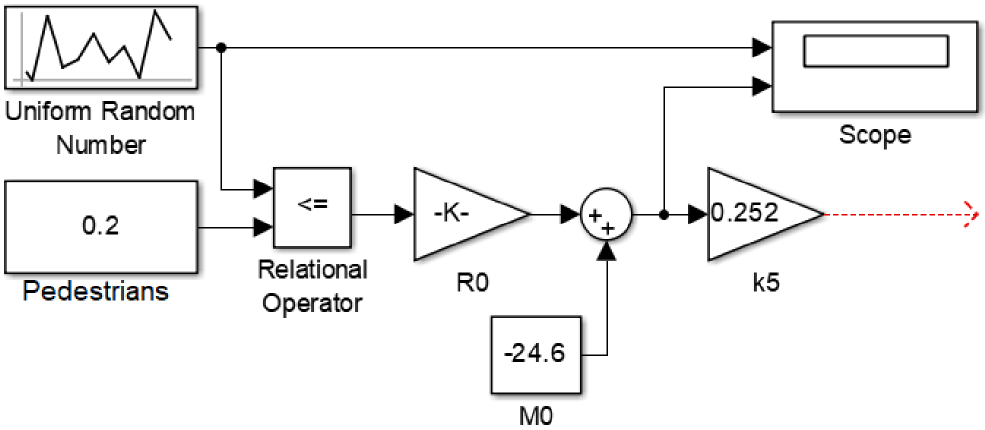


Figure 6. A stochastic pedestrian flow model.

Figure 7a shows the quality of generating a random signal by the URN block linked to real pedestrian flow. Figure 7b shows a variable simulating a pedestrian flow with a probability of 0.2 (the upper level corresponds to the presence of pedestrians).

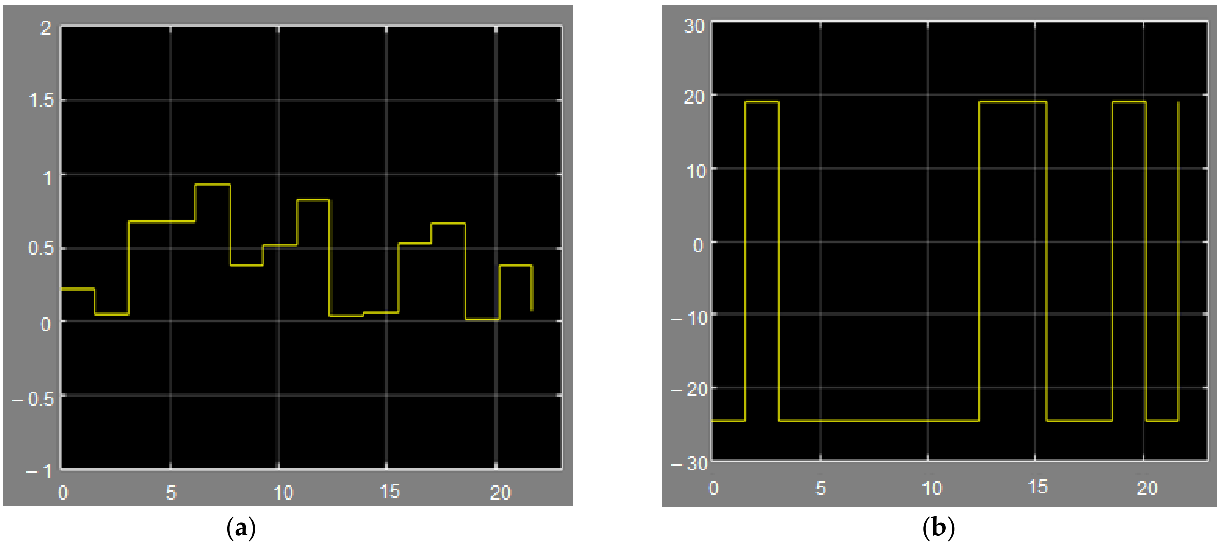


Figure 7. Generation of a random pedestrian flow with a probability of 0.2: (**a**) the quality of generating a random signal by the URN block linked to real pedestrian flow; (**b**) a variable simulating a pedestrian flow with a probability of 0.2.

2.3.3. Simulation of the Inertial Vehicle Flow

To simulate the dynamics of the vehicles passing the selected intersection, we supplement the static model with an inertial *Transfer Fcn* block simulating the vehicle acceleration inertia according to the first-order differential equation (aperiodic link). The final form of the dynamic model, including calibration blocks, is shown in Figure 8.

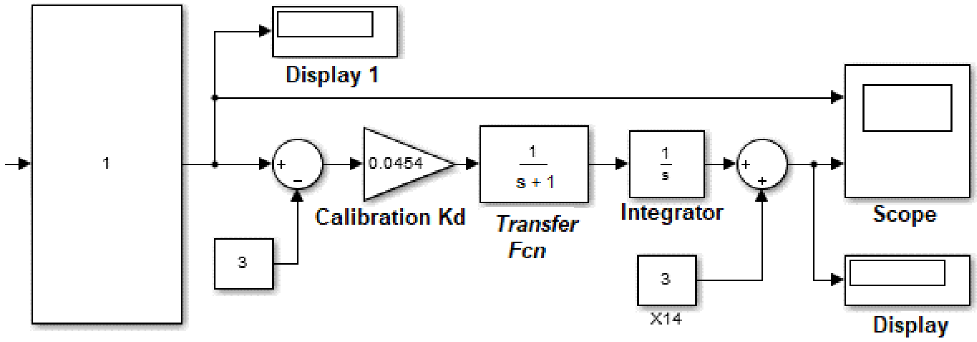


Figure 8. A dynamic simulation model of the selected intersection.

Figure 9a shows the relative dynamics at a pedestrian flow density of 60% of the maximum value, demonstrating the operation of a complete stochastic intersection model (right turn). The minimum level of the traffic flow of three units is determined from the initial data of the simulated intersection (Figure 9b).

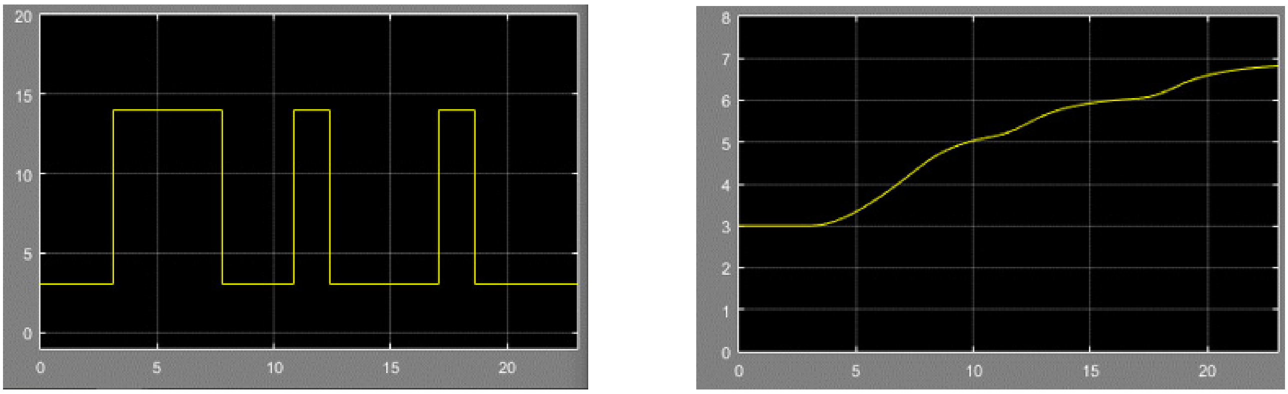


Figure 9. The dynamics of passing the intersection: (**a**) the vehicle arrival flow during the right turn during random breaks in the pedestrian flow with a density of 60%; (**b**) a graph of the increase in the flow of vehicles leaving the intersection (with inertial acceleration dynamics of 3 s).

Analysis of the simulated processes showed that when vehicle flow is interrupted by a random pedestrian flow, the traffic capacity of the intersection is significantly reduced.

Figure 10 shows the results of the experimental study of the size of the inertial vehicle flow passing an intersection, depending on the density of the random pedestrian flow.

Analysis of Figure 10 shows a deviation from the linearity of the relationship between the vehicle flow and the pedestrian flow in the opposite direction. It shows two model graphs with different vehicle acceleration inertia in 1 and 3 s. Notably, these results were obtained only for one of the probable pedestrian flow situations.

The main result of the study is the development and construction of a model of vehicles making a right turn at an urban signal-controlled intersection that approximates real-life conditions.

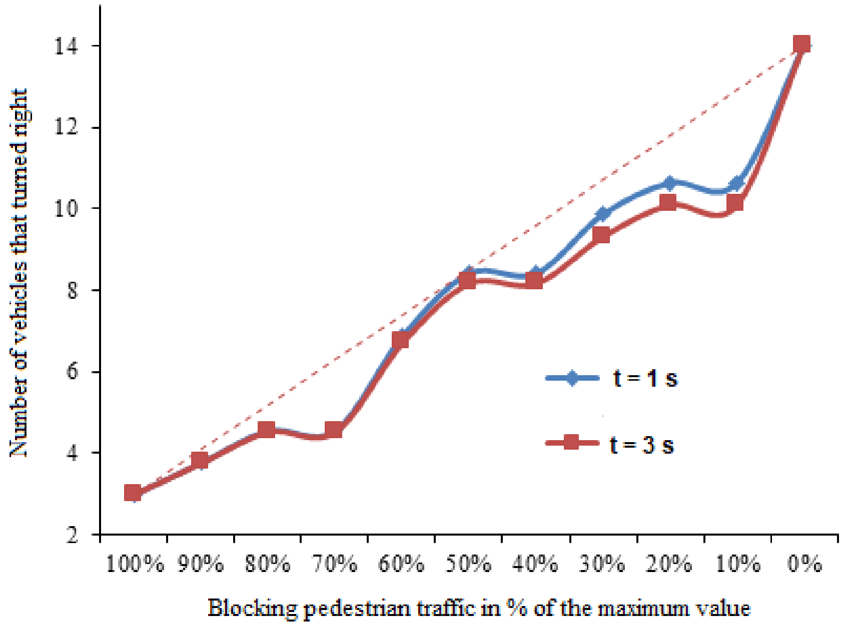


Figure 10. The dependence of the inertial vehicle flow on the intensity of the pedestrian flow.

3. Results

Fuzzy logic is a branch of mathematics that comprises classical logic and theory of sets emerged in the context of fuzzy sets. This method has the greatest practical application in fuzzy modelling. The fuzzy logic inference on Mamdani method is performed on fuzzy knowledge in which the values of input and output variables are given by fuzzy sets. The Mamdani method and many other fuzzy inference methods (Tsukamoto method; Larsen method; Sugeno method) have been used in software tools such as the Fuzzy Logic Toolbox (MATLAB), fuzzyTECH, and others.

3.1. Predicting Traffic Capacity Using the Fuzzy Logic Method

Shepelev et al. [7] carries out a preliminary analysis of the traffic capacity of an intersection using the fuzzy logic methods based on three factors that are essential in terms of their influence on the dependent value. These factors are reflected in Table 1 (column 4) in dark grey. However, for our stated task, the factors of both the pedestrian flow (x_5, x_6) and its continuity (x_8, x_{10}) are conceptually informative. A significant drawback of the previous analysis is also the non-Gaussian nature of the membership functions. However, this is acceptable for the preliminary approach discussed in this article.

Let us consider the predictive visualization of the traffic capacity of an intersection obtained by the minimized regression model (2), taking into account the aforementioned aspects: the use of conceptually informative independent variables and Gaussian membership functions.

The Development of the Model

The predictive model for assessing the influence of the total pedestrian flow and its continuity on the traffic capacity of an intersection is based on the fuzzy logic method and the programme *fuzzyTECH 8.77e*. The basis is the static regression Model (2). The dependent variable *TC_Prkr* (traffic capacity of an intersection) is predicted depending on the values of the independent variables *Psh_left_right* (pedestrian flows x_5 and x_6) and its instability factors—*TC_1Okno*, *TC_2Okno* (the first and second interruptions of the pedestrian flow—x_8 and x_{10}).

The block diagram of the constructed model is shown in Figure 11.

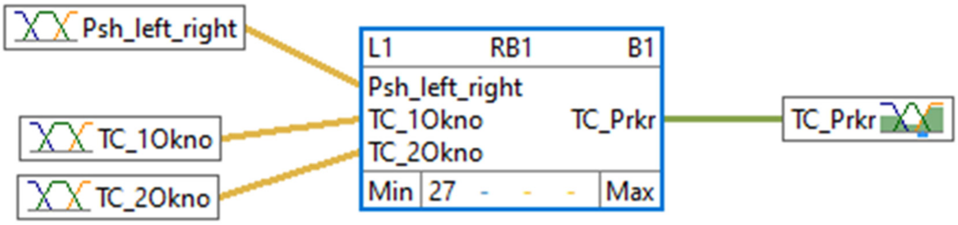
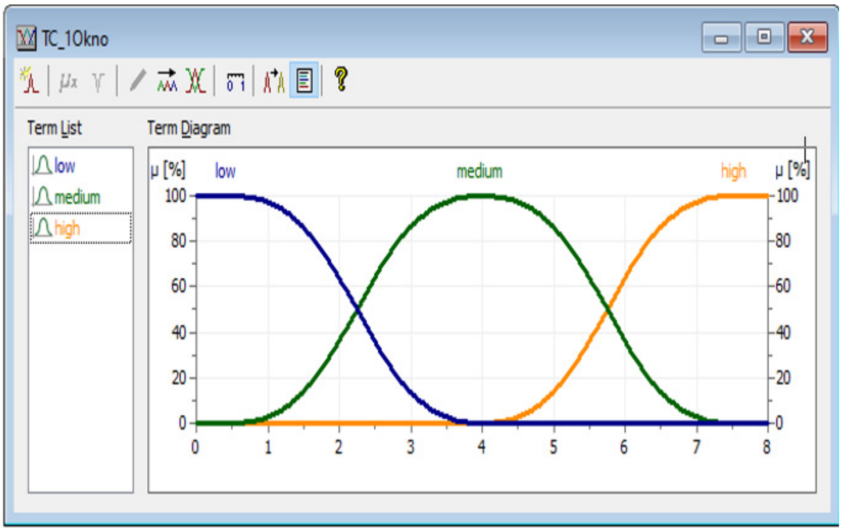


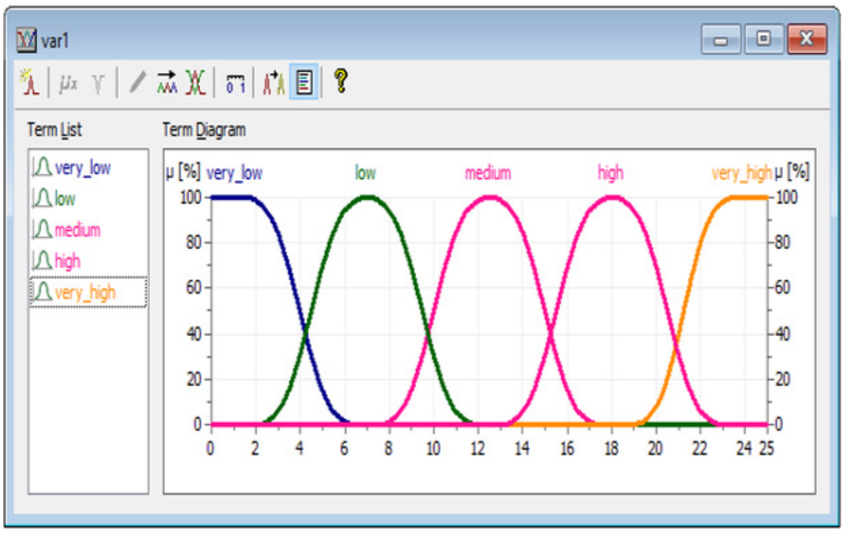
Figure 11. A block diagram of the model according to the fuzzy logic method.

At the stage of the fuzzification of variables, we chose Gaussian membership functions as splines rather than triangular ones. This is most consistent with the problem statement in the stochastic version. The parameters of the Gaussian terms are determined according to the authors' expert estimates based on practical work with the observation camera data.

There are three terms for independent variables and five for the dependent variable. The distribution of the values by the terms of the independent variable *TC_1Okno* and the dependent variable *TC_Prkr* is shown in Figure 12a,b, respectively.



(**a**)



(**b**)

Figure 12. Distribution of the term values for the variables: (**a**) the independent variable *TC_1Okno*; (**b**) the dependent variable *TC_Prkr*.

The values are distributed similarly for the independent variables *Psh_left_right* and *TC_2Okno*.

We determined a fuzzy logic model for predicting the values of the dependent variable by a table of its relationships with the independent variables using the Speadsheet rule editor block (Figure 13).

B1.G1	Psh_left_right	TC_1Okno	TC_2Okno	TC_Prkr
B1.G1.R1	Psh_left_right.high	TC_1Okno.low	TC_2Okno.low	TC_Prkr.very_low
B1.G1.R2	Psh_left_right.high	TC_1Okno.low	TC_2Okno.medium	TC_Prkr.very_low
B1.G1.R3	Psh_left_right.high	TC_1Okno.low	TC_2Okno.high	TC_Prkr.low
B1.G1.R4	Psh_left_right.high	TC_1Okno.medium	TC_2Okno.low	TC_Prkr.very_low
B1.G1.R5	Psh_left_right.high	TC_1Okno.medium	TC_2Okno.medium	TC_Prkr.low
B1.G1.R6	Psh_left_right.high	TC_1Okno.medium	TC_2Okno.high	TC_Prkr.medium
B1.G1.R7	Psh_left_right.high	TC_1Okno.high	TC_2Okno.low	TC_Prkr.low
B1.G1.R8	Psh_left_right.high	TC_1Okno.high	TC_2Okno.medium	TC_Prkr.medium
B1.G1.R9	Psh_left_right.high	TC_1Okno.high	TC_2Okno.high	TC_Prkr.medium
B1.G1.R10	Psh_left_right.medium	TC_1Okno.low	TC_2Okno.low	TC_Prkr.very_low
B1.G1.R11	Psh_left_right.medium	TC_1Okno.low	TC_2Okno.medium	TC_Prkr.low
B1.G1.R12	Psh_left_right.medium	TC_1Okno.low	TC_2Okno.high	TC_Prkr.medium
B1.G1.R13	Psh_left_right.medium	TC_1Okno.medium	TC_2Okno.low	TC_Prkr.medium
B1.G1.R14	Psh_left_right.medium	TC_1Okno.medium	TC_2Okno.medium	TC_Prkr.medium
B1.G1.R15	Psh_left_right.medium	TC_1Okno.medium	TC_2Okno.high	TC_Prkr.hight
B1.G1.R16	Psh_left_right.medium	TC_1Okno.high	TC_2Okno.low	TC_Prkr.medium
B1.G1.R17	Psh_left_right.medium	TC_1Okno.high	TC_2Okno.medium	TC_Prkr.hight
B1.G1.R18	Psh_left_right.medium	TC_1Okno.high	TC_2Okno.high	TC_Prkr.hight
B1.G1.R19	Psh_left_right.low	TC_1Okno.low	TC_2Okno.low	TC_Prkr.medium
B1.G1.R20	Psh_left_right.low	TC_1Okno.low	TC_2Okno.medium	TC_Prkr.medium
B1.G1.R21	Psh_left_right.low	TC_1Okno.low	TC_2Okno.high	TC_Prkr.hight
B1.G1.R22	Psh_left_right.low	TC_1Okno.medium	TC_2Okno.low	TC_Prkr.medium
B1.G1.R23	Psh_left_right.low	TC_1Okno.medium	TC_2Okno.medium	TC_Prkr.hight
B1.G1.R24	Psh_left_right.low	TC_1Okno.medium	TC_2Okno.high	TC_Prkr.very_high
B1.G1.R25	Psh_left_right.low	TC_1Okno.high	TC_2Okno.low	TC_Prkr.hight
B1.G1.R26	Psh_left_right.low	TC_1Okno.high	TC_2Okno.medium	TC_Prkr.very_high
B1.G1.R27	Psh_left_right.low	TC_1Okno.high	TC_2Okno.high	TC_Prkr.very_high

Figure 13. Table of rules for the relationship of the model variables.

The experimental studies of the constructed model allowed us to predict the dependent variable based on the actual values of the independent variables, as well as to create a graphic of the distribution field of the mutual influence of the variables in the form of three-dimensional surfaces.

3.2. Visualization of Predictive Situations

Let us look at the traffic capacity of the simulated intersection and its relation to the instability of the pedestrian flow (the first and second windows in the flow) at different intensity values of the pedestrian flow itself. Figures 14–16 show the graphs and the calculation of the predictions of the dependent variable (intersection capacity, *TC_Prkr*) on the influence of the pedestrian flow instability (independent variables *TC_1Okno*, *TC_2Okno*) at the intensity of the blocking pedestrian flow (variable *Psh_left_right*) of 10%, 50%, and 90% of the maximum values.

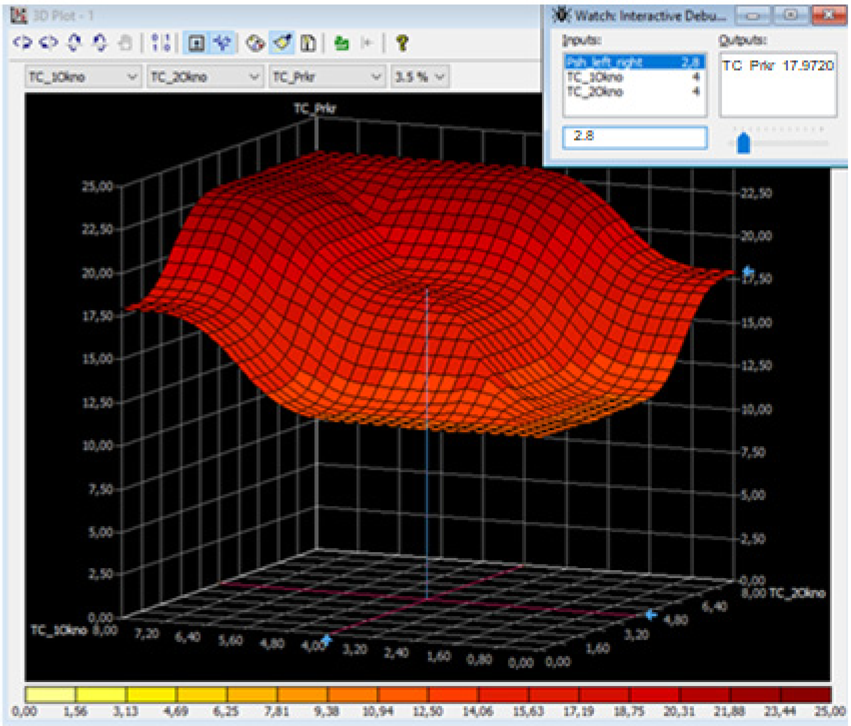


Figure 14. Experiment one: graph of the mutual influence of the variables at the intensity of the blocking pedestrian flow 10%.

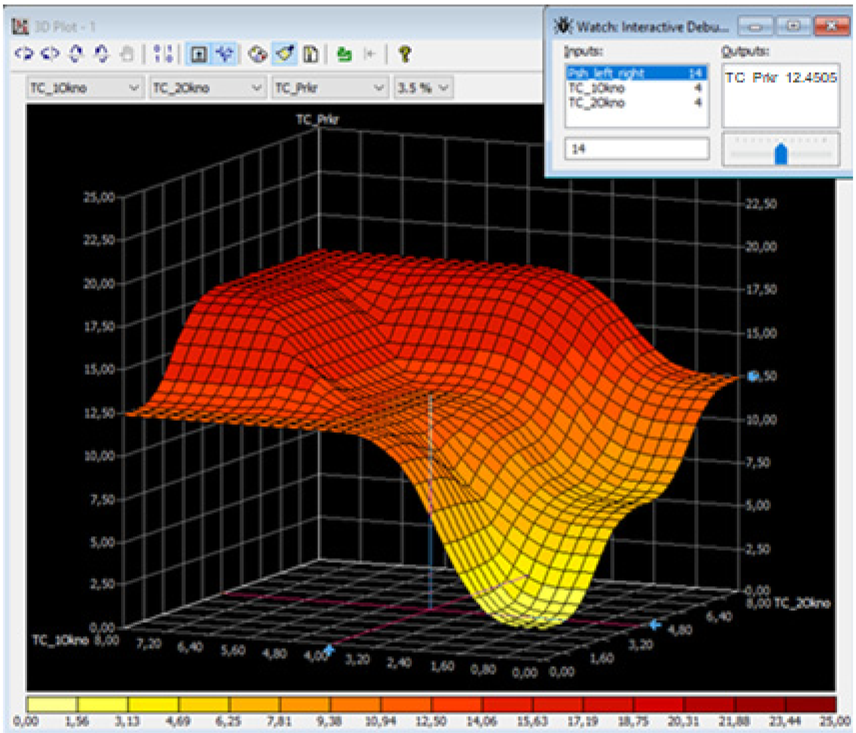


Figure 15. Experiment one: graph of the mutual influence of the variables at the intensity of the blocking pedestrian flow 50%.

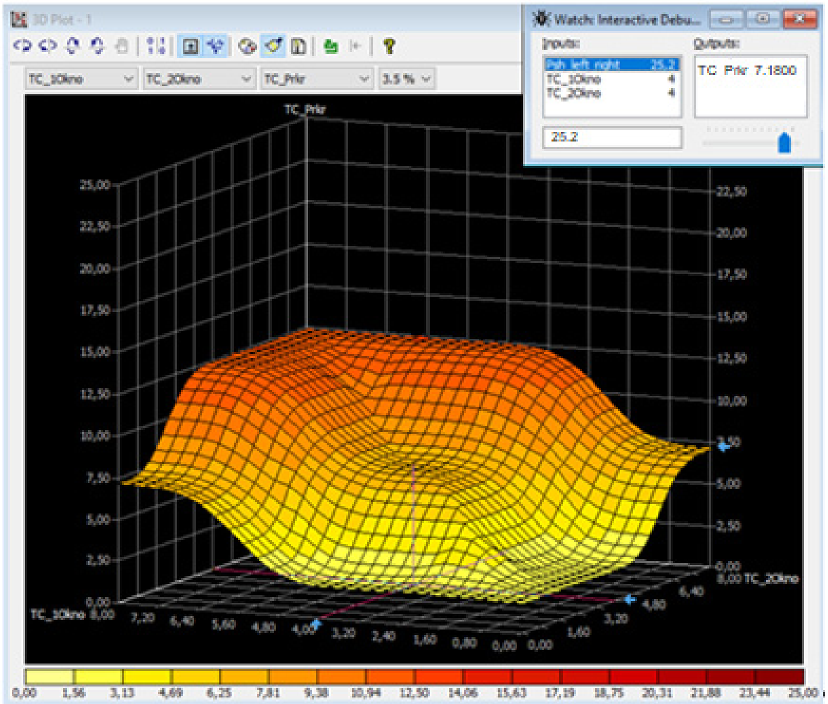


Figure 16. Experiment one: graph of the mutual influence of the variables at the intensity of the blocking pedestrian flow 90%.

A slightly different angle of view is provided by the graphical representation of the influence of two independent variables: *TC_1Okno* and *Psh_left_right* at similar gradations of the pedestrian flow discontinuity *TC_2Okno* of 90%, 50%, and 10% of its maximum value on the traffic capacity of the intersection. These graphs and predictions are shown in Figures 17–19.

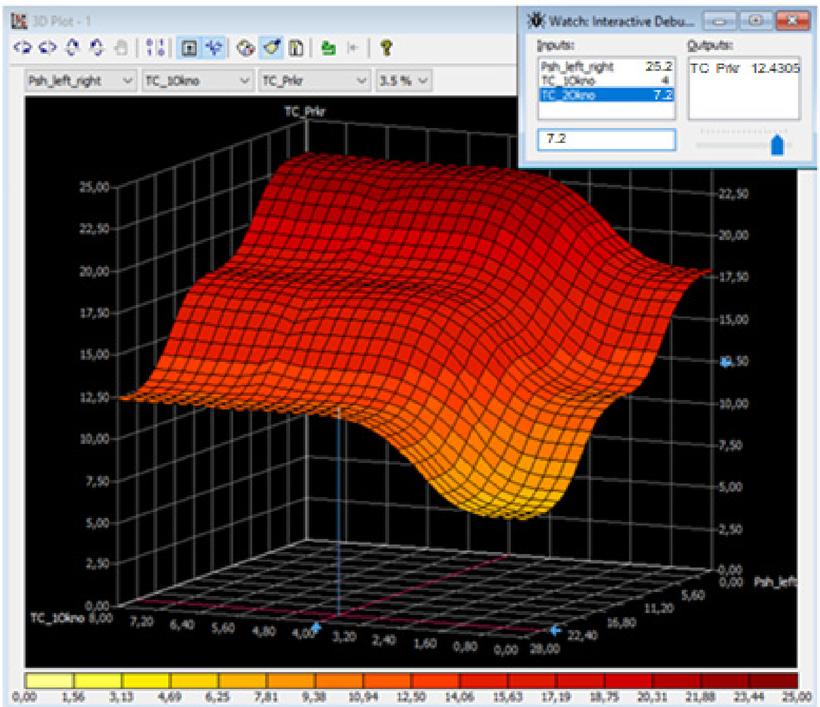


Figure 17. Experiment two: graph of the mutual influence of the variables at the intensity of the blocking pedestrian flow 10%.

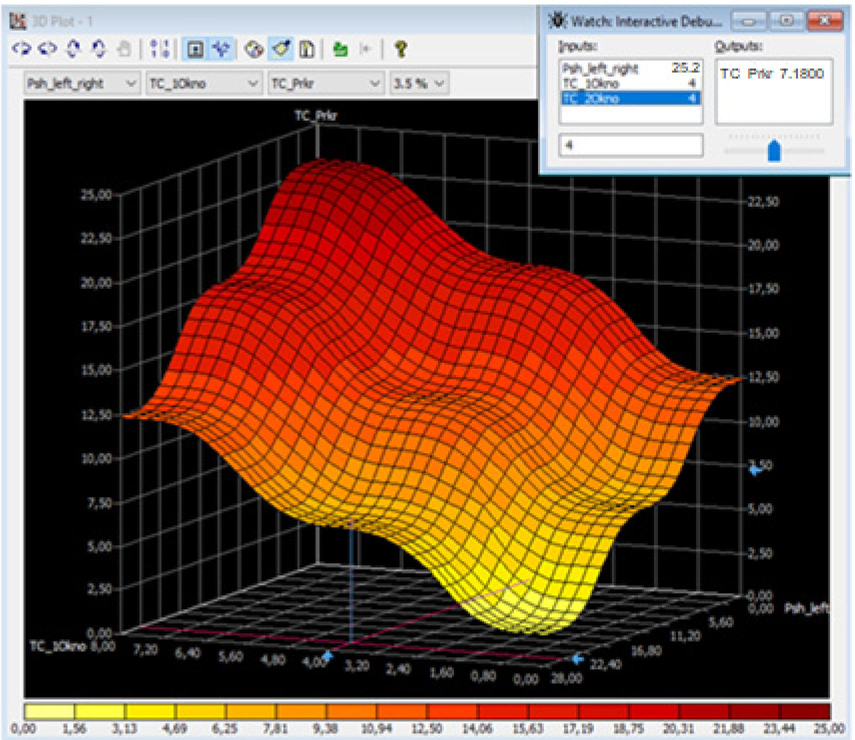


Figure 18. Experiment two: graph of the mutual influence of the variables at the intensity of the blocking pedestrian flow 50%.

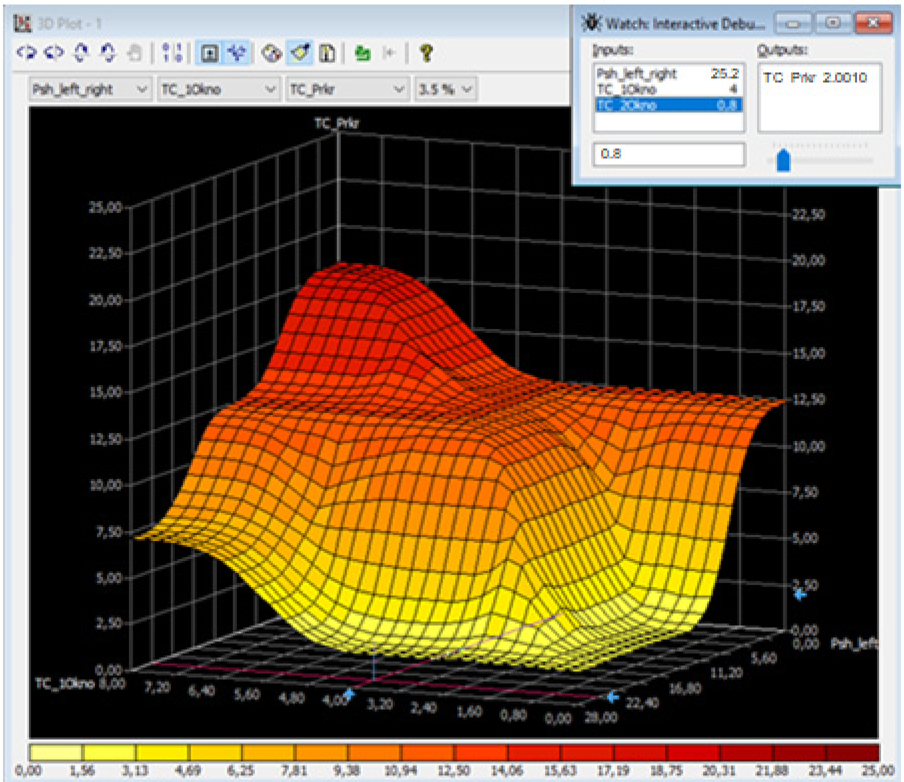


Figure 19. Experiment two: graph of the mutual influence of the variables at the intensity of the blocking pedestrian flow 90%.

Analysis of the results of the two experiments with the model based on fuzzy logic shows the sinking trend of the traffic capacity of an intersection and the influence of both the intensity of the pedestrian flow and its discontinuity.

This can serve as a solid basis for making grounded decisions on signal-controlled intersection management.

4. Discussion and Conclusions

We used both statistical analysis methods and various computer simulation approaches to assess and predict the influence of random factors of pedestrian flow and pedestrian flow continuity on traffic capacity during a right turn at a signal-controlled intersection. The results of the correlation analysis of the information on the vehicle movement at intersections obtained from video cameras allowed us to clarify the linear nature of the mutual influences of the intersection parameters on its traffic capacity. The multiple-regression model of the signal-controlled intersection obtained earlier based on these initial data is considered from a new angle. We assessed the influence of the main random factors (the intensity of the pedestrian flow and its discontinuity) on traffic capacity. Minimization of the regression model did not violate its statistical confidence, and its standardized coefficients showed the degree of influence of the main factors. On this basis, we constructed two fundamentally different models allowing us to carry out various experiments to determine the nature of the influence of the analysed factors. The basis of these constructions is a reasonably minimized regression model reflecting the influence of conceptually important factors.

A stochastic dynamic model (Q-scheme) was constructed through simulations in the MATLAB suite. The model allows us to carry out real-time experiments given varying probabilistic characteristics of pedestrian flow intensity, as well as varying average response time of vehicles, thereby contributing to the idea of real, possible situations at a signal-controlled intersection. The second model of vehicle movement at intersections is based on fuzzy mathematical logic and the corresponding *fuzzyTECH* software. This model allows us to predict the traffic capacity of intersections depending on uncertain factors such as the intensity of the pedestrian flow and its discontinuity. This analysis also provides a clear visualization of the obtained results.

The above models are open for further sophistication and introduction of other random factors into consideration. However, even in the proposed version, the models can support the development grounded decisions on signal-controlled intersection management. This study will generally enrich the literature on traffic modelling and will, thus, be useful in many applications of adaptive transport network planning and operation.

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Data Availability Statement: This repository contains source codes for the programme, which implements methods for calculating traffic parameters described in the research work at https://github.com/Readix/TrafficMonitoring (accessed on 5 September 2021). This programme counts vehicles in each of the four directions of movement and calculates the speed of vehicles by the method of prospective conversion.

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