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Research Paper

Training and Applying Artificial Neural Networks in Traffic Light Control: Improving the Management and Safety of Road Traffic in Tyumen (Russia)

Anatoly V. Pistsov, **Artur I. Petrov**

The Institute of Transport, Industrial University of Tyumen, Tyumen 625027, Russia

artigpetrov@yandex.ru

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Abstract

The article presents the initial experience (spring-summer 2023) of using artificial neural networks (ANN) in improving traffic management in the large Russian city of Tyumen. Using the example of one of the intersections of the city's road network, it is shown how much transport delays are reduced when the duration of the traffic light cycle phases is quickly adjusted to the actual traffic intensity when compared with the usual previously used traffic light predictive mode. For the specific intersection of Odesskaya and Kotovskogo streets in Tyumen, considered in this article, the traffic light control mode using an ANN can significantly (by 20.6 ... 22.4%) reduce the average delay time of vehicles. It is also important that the reduction in traffic delays, which is possible with the regulation of traffic using ANN, helps to reduce stress for road users and improve road safety. The article presents historical data illustrating the dynamics of changes in the field of traffic management and road safety in Tyumen. This information well confirms the thesis about the dialectic of systemic development and the need for a gradual increase in the intellectual component in traffic management in large cities. The Applications (Appendix A and Appendix B) present the code of the auxiliary procedures and functions module and the code of the main data collection module used to optimize the traffic light control mode at the experimental intersection of the Tyumen road network. The main conclusion of the study is that use of an ANN allows taking into account a much larger number of factors and optimizing the control of the entire object, consisting of several intersections, which is not achievable using predictive modes and local adaptive control.

Keywords: Management of road traffic; Traffic light control; Artificial neural networks; Safety of road traffic; City traffic efficiency; Tyumen (Russia)

1. Introduction

In 1914, Cleveland's police department installed a red and green traffic control light at the corner of 105-th Street and Euclid Avenue, the first permanent installation in the world [1]. Since then, the practice of using traffic lights in traffic control has rapidly spread throughout the world. Over the next century, the basic paradigm in the field of road safety science and its companion field of "traffic management" changed several times [2]. In the 2000s, the policy of mandatory use of the Intelligent Transportation System (ITS) took root in the practice of traffic management in the largest cities of the world [3], [4]. At the same time, we should note that this thesis is far from being true for all cities in the world. In the Russian Federation, for example, there are 1118 cities (in which 75.5% of the country's population live), but the ITS functions to one degree or another only in some cities with a population of more than 1 million people [5], [6].

Tyumen is a large Russian city with a population of 855.6 thousand people (2023), the transport system of which is managed by the specialized company «Tyumengortrans» (Tyumen City Transport) (https://tgt72.ru/). One of the tasks of this company is putting modern traffic control technologies into practice. The specialists of «Tyumengortrans» work together with the employees of the Industrial University of Tyumen. This article discusses one example of such collaboration - the use of artificial neural networks in optimizing the control of traffic lights. It is important to note that using machine learning and artificial neural networks (ANN) in organizing traffic light regulation in Tyumen is a relatively new thing. The city uses modern systems of coordinated and adaptive traffic light control, however, there is a known problem of using local adaptive traffic light control - such a controlled intersection must be located at a considerable distance from others that are in coordinated control mode. Local adaptive control leads to the fact that the cycle time is not constant and coordination between adjacent signalized intersections becomes impossible. The use of ANN makes it possible to use the optimal operating mode of a traffic light for a given duration of the traffic light control cycle or to control a group of neighbouring controlled intersections at once, which eliminates the problem of using independent local adaptive control at neighbouring intersections. Of the 428 traffic lights in the city, ANN-based regulation of the operating modes has been tested only on 15 of them, and they are far from being the most complex in terms of functionality. However, work in this direction continues.

The implications of this important work are multi-faceted. On the one hand, under the conditions of the rapid growth of motorization in Tyumen (A_{2000} ≈ 150 vehicles/1000 people; A_{2023} ≈ 495 vehicles/1000 people), traffic flow rates are quite stable and do not decrease; traffic jams are a relative rarity and are associated mainly with one-time cases of a sharp deterioration in weather conditions. On the other hand, road traffic accidents in the city are gradually decreasing. However, these processes are very heterogeneous. Thus, in 2015 ... 2022, the level of Human risk *HR* in the city decreased from HR_{2015} = 7.0 RTA deaths/100 thous. people down to HR_{2022} = 4.8 RTA deaths/100 thous. people (http://stat.gibdd.ru/). At the same time, the RTA severity level ($Severity_{RS\ 2015}$ = 2.1; $Severity_{RS\ 2022}$ = 2.0) in Tyumen has remained stable in recent years.

The purpose of this article is to familiarize the scientific community with the results of training and application of artificial neural networks (ANN) in the management of traffic lights in the large Russian city of Tyumen. The key tasks of the article include analysing the impact of the traffic light cycle optimization on the behavior of road users and, as a result, on road safety.

2. Literature Review

The Intelligent Transportation System (ITS) is an essential component of the Smart City infrastructure [7]. The basis of the ITS are information and communication technologies of Big Data [8]. The most important task of the ITS is to ensure the collection and processing of data on traffic flows with subsequent analysis of the possibilities for the most effective traffic management [9], [10]. The result of this analysis is a traffic forecast [11], [12]. Usually, the process of traffic forecasting (the most probable traffic flow rate, possible deviations from the probabilistic scenario) is based on taking into account historical observational data [13]. Theses data can be useful in applications such as traffic congestion control and traffic light regulation [14]. For example, one of the possibilities of the ITS is to calculate the probability of a traffic jam on the corresponding section of the road and provide the possibility of preparing for such a scenario [15].

Traffic forecasting methods are usually classified into parametric (including stochastic and time methods) and non-parametric. The nonparametric ones primarily include machine learning (ML) models [16]. A review made in [17] showed that non-parametric algorithms are significantly superior to parametric algorithms due to their ability to handle a large number of parameters in massive data.

The transition from the local level of the intelligent transport system to the network one became possible, among other things, thanks to the development of machine learning and artificial neural networks (ANNs) [18], [19]. This technology can be used to detect road anomalies [20] using GPS and smartphone acceleration data. In addition, the more frequent use of video cameras in cities has allowed the use of image recognition systems to count the number of cars

[21]–[23]. The study of the possibility of using machine learning to determine these anomalies [24] also provides an analysis of possible machine learning algorithms with their advantages and disadvantages in solving this problem. In addition, the possibility of controlling traffic lights based on machine learning models and the Internet of Things has been repeatedly considered [25]–[28].

The use of machine learning and artificial neural networks for adaptive control of traffic lights can be divided into systems with one and multiple agents for training a neural network. The study [29] considers the practice of using machine learning to implement adaptive control of traffic lights in a certain space of an urban area. One of the shortcomings of this approach given in the study is that all agents in the model must maintain a constant connection with the knowledge container, which imposes certain restrictions. Systems in which each individual intersection is an agent and an artificial neural network processes the data received from each agent demonstrate high efficiency [30]. So, in [31] the use of a neural network to control a traffic light cycle at an areal object consisting of 9 intersections of the city's road network was able to increase the speed of the traffic flow by 43.02% and reduce the delay time at intersections by 26.59%.

Under the conditions of non-uniform daily and hourly traffic flow rate, the problem of optimizing the parameters of the traffic light control cycle at the intersections is solved either by developing a large number of predictive signal plans, or by using adaptive control. Despite the fact that developing a large number of signal plans covering a wide range of vehicle and pedestrian traffic flows is theoretically possible, in practice, from 3 to 5 signal plans are used during the day in most Russian cities. Taking into account the non-uniform daily and hourly traffic flow rate, these signal plans do not always provide the optimal mode of operation of traffic lights for these conditions.

A limited number of predictive signal plans, coupled with deviations in traffic parameters associated with repairing road sections, road traffic accidents (RTA), and weather anomalies lead to an increase in traffic delays at a signallised intersection. The use of automated traffic control systems (ATCS) makes it possible to redistribute the available time reserves in real time by changing the duration of the traffic light control cycle and the values of phase coefficients.

3. Materials and Methods

3.1. Model example

Let us consider a specific example of traffic management at the intersection of Odesskaya and Kotovskogo streets in Tyumen.

As of the spring of 2023, the movement of vehicle and pedestrian flows was organized according to a 3-phase scheme (**Figure 1**).

The duration of each phase in the traffic light cycle is shown in **Table 1**. The total duration of the traffic light cycle in the daytime was 95 seconds.

In the spring of 2023, this intersection in Tyumen was chosen as an experimental one to implement adaptive control of traffic lights using machine learning and artificial neural networks.

Preliminary studies were carried out on the vehicle and pedestrian traffic flow rates. An assessment of the traffic flow rate variability in the

Table 1. Mode of operation of traffic lights in the daytime (6:00 – 22:00 on weekdays; 9:00 – 22:00 on the weekend)

№№ of directions	№№ of traffic lights	Schedule of traffic lights operation modes		
		Phase 1	Phase 2	Phase 3
1	t1, t2, t5, t6	31 3 3	56	2
2	t3, t4, t7, t8	37 2	31 3 3	19
3	p11, p12, p15, p16	78		10 3 4
4	p9, p10, p13, p14	78		10 3 4
Duration of phases, secs.		39	39	17

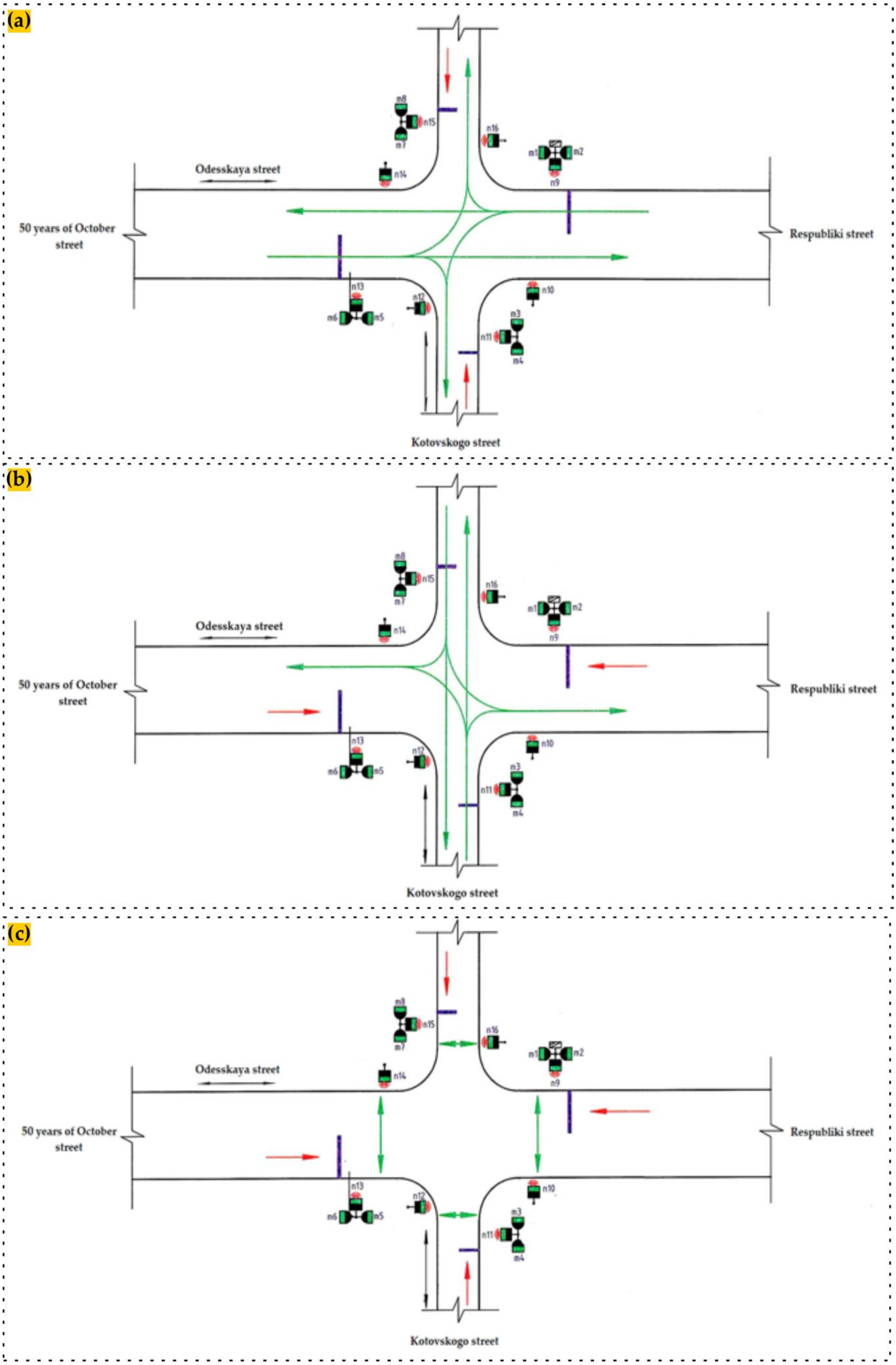

Figure 1. Phase-by-phase traffic schemes at the intersection: (a) Phase 1; priority direction of vehicle traffic: North – South, (b) Phase 2; priority direction of vehicle traffic: West – East, (c) Phase 3; directions of pedestrian traffic

morning hours (from 07:00 to 09:00) at the intersection of Odesskaya - Kotovskogo streets on various days (weekdays) in the spring of 2023 showed that this indicator varies in the range from 1245 to 1850 vehicles/hour. At the same time, it is technically possible for the traffic control center to receive data from transport detectors every 15 minutes. Despite this frequency of obtaining up-to-date data on traffic flow rates, in practice, the predictive traffic light operation mode is calculated for the hour of the highest traffic flow rate (from 07:00 to 08:00) and is valid for two hours (from 07:00 to 09:00). The signal plan is calculated for the average traffic flow rate, which in this case is 1593 vehicles/hour. Analysing the data indicated that it is advisable to use the traffic flow rate data presented in **Table 1** for the predictive mode of operation of the traffic light. Characteristic of the predictive mode of operation of the traffic light, calculated in the Lisa+ software package [32], is also presented in **Table 2**.

The traffic light operating mode presented in **Table 1** is the main one and is used from 6:00 to 22:00 on weekdays and from 9:00 to 22:00 on weekends. Of course, during the day, traffic conditions, in particular traffic flow rate, are constantly changing and this signal plan cannot theoretically be optimal for all hours of the day.

So, the predictive mode of operation of a traffic light is considered as the base one, against which other possible options for traffic control will be compared.

3.2. *Modelling Options*

Under the conditions of a non-uniform intrahour traffic flow rate, three ways to control the operation of traffic lights at the intersection can be compared:

- Predictive mode (**Table 1**), valid until summer 2023;
- Adaptive traffic light control mode based on the predictive mode;
- Traffic light control using a pre-trained ANN for this intersection.

Adaptive and neural network optimization options for the traffic light cycle are promising solutions for most Russian cities. Their comparison on a specific case allows us to draw the conclusions necessary for making the final management decision about choosing the priority method of traffic management in the city.

Vehicle delay time was estimated on a calibrated simulation model of an X-shaped intersection in PTV Vissim 11 [33].

3.2.1. *Adaptive Mode*

In recent years, in Russia, the most common way to improve the efficiency of the controlled intersections is to use adaptive traffic light control modes based on the possibility of reducing the duration of the main traffic light cycle in the event of a traffic flow gap lasting more than 3 seconds.

In our case, the cycle of traffic light control consists of three phases (two vehicle and one pedestrian) and the movement of cars in opposite directions is carried out in one phase. The algorithm checks for the presence of a gap in two opposite directions simultaneously. This approach allows one to change the values of the phase coefficients in real time. This results in a decrease in the average delay time of vehicles at the intersection and approaches to it. Based on the predictive mode, an adaptive control algorithm was developed in the Lisa+ software package [32] that makes it possible to reduce the duration of the main cycle in the event of a 3-second time gap between cars following each other (**Figure 2**).

3.2.2. *Artificial Neural Network (ANN) Mode*

As an alternative to the adaptive mode of traffic light control at the intersection under study, let us consider the use of a pre-trained artificial neural network (ANN). The neural network model was created in several stages:

Table 2. Characteristics of the predictive mode of operation of the traffic light (the duration of the traffic light cycle is 95 seconds) at the intersection of Odesskaya - Kotovskogo streets in Tyumen

Direction of vehicle movement	Traffic flow rate, vehicles/hour	No. of cycle phase	Phase coefficient
North South	580 305	1	0.45
East West	481 227	2	0.36
Pedestrians	850	3	0.19

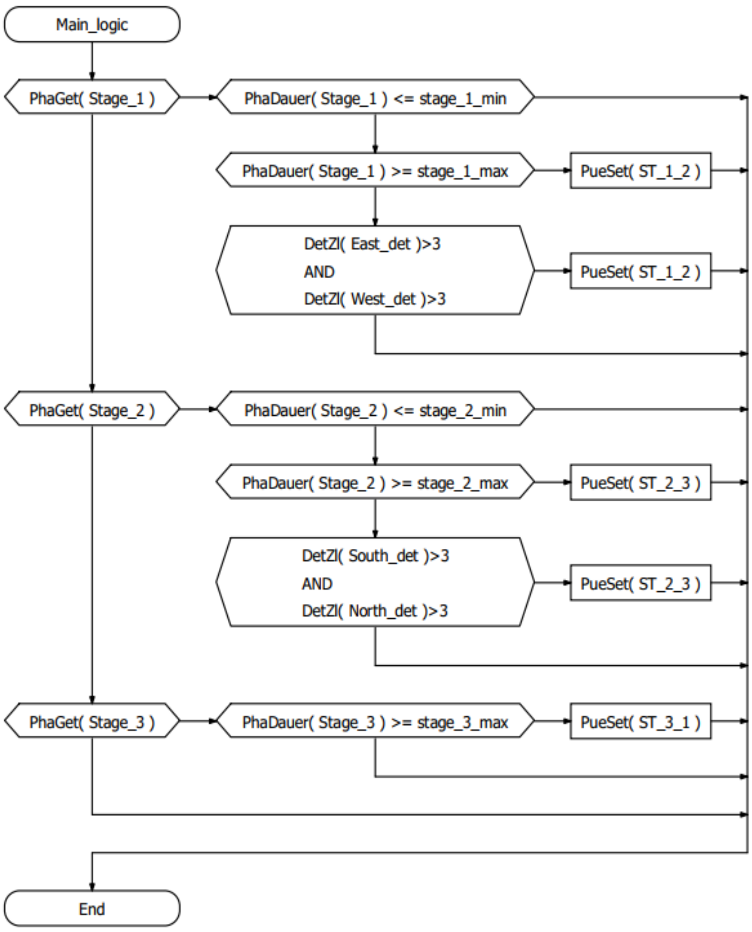

Figure 2. General view of the adaptive control algorithm in Lisa+ [32]

- Creating a data array containing various parameters of the traffic light cycle and traffic (traffic flow rates in all directions, vehicle traffic routes at the intersection);
- Collecting average delay time values at the intersection through simulation in PTV Vissim [33];
- ANN architecture planning and training.

The training was carried out on a sample size of 11,000 combinations of different values of the rate of the incoming flow and the parameters of the traffic light control cycle. As a result of this training, a model was obtained that allows real-time determination of the optimal signal plan for any combination of vehicle traffic flow rate values by directions.

To determine the optimal cycle parameters, a separate software module was developed that takes the values of traffic flow rates by directions and creates a data array with different signal plans with a given interval of changing the duration of the main cycles. Next, the trained neural network model calculates the average delay time for each signal plan. The obtained values are sorted and the traffic light cycle parameters that are optimal for a given traffic flow rate are displayed in a separate file. Sorting and determining the optimal mode are subject to the objective Eq (1):

$$Tdelay \rightarrow min \qquad (1)$$

The time spent on one iteration of the calculation of the average delay time ranges from 0.1 ms up to 0.5 ms (for an option based on PC with Core i7, 8 GB RAM). For comparison, the time to obtain the average delay time in PTV Vissim takes from 10 to 30 seconds. With pre-prepared possible options for the traffic light operation mode, the software module spends no more than 5 seconds to derive the optimal cycle parameters, processing thousands of possible combinations. The obtained values can be directly transmitted to the controller of the traffic light or to the traffic control center.

Since data from traffic detectors are received by the traffic control center every 15 minutes, the comparison of the effect of different control methods was carried out by estimating the average delay time for the whole model for each fifteen-minute time interval during the hours of the greatest traffic flow rate from 07:00 to 09:00: 00 (Table 3).

4. Automatic Data Collection Technology with PTV Vissim

The technology for creating a neural network model of a signallised intersection can be divided into the following stages:

- Creating a simulation model in PTV Vissim [33] and defining input parameters.
- Determining input parameter ranges and collecting big data through simulation.
- Processing the results obtained.
- Neural network training.

At a local intersection, the input parameters are: incoming flow rates by directions, shares of the incoming flow by directions, parameters of the traffic light control cycle (number of phases, phase coefficients, cycle duration). For linear and areal objects, vehicle routes and the offset of the starts of traffic light control cycles are added. The intervals of the values of these parameters should not only take into account statistically probable values, but also go beyond these limits for more accurate training of the model. When developing a data set for simulation modeling, an xls table is filled. With the help of MS Excel tools, both random and ordered sets of input parameters are created. The explanation of the column names is given in Table 4.

In the case of linear or areal objects, the number of input parameters increases. Along with this, the number of parameter sets should increase due to

Table 3. Traffic flow rates by directions

№	Time intervals	Traffic flow rate, vehicles/hour by directions			
		North	South	East	West
1	7:00 - 7:15	465	254	423	206
2	7:15 - 7:30	551	284	465	208
3	7:30 - 7:45	631	321	510	238
4	7:45 - 8:00	673	361	526	256
5	8:00 - 8:15	628	327	510	236
6	8:15 - 8:30	598	340	507	252
7	8:30 - 8:45	576	284	469	221
8	8:45 - 9:00	518	269	438	199

Table 4. Explanation of the column names in the input dataset for simulation modeling

No	Column name	Explanation	Range of values
1	num	Sequence number of the set of input parameters	1… n
2	n_1_1	Flow rate of incoming traffic flow 1 at intersection 1	50 – 1000
		………………………………………………………	
5	n_1_4	Flow rate of incoming traffic flow 4 at intersection 1	50 – 1000
6	phase_1_1_num	Sequence number of traffic light cycle phase for signal group 1 at intersection 1	1
7	t_green_1_1	Duration of signal group 1 at intersection 1	8 – 40
		………………………………………………………	
14	phase_1_5_num	Sequence number of traffic light cycle phase for signal group 5 at intersection 1	1 – 2
15	t_green_1_5	Duration of signal group 5 at intersection 1	8 – 40
16	share_1_1_1	Share of static route 1 of incoming traffic flow 1 at intersection 1	0.05 – 0.95
17	share_1_1_2	Share of static route 2 of incoming traffic flow 1 at intersection 1	0.05 – 0.95
18	share_1_1_3	Share of static route 3 of incoming traffic flow 1 at intersection 1	0.05 – 0.95
		………………………………………………………	
25	share_1_4_1	Share of static route 1 of incoming traffic flow 4 at intersection 1	0.05 – 0.95
26	share_1_4_2	Share of static route 2 of incoming traffic flow 4 at intersection 1	0.05 – 0.95
27	share_1_4_3	Share of static route 3 of incoming traffic flow 4 at intersection 1	0.05 – 0.95

the increase in the number of possible combinations. The combinations should take into account the distributions of parameters that are impossible in practice, for example, the unevenness of incoming flows by directions (1000, 1000, 1000, 50 vehicles/hour).

Big data is collected for model training automatically using scripts written in the Python programming language. The most robust and user-friendly operation is achieved using the three scripts:

a. Main script

Provides reading data from an array of input parameters, changes the parameters of the traffic flow in PTV Vissim, starts the simulation, and writes data to the output file.

b. Script with a set of custom functions

It contains functions for changing the parameters of the traffic light control cycle and reading the simulation results from the SQLite3 database file generated by PTV Vissim after each simulation. Using select functions allows you to make the code of the main script more readable. The main user functions are:

- Reading and writing values to the signal PTV Vissim program file (*.sig);
- Reading a database file with simulation results.

Work with the *.sig is done using the XML markup of the file. To do this, the specified tags are searched in order and the start and end times of each signal group are indicated. To transfer from the sequence numbers and phase durations from the initial data set to the markup format of the PTV Vissim signal program, the values are recalculated in the function.

c. PTV Vissim operation control script in case it freezes

Controls the resizing of the output file. If the file size has not changed within the specified time, PTV Vissim is forced to restart. The simulation that caused the error in this case is skipped and work continues with the next set of input data (a row in the input data table).

The work of the main script with input parameters is carried out using the Pandas library. Starting PTV Vissim, changing the parameters of the traffic flow and simulating are performed by connecting the script via the COM server. To launch PTV Vissim and set the fast simulation mode the following code was used:

```
Vissim=com.gencache.EnsureDispatch("Vissim.Vissim.11")
Vissim.LoadNet (Model_Path)
Vissim.Graphics.CurrentNetworkWindow.SetAttValue("QuickMode",1)
```

Next, a loop is initiated (the number of iterations is equal to the number of rows in the original data set), in which the following actions are performed (**Figure 3**):

a. Changing the values of incoming flows in the simulation model through a nested loop (n_1_1, …, n_1_4). The change is made using COM and the PTV Vissim function «*Vissim.Net.VehicleInputs.ItemByKey(i).SetAttValue*», where i is the sequence number of the incoming flow in the simulation model.
b. Changing the shares of static routes in the simulation model (share_1_1_1, …, share_1_4_3). The change is made using COM in the same way as changing the values of incoming flows.
c. Changing the parameters of the traffic light control cycle using a script with a set of user functions (phase_1_1_num, t_green_1_1, …, phase_1_5_num, t_green_1_5).
d. Running a simulation.
e. Reading simulation results with a custom function.
f. Writing to a file with output data.

The script generates an output file with a table, the number of rows in which is equal to the number of rows in the table with the input parameters (except for the rows that caused PTV Vissim to freeze).

The following columns are added to the output file: arg_timeinterval, arg_vehicleclass, object_id, delayavg, stopsavg, speedavg, delaystopavg, disttot, travtmtot, delaytot, stopstot, delaystoptot, vehact, veharr, arg_timeinterval, object_id, delaylatent, demandlatent, demandlatentbase. The values of these columns determine the parameters of the PTV Vissim simulation results for each iteration.

Preliminary processing of the obtained results is performed using the Python and the Pandas library and is divided into the following stages:

a. Accounting for undesignated vehicles.
b. Converting shares of static routes into numerical values of traffic flow rate.

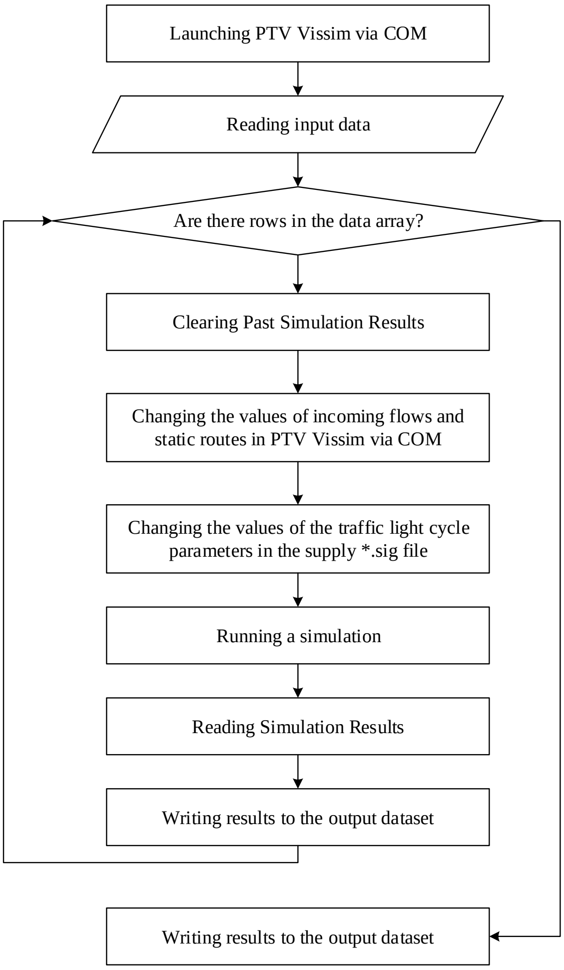

Figure 3. Flow chart of the data collection algorithm

Accounting for undesignated vehicles is carried out by mathematical calculations:

df['total_flow']=df['DEMANDLATENT']+df['VEHACT']+df['VEHARR']

df['total_delay_time']=(df['DELAYLATENT']+df['DELAYTOT'])/3600

*df['avg_delay_time']=3600*df['total_delay_time']/df['total_flow']*

df['DELAYAVG'] = df['avg_delay_time']

Thus, after conversion the *'DELAYAVG'* column contains data on the average delay time, taking into account undesignated vehicles.

Shares of static routes are converted into numerical values of traffic flow rate by multiplying the rate of each incoming flow by the share of a particular route. A nested loop is used to reduce the amount of coding.

The neural network is built on the basis of the Keras libraries for TensorFlow [34]. The average delay time (*DELAYAVG*) is used as the output value. The factors are the values of the parameters of the traffic flow and the traffic light cycle (**Table 5**).

In this particular example, the duration of the last signal group is not taken into account. This group implies a dedicated pedestrian phase and its duration is constant (20 seconds). Additionally, the factors do not include the incoming flow rate, since traffic flow rates on static routes take it into account.

The neural network architecture implies an input layer with the number of neurons equal to the number of factors, one or more hidden layers, and an output layer with one neuron that determines the value of the average delay time. An example of an architecture with one hidden layer is shown in **Figure 4a.** In this case, the hidden layer contains 43 neurons connected to 21 input neurons (by number of factors). When training a neural network, the loss function and the number of generations are determined (**Figure 4a**).

To solve different types of problems, networks of different architectures with different numbers of layers and neurons are used. In addition, the type of neuron activator affects the accuracy of the model (**Table 6**).

Table 5. List of factors for neural network training

No	Column name	Explanation
1	phase_1_1_num	Sequence number of traffic light cycle phase for signal group 1 at intersection 1
2	t_green_1_1	Duration of signal group 1 at intersection 1
		....
9	phase_1_5_num	Sequence number of traffic light cycle phase for signal group 5 at intersection 1
10	share_1_1_1	Traffic flow rate of static route 1 of incoming flow 1 at intersection 1
11	share_1_1_2	Traffic flow rate of static route 2 of incoming flow 1 at intersection 1
12	share_1_1_3	Traffic flow rate of static route 3 of incoming flow 1 at intersection 1
		....
19	share_1_4_1	Traffic flow rate of static route 1 of incoming flow 4 at intersection 1
20	share_1_4_2	Traffic flow rate of static route 2 of incoming flow 4 at intersection 1
21	share_1_4_3	Traffic flow rate of static route 3 of incoming flow 4 at intersection 1

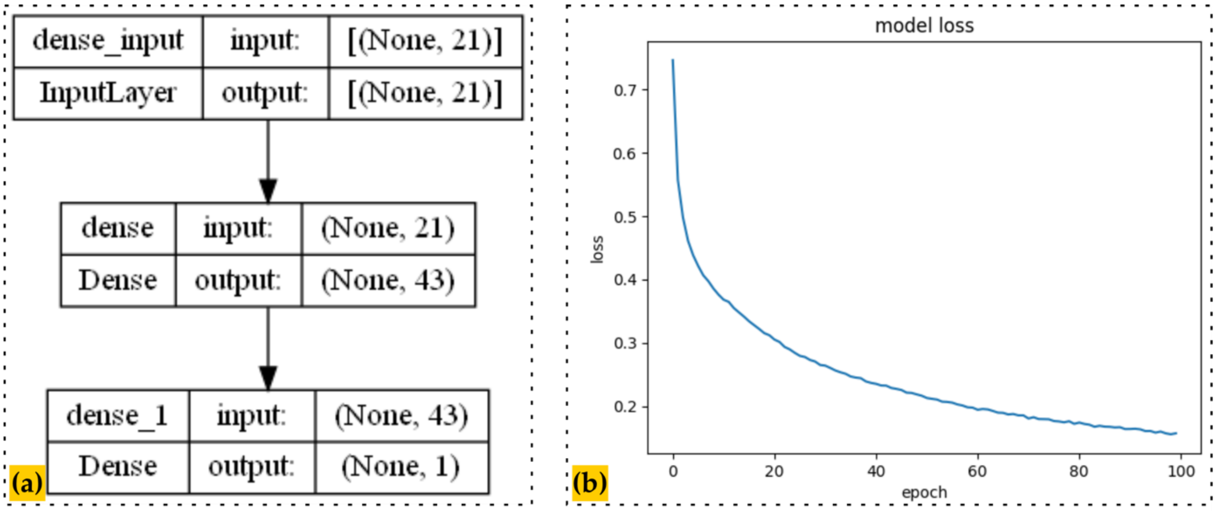

Figure 4. Neural network architecture and training through loss function: (a) Neural network architecture with one hidden layer; (b) Neural network training through loss function

Table 6. Neural network accuracy (50 generations; sample size: 19321 sets of values; test sample: 20% of the total number)

No	Number of hidden layers, units	Total number of neurons, units	Activator type	Model accuracy (R^2)
1	1	65	relu	0.703
2	1	65	tanh	0.602
3	1	65	linear	0.199
4	2	152	relu	0.879
5	2	152	tanh	0.708
6	2	152	elu	0.838
7	2	152	selu	0.579
8	2	152	softmax	0.801
9	3	327	relu	0.866
10	3	327	elu	0.861
11	3	327	softmax	0.794
12	4	678	relu	0.827
13	4	678	elu	0.798

When working with an individual intersection, the best accuracy is provided by a neural network with two hidden layers. The activation function «relu» shows the best result among other functions.

After training the model, it should be saved as a separate file, which will be used in the future to solve the inverse problem of determining the optimal parameters of the traffic light control cycle. To determine these parameters, it is necessary to determine the traffic flow rates and shares of static routes. Further, by means of a nested loop, a data set is created, where n_1_1, …, n_1_4, share_1_1_1, …, share_1_4_3 are constant, and the durations of permitting signals change in a given range with a given interval in various combinations of signal groups. For example, when changing the duration of the permitting signal in the range from 10 to 60 seconds with a change interval of 5 seconds, taking into account the filtering of duplicates, the data set has 11100 different combinations of signal plans.

Next, the previously trained model determines the value of the average delay time for each signal plan. Unlike PTV Vissim, calculations based on a trained neural network are performed almost instantly (**Figure 5**). The signal plan with the minimum average delay time is exported to a separate file.

With the practical implementation of this technology, we can directly input data from transport detectors and directly output cycle parameters to the controller of a traffic light object.

Under the conditions of non-uniform daily and hourly traffic flow rates, the task of optimizing the parameters of the traffic light control cycle at

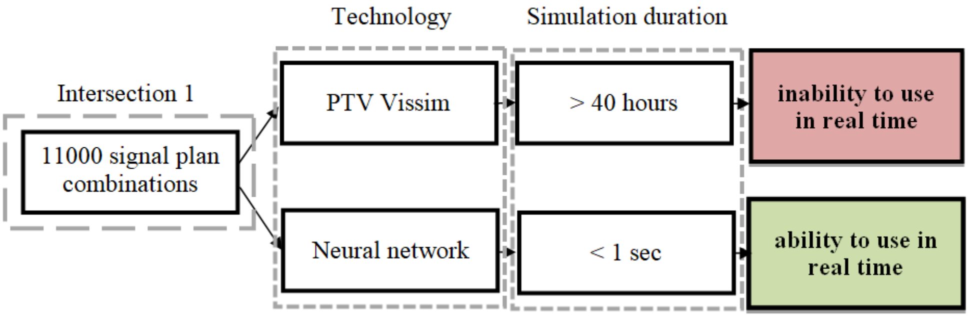

Figure 5. Advantage of mathematical simulation using a neural network

intersections is reduced either to the development of a large number of predictive signal plans, or to the use of adaptive control. Despite the theoretical possibility of developing a large number of signal plans covering a wide range of traffic flow rates, deviations are always possible in the form of repair of the road section, accidents, and meteorological factors. Various adaptive control methods often show their superiority over the predictive mode at a particular local intersection. However, to solve optimization problems on areal or linear objects, the use of local adaptive control has a lower efficiency in comparison with the optimal predictive mode. Predictive modes at objects with several signalised intersections are quite laborious in calculations due to the large number of factors that must be taken into account (Figure 6). Therefore, such objects rarely utilise more than four or five predictive modes.

On an areal object, to determine the optimal parameters of the traffic light control cycle at each intersection and the value of the cycle start offsets, it is necessary to take into account the rates of incoming flows (n_1_1, n_2_1, etc.), the distribution of flows at each intersection (D_1, D_2, etc.), and the traffic flow rates along the routes (r_1_2, r_8_3, etc.). Machine learning and neural networks make it possible to create mathematical models that take into account such a number of input parameters.

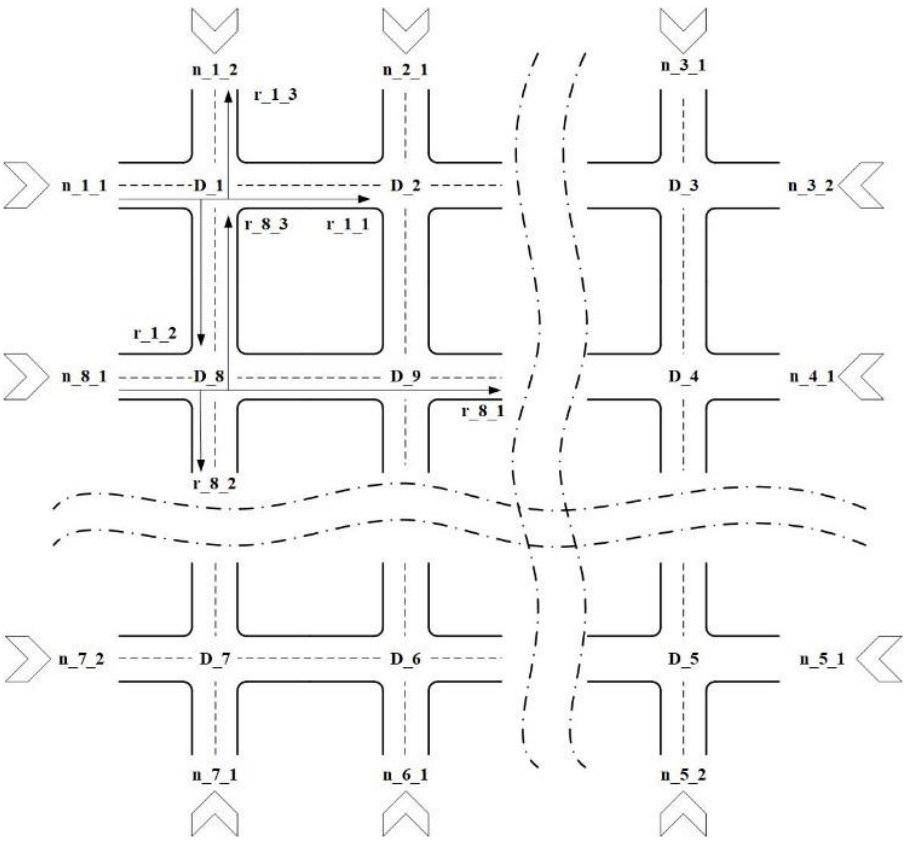

Figure 6. Traffic parameters on an areal object

When using the simulation of a given object in PTV Vissim for training a neural network, it is possible to obtain a model that allows real-time determination of the optimal parameters of the traffic light operation mode for the entire section, which allows integrating this technology into a traffic control system (Figure 7).

The use of a neural network trained for a specific object through the calculation and optimization module allows one to instantly obtain the optimal parameters of the traffic light operation mode, depending on the traffic parameters. Traffic parameters can be obtained from installed detectors or from video cameras (a pattern recognition system is required). In this case, the operator in the traffic control center performs a control function and acts as an observer. The operation of the software is described by the following steps:

a. Receipt of data from transport detectors by the module of calculation and optimization.
b. Calculation of the optimal cycle parameters.
c. Transfer of the optimal cycle parameters via the module of interaction with the traffic light controller.
d. Recalculation of the cycle and changing the parameters of the traffic light.

Simulation modeling of the section is necessary when designing the system and upgrading it in case of a change in the traffic scheme (Figure 8).

Despite the presence of simulation modeling in the system, it is used exclusively for training a neural network to create a digital mathematical

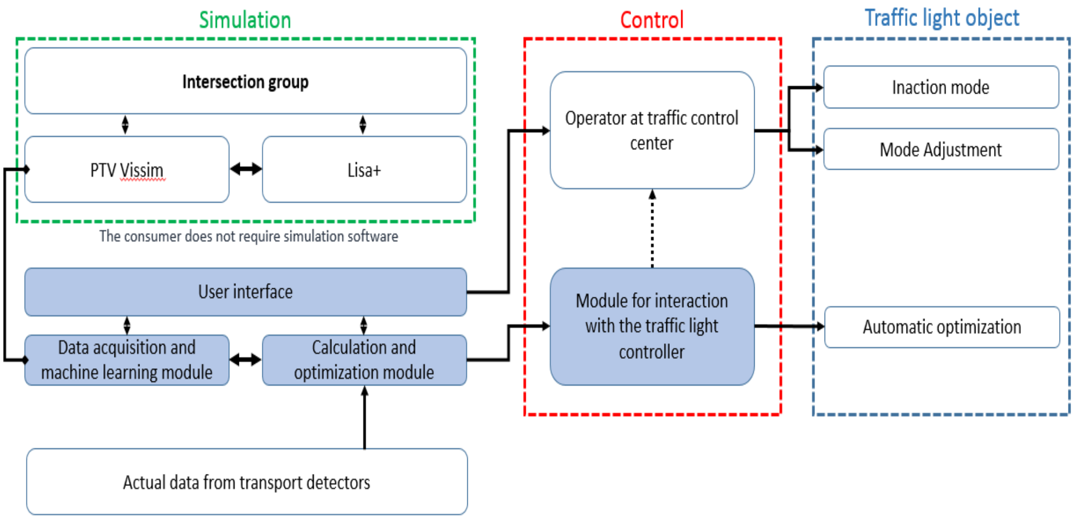

Figure 7. Integrating neural network software into a traffic management system

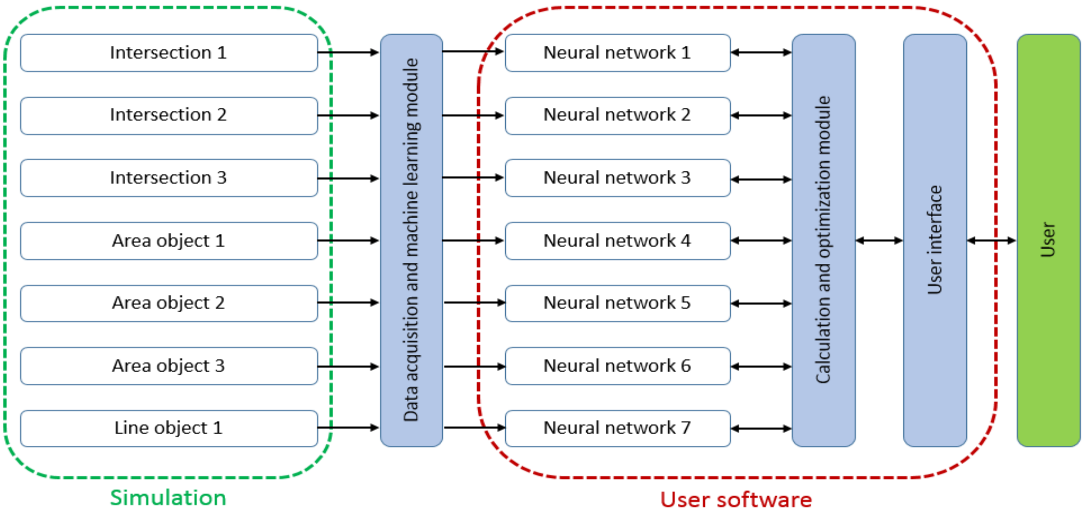

Figure 8. Scheme of software operation for a set of traffic lights in the city

twin of an intersection, a linear or areal object. When calculating a signal plan, simulation modeling by means of PTV Vissim [33] is not used. Modern computing power allows real-time calculations based on trained neural networks, which ensures uninterrupted optimization of the parameters of traffic light control cycles depending on the traffic situation.

5. Results and Discussion

For each of the eight fifteen-minute time intervals, the optimal cycle of traffic light control was determined using an ANN (**Table 7**). Further, the parameters of the traffic light operation mode and the values of the traffic flow rate were automatically transferred to PTV Vissim 11 [33] and the simulation process was initiated. The collection of simulation results was also carried out automatically. During the ANN operation, restrictions were introduced that did not allow increasing the cycle time to more than 95 seconds. For each time interval, except for 7:30-7:45 and 8:00-8:15, the ANN determined a unique traffic light operation mode, taking into account the restrictions (maximum cycle duration, maximum duration of the main cycle for one of the directions) (**Figure 9**).

As a result, for each 15-minute time interval, the values of the average delay time were obtained using the predictive mode and traffic control through the ANN (**Figure 10**). **Table 8** presents the comparative results of assessing the vehicle delay at the intersection calculated for two options (predictive - **Table 1**; using an ANN - **Table 6**) of the traffic light management. The use of ANN control of a traffic light object makes it possible to obtain a significant reduction in the average delay time in the case of the maximum traffic flow rate and a slight reduction in delay in a number of cases with a low actual traffic flow rate.

Table 7. Parameters of the traffic light control cycle obtained using an ANN

No	Time interval	Phase coefficient			Duration of traffic light cycle (s)
		Phase 1	Phase 2	Phase 3	
1	7:00 - 7:15	0.39	0.33	0.28	61
2	7:15 - 7:30	0.41	0.35	0.24	71
3	7:30 - 7:45	0.43	0.38	0.19	87
4	7:45 - 8:00	0.44	0.38	0.18	94
5	8:00 - 8:15	0.43	0.38	0.19	87
6	8:15 - 8:30	0.42	0.38	0.20	85
7	8:30 - 8:45	0.42	0.36	0.22	77
8	8:45 - 9:00	0.41	0.33	0.26	66

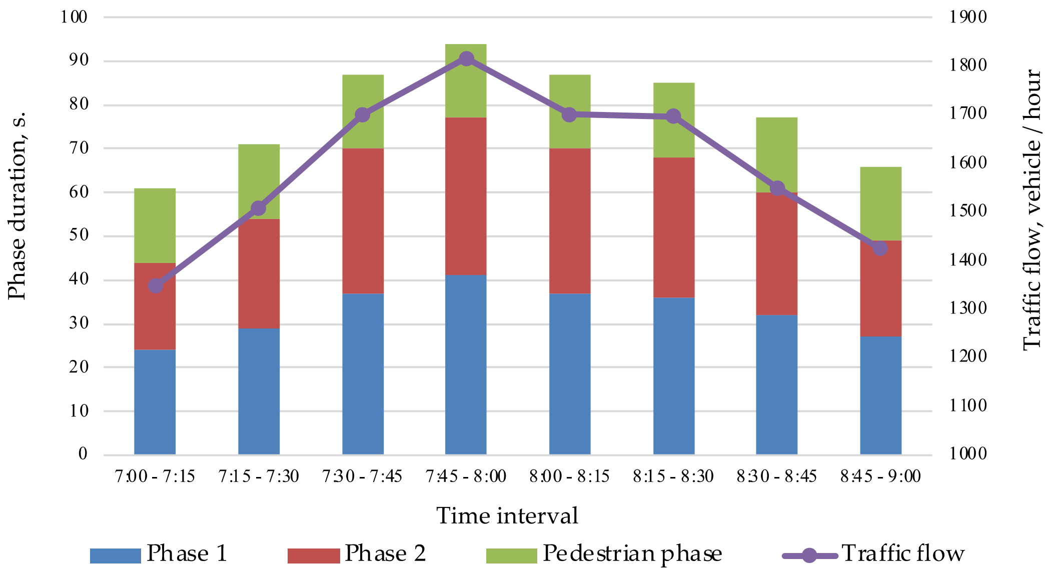

Figure 9. Ratio of the duration of the phases in the cycle, taking into account the vehicle actual traffic flow rate at the intersection

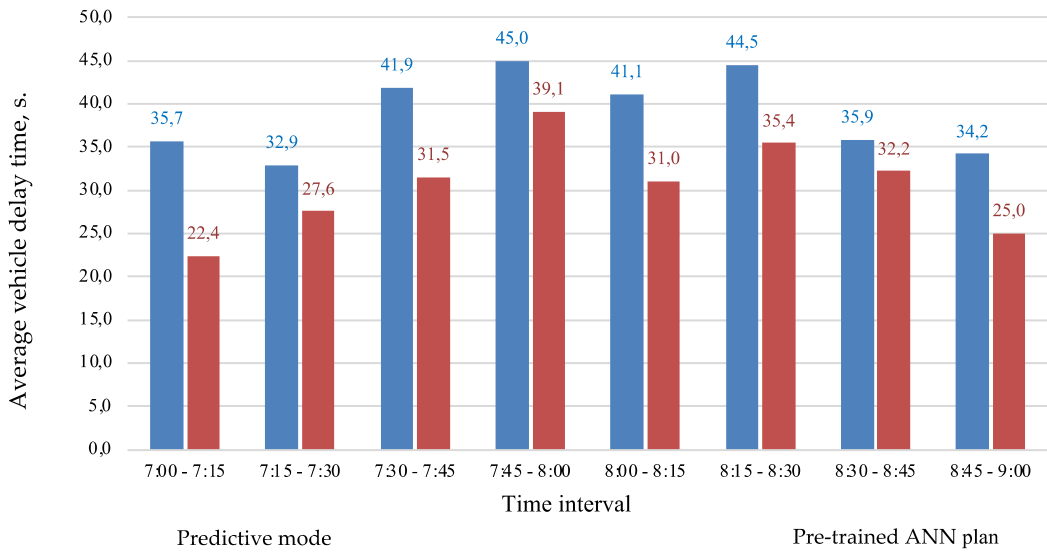

Figure 10. Comparison of the average vehicle delay time for traffic light control options using a predictive mode and a pre-trained ANN

Table 8. Comparative results of assessing the vehicle delay at the intersection calculated for 2 options for managing the work of a traffic light object

No	Time interval	Average vehicle delay time for different modes of traffic light cycle management (s)	
		Predictive mode	ANN
1	7:00 - 7:15	35.7	22.4
2	7:15 - 7:30	32.9	27.6
3	7:30 - 7:45	41.9	31.5
4	7:45 - 8:00	45.0	39.1
5	8:00 - 8:15	41.1	31.0
6	8:15 - 8:30	44.5	35.4
7	8:30 - 8:45	35.9	32.2
8	8:45 - 9:00	34.2	25.0

Table 9 provides the values of the average vehicle delay at the intersection (in the morning hours of the day under conditions of a high traffic flow rate).

ANN control shows a 22.4% decrease in delay time for the time interval 07:00-08:00 and a decrease in delay time by 20.6% for the time interval 08:00-09:00 relative to the predictive mode. Note that reducing the delay has a very positive effect on the environmental state of the city [35].

6. Historical Background of Traffic Management in Tyumen (Russia), its Impact on Traffic Safety and an Explanation of the Choice of Traffic Lights for the Development of Innovative Practices

Tyumen is a good example of the dynamic development of both the city and its transport system. The population of the city for the period from 1956 to 2023 increased by almost 7 times

Table 9. Values of the average vehicle delay time when using different methods of controlling a traffic light object at a controlled intersection

Control method	Average delay time by time intervals (s)		
	07:00 – 08:00	08:00 – 09:00	07:00 – 09:00
Predictive mode	38.9	38.9	38.9
ANN	30.2	30.9	30.5

(from 125 thousand people to 855 thousand people) [36]. The level of motorisation during this time increased from 9 to 495 vehicles/1000 people; the structure and quality characteristics of the vehicle fleet have changed qualitatively [37]. The length of transport routes in the city has sharply increased and their quality has improved.

Of course, the processes of traffic management in the city also proceeded very intensively.

Table 10 shows the actual dynamics and its forecast regarding the development of traffic light control in the city for the period from 1970 to 2030.

Data on the dynamics of motorisation and changes in the road traffic accident rate in Tyumen in 2000 ... 2023 are given in **Table 11** [38]. It can be noted that the dynamics of Human risk in 2000 ... 2023 fully corresponded to the well-known law of R. Smeed [39].

Comparing the data of **Table 10** and **Table 11**, we can see that the dynamics of the increase in the number of traffic lights (+114%) in 2000…2022 is quite consistent with the growth in motorisation (+98%). Relative indicators of road safety (*HR* and *RTA Severity*) have decreased during this time by almost three times.

At the same time, a slight increase in road safety indicators in the last three years (2022/2020) is of some concern. Perhaps this is one of the factors that significantly influenced the introduction of new methods of traffic management in 2023 (Control of traffic lights using a pre-trained ANN for a specific intersection). It is possible to assess the impact of the benefits of using ANNs in traffic management and its positive impact on traffic safety in relation to a specific object - the very intersection of Odesskaya-Kotovskogo streets, for which the research work was carried out. To do this, let us compare the statistics of accidents at the intersection over the past 4.5 years (2019…2023) (http://stat.gibdd.ru/).

Thus, it can be noted that in Tyumen the start of work (spring 2023) on the gradual replacement of the adaptive mode of traffic light regulation with traffic light control using a pre-trained ANN was initiated, first of all, by the loss of pace in the process of reducing road traffic accidents (**Table 11**). The choice of Tyumen intersections, for which this work began in the first place, is explained by the dynamics of the increase in road accidents recorded in recent years (**Table 12**).

Table 10. Dynamics of the traffic light system development in Tyumen

Characteristics	Years							
	1970	1980	1990	2000	2010	2017	2023	2030
Number of traffic lights, units	25	65	125	200	285	315	428	550
Main mode of traffic light operation	2-phase	2-phase	2-3-phase	2-4-phase	Multi-phase with time cut-off	Multi-phase + dedicated pedestrian phase	Adaptive multi-phase + ANN elements	Priority use of ANN
Number of traffic lights in ATCS, units	-	-	-	-	85	240	374	550

Note. Expert assessments of veterans of the transport sector (1970 ... 2010) and data from the specialized organization «Tyumengortrans" are given. (2017…2030) (https://tgt72.ru/)

Table 11. Dynamics of motorisation and road traffic accidents in Tyumen [38]

Characteristics	Years					
	2000	2005	2010	2015	2020	2022
Motorisation, vehicles/1000 people	250	308	434	466	486	495
Number of RTAs, units	889	1668	1397	1482	1356	1532
RTA injuries, people	1062	2203	1902	2013	1909	2055
RTA deaths, people	79	75	60	41	36	41
Human risk, deaths/100 thous. people	13.9	13.9	10.3	7.0	4.5	4.8
RTA severity, %	6.6	3.4	3.1	2.1	1.9	2.0

Table 12. Statistics of road traffic accidents at the intersection of Odesskaya - Kotovskogo streets (Tyumen) with a reformed traffic light control mode [8]

Indicators	Years				
	2019	2020	2021	2022	half 2023
Number of RTAs, units	1	1	1	2	0
RTA injuries, people	1	1	1	4	0

Perhaps it is important to explain the essential relationship between the results of neural network optimization of the duration of the traffic light cycle and its distribution by phases at a specific traffic light object at the intersection of Odesskaya and Kotovskogo streets and the actual accident rate. In the opinion of the authors, the main factor in reducing the accident rate at the intersection is a decrease in the emotional tone of drivers who are forced to waste time in a traffic jam [40], and, as a result, a positive effect of a qualitative change in the nervousness of road users on traffic safety [41].

7. Conclusions

The practice of using artificial neural networks in managing traffic lights is still quite new for Russian cities. Only in a very small number of Russian cities [42] and regions [43] have any ITS elements been introduced to one degree or another. The practice of neural network programming of the modes of functioning of traffic lights in Russian cities is very innovative. However, the process of introducing the technology of using artificial neural networks in the management of traffic lights in most cities of Russia with a population of more than 500 thousand people has already started and is gradually developing.

One of the intersections in the city of Tyumen is an example of the development and implementation of a traffic light cycle control mode using an ANN. Based on the results of the research work, the following main conclusions can be drawn.

a. The use of an ANN in the practice of optimizing traffic light cycles can dramatically increase the efficiency of traffic management and reduce the emotional stress of its participants. This has a positive effect both on increasing the traffic capacity of the road network and on reducing the road traffic accident rate.
b. For the specific intersection of Odesskaya and Kotovskogo streets in Tyumen, considered in this article, the traffic light control mode using an ANN can significantly (by 20.6 ... 22.4%) reduce the average delay time of vehicles.
c. In the case of an individual intersection, the use of an ANN can be replaced by the use of well-established formulas and models in the transport sector for calculating traffic light cycle parameters based on traffic flow rate. However, in the case of linear and area objects, the application of the above formulas and models is reduced to finding the optimum for each individual intersection, and not for the object as a whole. The use of an ANN allows taking into account a much larger number of factors and optimizing the control of the entire object, consisting of several intersections, which is not achievable using predictive modes and local adaptive control. The use of the approach to control a traffic light object presented in this study can be considered as an independent alternative to traditional adaptive control, and as a technology for managing area or linear objects with several intersections. In this case, the number of factors and parameters increases multiple times and after training, the neural network model is able to control all traffic light objects at each intersection at once according to its target function.
d. This article presents the results of controlling a traffic light based on a pre-trained ANN with a change in cycle parameters every 15 minutes. If it is technically possible to transmit data on the actual traffic flow rate for shorter periods of time or in real time, the effect of using an ANN in an intelligent transport system can potentially be much higher [44]–[46].
e. The next stage of research in this area will be approbation of the technology on linear and areal objects with subsequent assessment of their effectiveness.

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Author's Declaration

Authors' contributions and responsibilities

Conceived and designed the experiments (A.V.P, A.I.P); Performed the experiments (A.V.P, A.I.P); Analysed and interpreted the data (A.V.P, A.I.P); Wrote the original paper (A.V.P, A.I.P); and Wrote the revised manuscript (A.V.P, A.I.P).

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Availability of data and materials

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Competing interests

The authorsdeclare no competing interest.

Additional information

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Appendix A

The code of the auxiliary procedures and functions module

```
import pandas
def WriteToSig (sig_file_path, ds = pandas.Series): # write data to PTV *.sig file
    import xml.etree.ElementTree as ET # *.sig file has XML structure
    input_data_sig = [40,40,27,27,30]
    input_data_phase = [1,1,2,2,3]
    sg_count = 1
    df = pandas.DataFrame(columns=['sg','phase','start','end'])
    c = 0
    pos = 0
    while c < len(ds)-1:
        input_data_phase[pos] = int(ds[c])
        input_data_sig[pos] = int(ds[c+1])
        c = c + 2
        pos = pos + 1
    phase_start = 0
    for sg_count in range(0, len(input_data_sig)) : # cycle for calculate phases start/end points
        df['start'].iloc[sg_count] = phase_start
        df['end'].iloc[sg_count] = (phase_start + input_data_sig[sg_count] + 6)
        if sg_count < len(input_data_sig)-1 :
            if (input_data_phase[sg_count] != input_data_phase[sg_count+1])  :
                if sg_count >0 :
                    phase_start = max (df['end'].iloc[sg_count],df['end'].iloc[sg_count-1]) + 3
                else:
                    phase_start = df['end'].iloc[sg_count] + 3
        else :
            df['end'].iloc[sg_count] = df['end'].iloc[sg_count] - 6
            cycle_lenght = df['end'].iloc[sg_count] + 3
    for sg_count in range(0, len(input_data_sig)) :
        df['start'].iloc[sg_count] = df['start'].iloc[sg_count]*1000
        df['end'].iloc[sg_count] = df['end'].iloc[sg_count]*1000
        df['phase'].iloc[sg_count] = input_data_phase[sg_count]
    sg_count = 0
    for elem in root: # write phases start/end points into *sig file
        for subelem_1 in elem.findall('prog'):
            subelem_1.set('cycletime', str(int(cycle_lenght*1000)))
            for subelem_2 in subelem_1.findall('sgs'):
                for subelem_3 in subelem_2.findall('sg'):
                    for subelem_4 in subelem_3.findall('cmds'):
                        for subelem_5 in subelem_4.findall('cmd'):
                            if subelem_5.get('display')=='3':
                                subelem_5.set('begin', str(int(df['start'].iloc[sg_count])))
                            if subelem_5.get('display')=='1':
                                subelem_5.set('begin', str(int(df['end'].iloc[sg_count])))
                    sg_count = sg_count+1
            tree.write(sig_file_path)
    return df

def ReadDataBaseVissim (database_file_path) : # function for read output data
```

```
    import sqlite3 # output data storage in sql database
    con = sqlite3.connect(database_file_path)
    cursorObj = con.cursor()
    cursorObj.execute('SELECT * FROM VEHICLENETWORKPERFORMANCE
MEASUREMENT_EvaluationTimeIntervalClass ') # select data from sql database
    database_names = list(map(lambda x: x[0], cursorObj.description)) #parse names
    rows = cursorObj.fetchall()
    cursorObj.execute('SELECT * FROM VEHICLENETWORKPERFORMANCE
MEASUREMENT_EvaluationTimeInterval ') # select data from sql database
    database_names_latent = list(map(lambda x: x[0], cursorObj.description))
    rows_latent = cursorObj.fetchall()
    rows [0] = rows[0] + rows_latent[0]
    database_names = database_names + database_names_latent
    input_row = pandas.Series(rows[0],index = database_names)
    output_df = pandas.DataFrame (input_row).T
    con.close()
    return output_df
```

Appendix B

The code of the main data collection module

```
import win32com.client as com # for connection with PTV Vissim
import pandas

# files' paths
Model_Path = "C:\\Projects\\ComServerDataGain\\model\\4_4_Base.inpx"
Input_Data_For_Model = "C:\\Projects\\ComServerDataGain\\input_for_stability.xlsx"
sig_file_path = "C:\\Projects\\ComServerDataGain\\model\\4_4_base.sig"
database_path = "C:\\Projects\\ComServerDataGain\\model\\4_4_Base.results\\1.db"

# connect to Vissim via COM
Vissim = com.gencache.EnsureDispatch("Vissim.Vissim.11")
Vissim.LoadNet (Model_Path)
Vissim.Graphics.CurrentNetworkWindow.SetAttValue("QuickMode",1)

# read input data
input_data_set = pandas.read_excel(Input_Data_For_Model)
cols_with_flow = 4
cols_with_sig_count = 10
cols_with_share = 12

from pandas import concat
from API_Vissim import WriteToSig
from API_Vissim import ReadDataBaseVissim

for z in range(0,len(input_data_set)) : # main cycle (each row in dataset = 1 simulation)
  link_count = 0
  for SimRun in Vissim.Net.SimulationRuns :
      Vissim.Net.SimulationRuns.RemoveSimulationRun(SimRun) # clear Vissim output
  try :
    for i in range(1, Vissim.Net.VehicleInputs.Count+1):
      replaced_input_value = int(input_data_set[input_data_set.columns[first_flow_row_position + 
link_count]].iloc[z])
      try :
        Vissim.Net.VehicleInputs.ItemByKey(i).SetAttValue('Volume(1)', replaced_input_value) # 
changing vehicle input value
      except :
        print ('Error in write vehicleinput')
      link_count +=1
  except : # Vissim reboot on failure
    print ('Strange error')
    Vissim.Exit
    Vissim = com.gencache.EnsureDispatch("Vissim.Vissim.11")
    Vissim.LoadNet (Model_Path)
    Vissim.Graphics.CurrentNetworkWindow.SetAttValue("QuickMode",1)
    continue
  dff = pandas.Series(input_data_set[input_data_set.columns[cols_with_flow + 1:cols_with_flow + 
cols_with_sig_count + 1]].iloc[z])
  WriteToSig (sig_file_path, dff) # changing traffic light parameters
```

```
    link_count = link_count + cols_with_sig_count
    for j in range(1, Vissim.Net.VehicleRoutingDecisionsStatic.Count+1):
        for jj in range(1, Vissim.Net.VehicleRoutingDecisionsStatic.ItemByKey(j).VehRoutSta.Count+1):
            try : # changing static routes parameters
Vissim.Net.VehicleRoutingDecisionsStatic.ItemByKey(j).VehRoutSta.ItemByKey(jj).SetAttValue('RelFl
ow(1)', float(input_data_set[input_data_set.columns[first_flow_row_position + link_count]].iloc[z]))
            except :
                print ('Error in write routes')
            link_count +=1
    Vissim.Simulation.SetAttValue('UseMaxSimSpeed', True)
     try :
        Vissim.Simulation.RunContinuous() # simulation run
    except :
        Vissim.Exit
        print ('Vissim reboot on simulation ' + str(z))
        Vissim = com.gencache.EnsureDispatch("Vissim.Vissim.11")
        Vissim.LoadNet (Model_Path)
        Vissim.Graphics.CurrentNetworkWindow.SetAttValue("QuickMode",1)
        continue

    output_df = ReadDataBaseVissim(database_path) # read Vissim output data
    export_data_ser = pandas.concat([input_data_set.iloc[z],output_df.iloc[0]],axis=0,
ignore_index=False)
    export_data_ser = pandas.DataFrame(export_data_ser).T
    if z == 0 :
        export_data_frame = pandas.DataFrame(export_data_ser)
    else :
        export_data_frame = pandas.concat ([export_data_frame,export_data_ser],axis=0,
ignore_index=True)
    export_data_frame.to_excel("output.xlsx")
```