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Adaptive control of transportation infrastructure in an urban environment using a real-coded genetic algorithm

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Abstract

The management of urban areas requires the development of an effective strategy for the evolution of transportation infrastructure to ensure the smooth flow of traffic and pedestrians. A crucial component of this infrastructure is the traffic light system, which plays a vital role in traffic control and traffic safety. Improving the efficiency of traffic control systems in intelligent transportation systems (ITS) has a significant impact on a city's economy. As a result, the cost of fuel for road users can be reduced, and their level of social comfort can be improved, among other benefits. This paper proposes a novel approach to optimizing traffic flows in smart cities, based on the combined use of the genetic optimization algorithm and the ITS simulation model we developed. The proposed method aims to enhance the efficiency of existing traffic control systems and achieve optimal traffic flow patterns, thereby contributing to a more sustainable and efficient urban environment. The optimization algorithm shown here aggregates the objective functions using a simulation model of a real region of the Moscow road network. The model includes intersections, pedestrian crossings and other features that are implemented in the AnyLogic system. The research aims to create a decision-support system for managing urban transport infrastructure. This system will be used to optimize the duration of traffic light phases in order to minimize the time vehicles spend passing through key nodes in the urban road network. It will also optimize pedestrian flow, reducing the impact of traffic on the environment and improving fuel efficiency. By applying this approach, the capacity of the street network can be significantly increased. Additionally, the negative effects of traffic flow on the environment can be reduced by optimizing fuel use and reducing waiting times at intersections managed by traffic lights. The research methodology involves the development of a hybrid evolutionary search algorithm, the creation of a simulation model for transportation and pedestrian flows in the AnyLogic and a series of optimization experiments that demonstrate the effectiveness of the proposed approach when applied to the modeling of complex urban transportation systems.

Keywords: urban planning and development, municipal management, intelligent transportation systems, smart city, real-coded genetic algorithms, traffic flow simulation, traffic control, AnyLogic

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Introduction

Evolutionary development of transport infrastructure, in particular, through the design and implementation of intelligent transportation systems (ITS) is an important area of business informatics that is relevant for state, municipal and private enterprises responsible for the creation and maintenance of a comfortable and safe urban environment. In the conditions of accelerated urbanization and constant growth of the number of vehicles, the problem of effective management of traffic and pedestrian flows is timely. The complexity of the task of optimizing traffic flow is due to the multifactor and dynamic nature of the processes occurring in urban space which necessitates the use of modern methods of mathematical and simulation modeling of ITS.

Various approaches are known in the field of traffic light control optimization, including the use of genetic optimization algorithms [1–3], machine learning methods [4], artificial neural networks [5], fuzzy logic [2] and clustering [1, 6]. However, it should be considered that most of these approaches are aimed at studying the behavior of agents in digital road networks, the configuration of which differs significantly from real urban road networks [1, 2], or are applied to cases with transport systems of simple structure – with a small number of intersections and lanes [5, 7]. Simulation modeling is a powerful tool for research and analysis of transport systems, allowing us to recreate and study the behavior of complex systems in a controlled virtual environment [8]. In particular, the application of hybrid algorithms combining the advantages of swarm [9, 10] and genetic optimization methods [1, 2, 11, 12] opens new perspectives for improving the efficiency of traffic flow control.

The purpose of this research is to study the possibilities to improve the performance of urban transport infrastructure objects (in particular, traffic lights) using the proposed methods of evolutionary search for optimal solutions. Within the framework of this approach, we have developed a simulation (agent-based) model of a real section of the Moscow street road network using the AnyLogic system, proposed an improved genetic algorithm of real coding aggregated by target functionals with the created simulation model of traffic and pedestrian flows. The approach we present is aimed at optimizing the duration of phases of traffic signals, in particular, to minimize the time and material costs of vehicles to pass the studied local section of the street road network, as well as to improve the traffic conditions of pedestrian flows at intersections and pedestrian crossings. As a result, the adaptation of control parameters of traffic lights to the current traffic conditions is provided, considering the optimization of fuel consumption and reduction of harmful emissions into the atmosphere. The simulation model we developed for the multi-agent ITS includes elements of the street road network (roads, traffic lights, intersections, etc.), traffic and pedestrian flows, consisting of individual agents – interacting road users with their own rules of individual decision-making. The designed system is intended to analyze the impact of different strategies for controlling the phase duration of traffic signals affecting the efficiency of traffic flows in urban environments. The study contributes to the development of methods of evolutionary modeling of urban transport infrastructure, demonstrating the high potential of genetic optimization algorithms in solving urgent problems of urban planning and municipal management.

1. Traffic and pedestrian flow simulation model

The proposed approach is based on the development of a complex simulation model of traffic flows implemented in an AnyLogic environment. Unlike previously developed systems of this type [1, 13], this model includes the digital design of a real section of the Moscow road network with controlled traffic lights, vehicles, and pedestrian flows (*Figs. 1, 2*). The key elements of the model are:

- **Road infrastructure:** real road geometry is designed (in the AnyLogic digital environment), including the number of lanes, traffic directions, intersections and pedestrian crossings.
- **Vehicles and pedestrians:** individual and group behavior of road users, their speed, routes and inter-action with road network elements are simulated.
- **Traffic lights:** traffic lights are modeled, with the possibility of changing their parameters (phase duration) to optimize traffic flow.

To implement the proposed methodology, the AnyLogic software package was used. It allows modeling complex traffic flows in the conditions of urban infrastructure. AnyLogic allows us to qualitatively combine elements of system dynamics, agent-based and discrete-event modeling [13–16]. Integration with AnyLogic is provided by exporting the simulation model in jar-file format, which allows us to automate the process of assessing the efficiency of traffic lights and their impact on traffic flows.

An important feature of the methodology is to consider the interaction of vehicles with pedestrian flows. This is provided through the use of spatial markup elements and pedestrian library AnyLogic. This enables us to simulate realistic scenarios of transport system operation and to evaluate the effectiveness of the proposed optimization measures as a whole.

Within the framework of an integrated approach to the analysis and optimization of urban traffic flows, special attention is paid to modeling the interaction between vehicles and pedestrian flows [1, 12]. For this purpose, the simulation model developed in the AnyLogic environment includes a detailed scheme of pedestrian crossings using elements of the Space Markup library. This allows us to accurately recreate the conditions of their functioning and their impact on the overall efficiency of traffic. The implementation of pedestrian crossing sections in the area of Yugo-Zapadnaya metro station in the digital model is shown in *Fig. 3*.

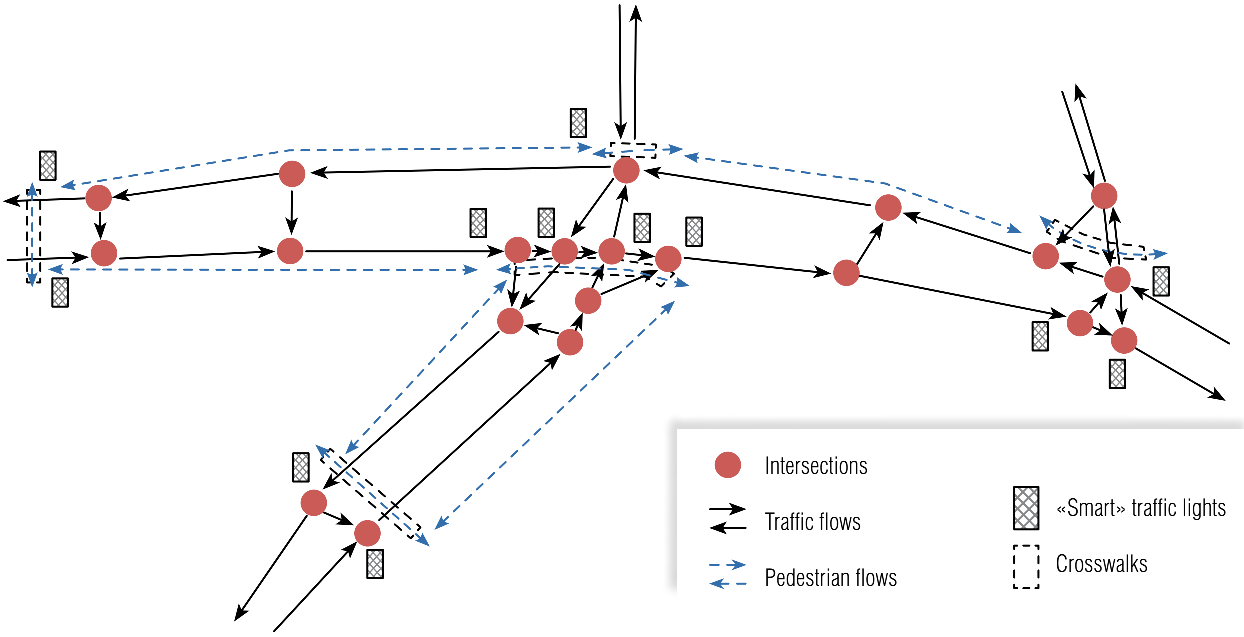

Fig. 1. Designed model of the digital section of the street road network.

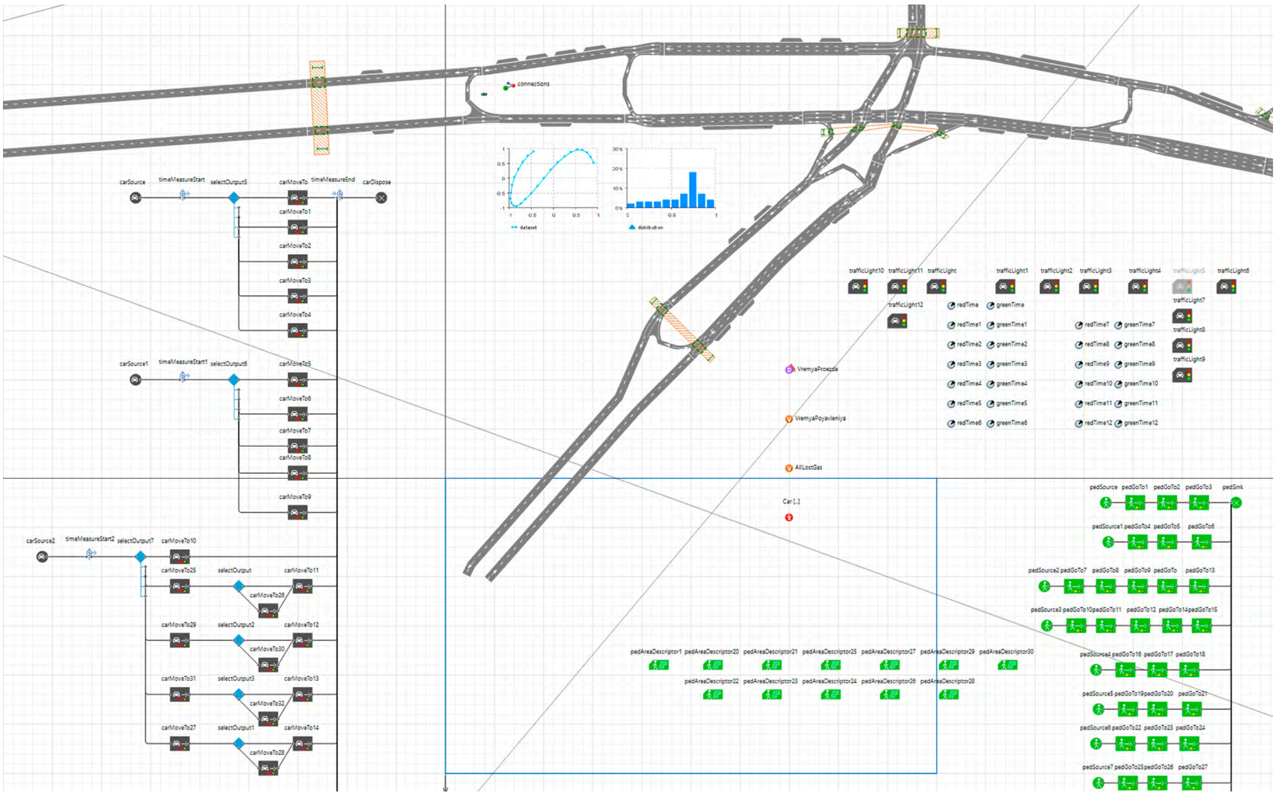

Fig. 2. Implementation of a digital model of a street road network section in an AnyLogic environment.

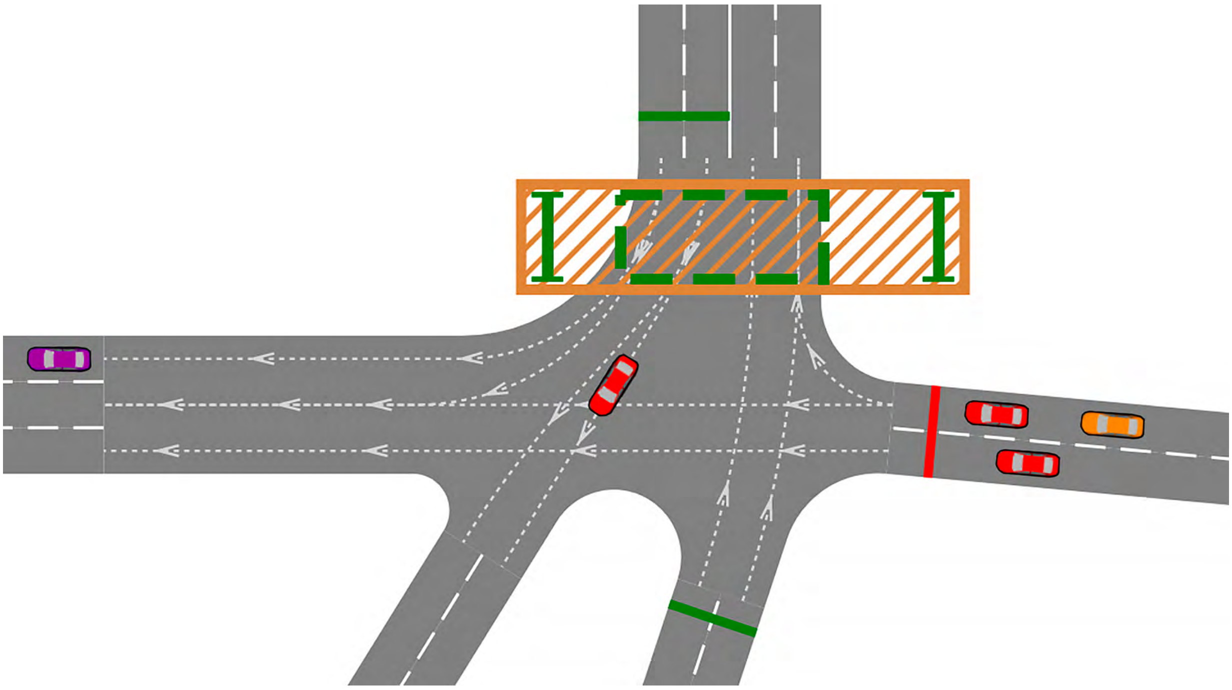

Fig. 3. Implementation of pedestrian crossing sections in the area of Yugo-Zapadnaya metro station in the digital model.

Structural elements of pedestrian traffic modeling:

- **Walls:** function as elements that limit the pedestrian movement area, creating an environment as close to reality as possible, where pedestrian flows cannot cross the roadway randomly, but are directed to pedestrian crossing areas.
- **Targetlines:** define pedestrian arrival and departure points in the model, as well as pedestrian waiting areas, including public transport stops, building entrances and other key pedestrian infrastructure points.
- **Polygon Node (Area):** used to detail the crossing area, including its geometry and specific pedestrian movement conditions.

Pedestrian Movement Logic. The model includes a set of logic blocks from the Pedestrian Library that are responsible for regulating pedestrian movement:

- **Pedestrian Movement Units (pedGoTo):** provide dynamic pedestrian movement control to guide pedestrians to specified targets, including pedestrian crossings, public transport stops and other important locations.
- **Node Control Units (pedAreaDescriptor):** allow you to define traffic rules for specific areas, including the availability of pedestrian crossings based on traffic signals.
- **Removal block (pedSink):** responsible for removing pedestrians from the model when they reach their final destination, allowing analyses of pedestrian traffic flows and densities.

Figure 4 shows the overall pedestrian movement logic in the model. *Table 1* summarizes the building blocks on which the pedestrian movement and pedestrian crossing logic is based.

The problem of increasing levels of air pollution associated with the overall growth of the world economy, including the growth of road transport, has long

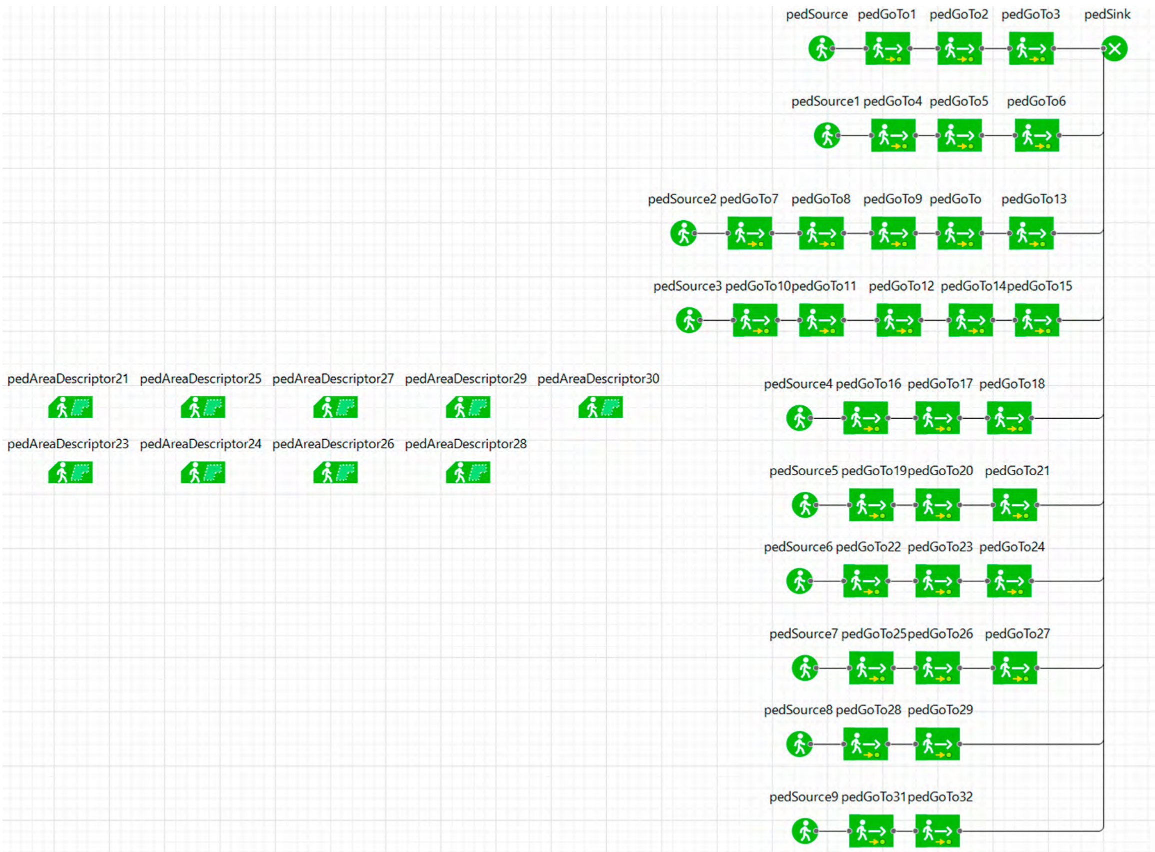

Fig. 4. Fragment of the traffic simulation model developed using the AnyLogic pedestrian library.

Table 1.

Structural blocks of the model

Title	Function	Characteristic
pedSource, pedSource1, …, pedSource9	Establishing where pedestrians will appear	Necessary for pedestrian agents to appear
pedGoTo, pedGoTo1, …, pedGoTo32	Setting a pedestrian destination and controlling pedestrian movement	Necessary to control the directional movement of pedestrians
pedSimk	Removing pedestrians from the model	Necessary to clear the model of pedestrians who have reached their final destination
PedAreaDescriptor, pedAreaDescriptor1, …, pedAreaDescriptor30	Define movement rules for pedestrians at specific nodes	Required to control pedestrian crossings according to traffic light phases

been a global problem. Improving the level of ecology in combination with economic indicators by means of modeling is also an urgent task. In this regard, in order to assess the environmental efficiency of the transport system, a system of variables and elements of system dynamics within Car agents is introduced in the model. This enables us to analyze fuel consumption depending on traffic conditions (*Fig. 5*):

- **Fuel consumption and speed variables:** simulate vehicle fuel consumption in real time, taking into account vehicle speeds and stops at traffic lights.
- **Stop and restart events:** regulate the change in fuel consumption when a vehicle stops and starts, allowing a more accurate assessment of the impact of congestion and frequent stops on environmental performance.
- **The integration of pedestrian flows and fuel consumption analysis** not only optimizes traffic flow in terms of travel time, but also improves conditions for pedestrians and reduces the environmental impact of transport.

In the traffic flow simulation model, agent vehicles are equipped with a number of variables reflecting their fuel characteristics and driving dynamics. The main variables include fuel volume (GasVol), consumption per 100 km (GasUsage), and consumption at rest (GasUsageStop), generated randomly from predefined ranges. The system dynamics of the model accounts for changes in fuel volume (GasVol1) and total fuel consumed (EndGas) governed by agent activity and events controlling movement and stopping. Accounting for agent acceleration through the MeanAcc variable and the SpeedMemAcc and MeanCalc events facilitates the modeling of fuel economy during aggressive acceleration, showing a possible reduction in consumption of up to 10% [17]. This fact was accounted for in the form of reduced consumption under high acceleration. Thus, the value of fuel consumption is determined by formula (1), and all variables and their characteristics are presented in *Table 2.*

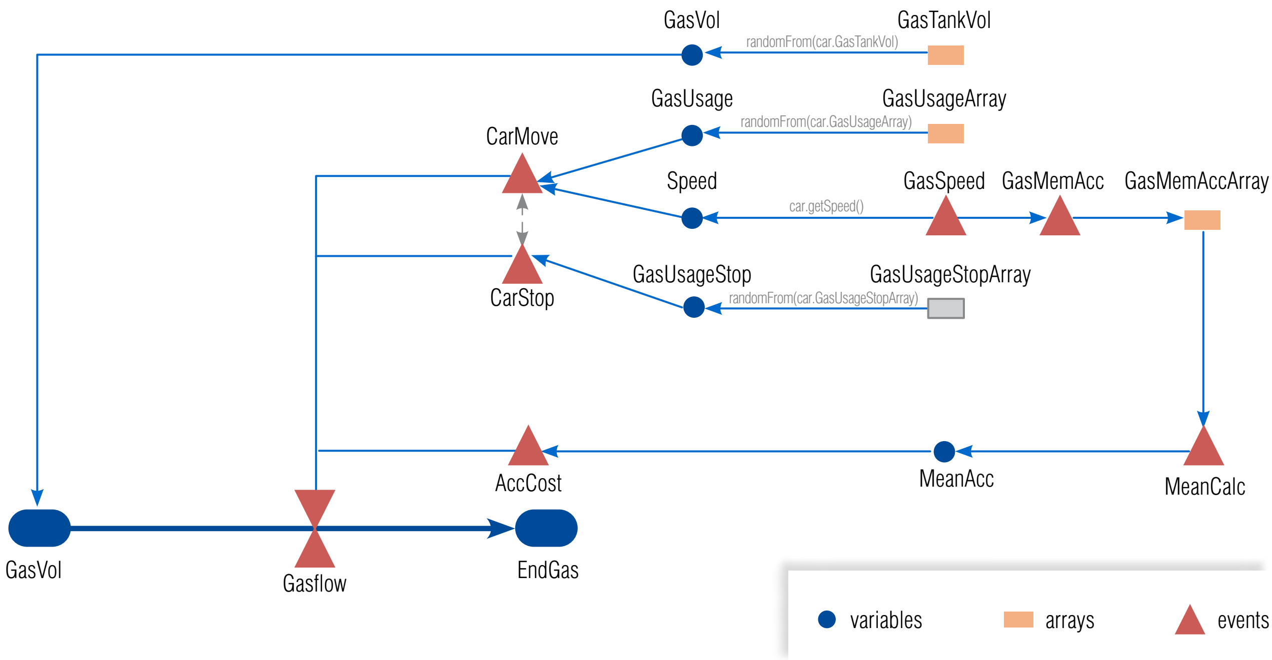

Fig. 5. Variables, events, and elements of system dynamics belonging to the agent.

$$\frac{dE}{dt} = \begin{cases} U \cdot S & S > 0, \\ K & S = 0, \\ A \sum_{i=0}^{n} (a[i+1] - a[i]) / (n-1) < 1.45, & \end{cases} \quad (1)$$

where:

E – fuel consumed;

U – agent's fuel consumption;

S – agent's speed at the moment of time;

K – consumption when there is no movement;

A – fuel consumption at the time of acceleration with correction for aggressive acceleration;

a – every second measurements of the agent's speed after no movement.

Upon removal from the model, the EndGas value of the fuel spent during the model run of a particular agent is added to the Total Fuel Spent (AllLostGas) variable.

2. Genetic algorithm for control of traffic lights

The proposed approach is based on the use of the ***genetic algorithm of real coding*** [1, 2, 11, 12] modified for the task of optimizing the operation modes of traffic light objects in an urban environment. The algorithm is aggregated with an ITS simulation model developed in AnyLogic environment, which allows us to consider the specifics of road traffic and interaction of traffic flows with infrastructure on specific sections of the road network.

Population initialization in a genetic algorithm starts with the creation of twenty individuals representing parameter sets for traffic light regulation, including green and red signal times, initialized randomly at given intervals (see (2)–(4)). This step sets the initial diversity of solutions critical for efficient search in the solution space and avoiding premature convergence [18]. Each individual is modeled by a class with green and red signal duration parameters determined randomly. The process of generating potential solutions is based

Table 2.

Table of variables and their characteristics

Variable	Description	Source of value
GasVol	Agent's fuel volume at the time of emergence	Random value from GasTankVol
GasUsage	Fuel consumption per 100 km	Random value from GasUsageArray
GasUsageStop	Fuel consumption at rest	Random value from GasUsageStopArray
Speed	Current speed of the agent	Updated via CarSpeed event
GasVol1	Actual fuel volume	Changes with agent movement
GasFlow	Fuel consumption	Adjusted by CarStop and CarMove events
EndGas	Total fuel consumed	Changed according to GasFlow
MeanAcc	Average acceleration of the agent	SpeedMemAccArr based calculation

on the creation of individuals with a variety of parameters through the *Swarm*() function, which facilitates a broad exploration of the solution space (see (5)). This stage is necessary for the subsequent steps of the algorithm, providing an initial basis for the evolution of the population through selection, interbreeding and mutation aimed at optimizing traffic regulation.

To generate a random value of x in the interval $[a, b]$, where a is the lower bound, b is the upper bound, the expression is used

$$x = a + (b - a) \cdot Random.nextDouble(). \qquad (2)$$

Thus, the following expressions are used to initialize the parameter *green* (phase duration of green traffic signal) from the interval $[green_{min}, green_{max}]$, and *red* (phase duration of red traffic signal) from the interval $[red_{min}, red_{max}]$:

$$green = green_{min} + (green_{max} - green_{min}) \cdot Random.nextDouble(). \qquad (3)$$

$$red = red_{min} + (red_{max} - red_{min}) \cdot Random.nextDouble(), \qquad (4)$$

where

$green_{min}$, $green_{max}$ – lower and upper limits for parameter *green*;

red_{min}, red_{max} – lower and upper limits for parameter *red*;

Random.nextDouble() – random number in the range [0, 1] generated by *the nextDouble*() function.

In this case, an initial population of individuals containing the values of the vector of sought variables is created using the following expression:

$$\mathrm{P} = \{(Swarm(x_i)| \; i = 1, 2, ..., N\}, \qquad (5)$$

where

$Swarm(x_i)$ – a function that creates a new individual with randomly initialized parameters;

N– population size (number of individuals in the population).

The selection of individuals in the genetic algorithm for optimizing the duration of phases of traffic signals is carried out according to the criterion of minimizing the average travel time of traffic. Population initialization precedes selection, where initially selection may be uninformed. With subsequent iterations based on the inverse of the mean travel time as the target function, the best adapted individuals are selected. The efficiency of selection is determined by a selection coefficient, which specifies the proportion of the population to interbreed, and a ranking method can be applied to determine the adaptability of individuals [19]. This process guides the evolution of the population, improving its performance and increasing the probability of finding an optimal solution. Selection of the best individuals is key to further steps in the genetic algorithm, including crossbreeding and mutation, which promotes genetic diversity and population adaptation to the task.

Crossbreeding (*crossover*) in the real-valued coding genetic algorithm used to optimize traffic light performance is performed using the Panmixia method, ensuring that each individual has an equal chance of participating in reproduction. The stage generates offspring with parameters defined in the range of parent values according to an intermediate value calculated using (6). The crossbreeding procedure introduces genetic diversity into the population by combining the genetic material of selected individuals, which is a key factor for efficient search for optimal solutions in the traffic light control parameter space:

$$Descendant = Parent1 + \alpha \cdot (Parent2 - Parent1). \qquad (6)$$

Here, the coefficient $\alpha = 0.5 \cdot search\ space$ (the range of acceptable values of the searched variable).

In accordance with this, each member of the population is matched with a random integer on the interval [1, N]. We will consider these numbers as numbers of individuals that will take part in crossbreeding. Some members of the population will take part in the reproduction process repeatedly with different individuals of the population [12]. However, it is rather critical to the population size, since the efficiency of the algorithm implementing this approach decreases as the population size increases [12].

Let G_1 and R_1 be the gene values of the first parent, G_2 and R_2 be the gene values of the second parent, G_{child} and R_{child} be the gene values of the offspring. Then the crossover operator for each gene is as follows:

$$G_{child} = \textit{random number} \text{ beetween } \min(G_1, G_2) \text{ and } \max(G_1, G_2), \tag{7}$$

$$R_{child} = \textit{random number} \text{ beetween } \min(R_1, R_2) \text{ and } \max(R_1, R_2), \tag{8}$$

The goal of inbreeding is to generate offspring with potentially superior characteristics to the parents through recombination of genetic strategies. This process increases population diversity and contributes to optimizing solutions. Inbreeding enriches the population with new genetic variations necessary for adaptation and evolution in the context of the task, allowing the algorithm to efficiently explore and improve traffic regulation strategies.

Crossbreeding provides an adaptation of the genetic algorithm to optimize traffic lights, taking into account the complex aspects of traffic network management. This approach considers the interdependence of parameters in the traffic light network, requiring an integrated approach for optimization, thus avoiding isolation of individual element settings without considering system dynamics. The intermediate recombination chosen for the algorithm allows for the generation of offspring with traits within the range of parental genotypes, providing genetic diversity and improving offspring adaptation. This method accelerates the convergence of the algorithm, guiding the search towards optimal traffic management solutions by effectively balancing the exploitation and exploitation of the search space, which is important for complex urban traffic infrastructure.

In a subsequent step, each individual is mutated to introduce additional diversity into the population and avoid premature convergence to local optima. Mutation is performed using (9)–(12), guaranteeing a small change in parameters with a certain probability [12].

Mutation is a mechanism for introducing random changes in the genetic material of an individual which increases the genetic diversity in the population and prevents premature convergence of the algorithm to local optima [20]. In the context of optimizing traffic light parameters, mutation allows us to explore new regions of the search space, all of which may lead to the discovery of more efficient traffic light configurations:

$$\textit{New traffic light signal time} = \textit{previous value} \pm \alpha \cdot \delta, \tag{9}$$

where

signs "+" or "–" are chosen with equal probability;
δ – coefficient equal to

$$\delta = \sum_{i=1}^{m} \alpha(i)\, 2^{-i}, \tag{10}$$

where

$$\alpha(i) = \begin{cases} \dfrac{1}{m}, & \text{if } u(0,1) \le \bar{p}, \\ 0, & \text{if } u(0,1) > \bar{p}. \end{cases} \tag{11}$$

Here,

m – is the algorithm parameter (chosen equal to 20);

$u(0, 1)$ – is a random number uniformly distributed on the interval;

$\bar{p}$ – probability of mutation.

The new individual resulting from such a mutation, in most cases, does not differ much from the old one. This is due to the fact that the probability of a small mutation step is higher than the probability of a large step [12].

If we consider the formulas separately for green – G and red – R traffic signals, then the mutation formulas for each gene G and R will look as follows:

$$G_{new} = G_{old} + M \cdot \textit{random number}, \tag{12}$$

$$R_{new} = R_{old} + M \cdot \textit{random number}, \quad (13)$$

here:

$$M = 198 \cdot 0{,}5 \cdot \sum_{i=1}^{20} p_i(0,1), \quad (14)$$

where $p_i(0, 1)$ – random values uniformly set on the interval [0, 1] (mutation probabilities for each of the 20 genes).

Mutation involves randomly changing the timing of traffic light signals in a population, with variations within a given range, and this affects the genetic material differently. The mutation technique involves adding or subtracting a value to the traffic light parameters based on the mutation coefficient. The purpose of mutation is to introduce diversity by avoiding local optima and improving the global search for solutions, which can lead to individuals with unique characteristics [21]. Mutation promotes genetic diversity critical for search efficiency, enabling adaptation to change and exploration of the solution space, generating new configurations to optimize traffic lights in dynamic urban traffic.

The mutation mechanism is introduced to balance between accelerating convergence through intermediate recombination to prevent premature convergence to local optima by changing genetic information without modifying the number of genes [22]. Mutation adapted to real individuals (i.e., real-coded mutation) provides minimal but meaningful changes, allowing fine-tuning without the risk of losing valuable genetic combinations. This facilitates escape from local optima and increases genetic diversity, stimulating the exploration of new areas and the discovery of better solutions to optimize traffic management. In combination with intermediate recombination, mutation increases adaptability and search efficiency in complex traffic flow control problems.

To optimize traffic flow control through traffic lights, the algorithm computes a target function (e.g., average travel time) for each individual and then eliminates the least successful ones, preserving the population size. The target function reflects the efficiency of management and can include different parameters like average travelling time or number of vehicles passed. Selection of the most promising individuals for the next generation occurs through methods such as ranking or tournament selection [23]. This process, adapted to the unique conditions of each intersection, iteratively refines and improves the population, bringing it closer to the optimal solution and allowing the algorithm to adapt to changes and explore possible solutions.

The genetic algorithm we developed utilizes a Panmixia strategy for crosses to ensure random pair selection and support genetic diversity, and this prevents premature convergence and facilitates exploration of a wide solution space [24]. The elimination of repeated selection of an individual in a pair enhances this effect. Elite selection ensures the retention of highly adapted individuals, enriching the population with valuable genetic combinations and increasing the chances of optimal solutions [25].

The iterative process of the genetic algorithm, including selection, interbreeding, mutation, and evaluation of the target function, is performed repeatedly, providing a gradual approach to the optimal parameters of traffic light control. The stages, reflecting the dynamics of algorithm adaptation to traffic conditions and traffic flow improvement, are systematized in *Fig. 6.* This approach contributes to reducing travel time and optimizing traffic flow, confirming the effectiveness of the algorithm under variable traffic conditions.

3. Results of optimization experiments

In the course of optimization experiments using the genetic algorithm we developed, data demonstrating changes in the key parameters of the traffic flow control system from the first to the twentieth iteration were obtained. A detailed analysis of the results allows us to evaluate the effectiveness of the algorithm in the dynamics of the evolutionary process. *Figs. 7–9* show

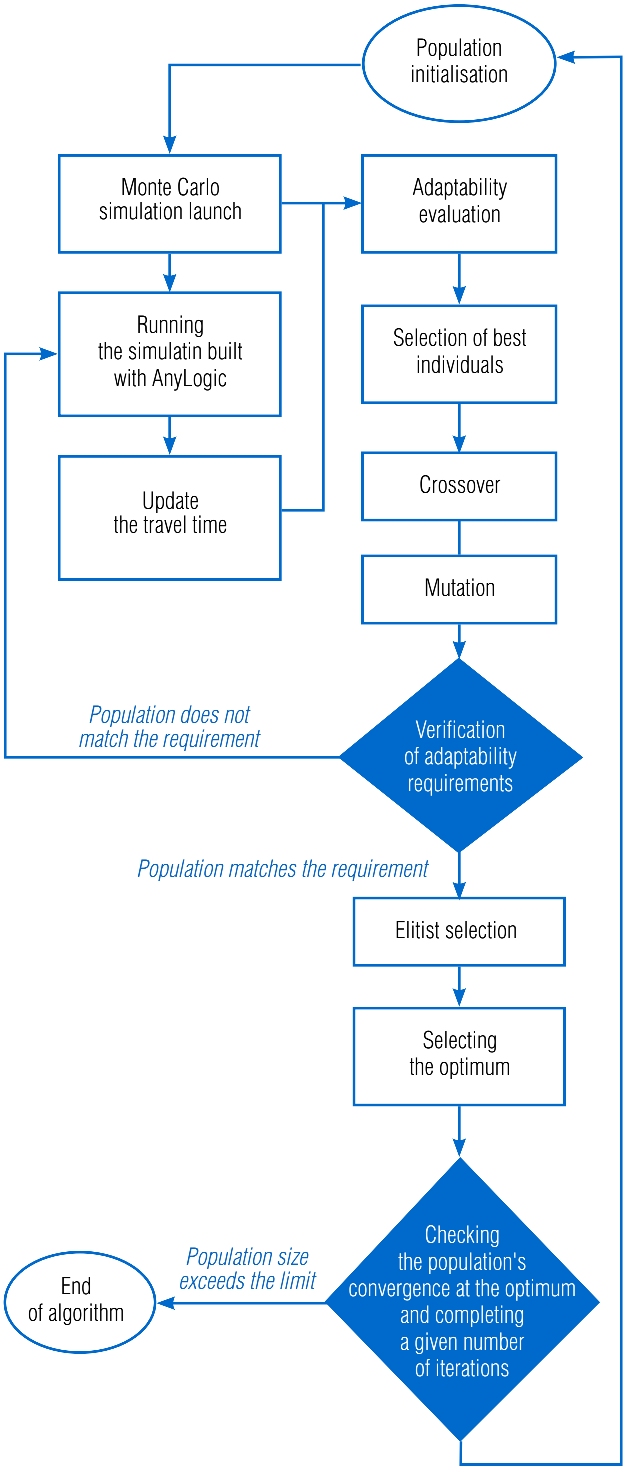

Fig. 6. Average fuel costs at RUB 60 per liter and total fuel costs for 100 000 vehicles travelling the route.

the iterations of the genetic algorithm (convergence dynamics) numbered in the format [*m*, *n*] where *m* is the iteration number and *n* is the population number, from the initial [0, 1] to the final [19, 20]. This indicates that each point marked on the abscissa axis corresponds to a new cycle of optimizing the traffic control parameters using the new phase durations of the traffic light control signals calculated at this iteration.

The result of the first iteration: the range of average travelling time at the initial stage of the experiment ranged from 1.627109 to 1.670166 minutes, reflecting an initial variation in the effectiveness of the regulatory strategies. The amount of fuel expended ranged from 317.595 to 325.999 liters per 10 000 vehicles travelled, reflecting initial suboptimality in fuel resource consumption. The cost of fuel consumed ranged from RUB 19 055.7 to RUB 19 559.95615, indicating significant economic cost.

The result of the last (twentieth) iteration: improvement in average travel time was recorded with a slight increase in the range to 1.735787–1.746299 minutes, indicating stabilization of travel time characteristics while other parameters improved. The reduction in fuel consumed to 292.144860–293.914192 liters per 10 000 vehicles travelled demonstrates the improvement in fuel efficiency as a result of regulatory optimization. The economic efficiency was expressed in the reduction of the cost of fuel expended to 17 528.69161–17 634.8515 rubles, confirming the feasibility of the proposed optimization algorithms.

A direct comparison of the results of the first and twentieth iteration reveals positive dynamics in the optimization of traffic flows. A significant reduction in the amount of fuel consumed and the corresponding cost with a relatively stable average journey time indicates an increase in the fuel and economic efficiency of the regulation system developed here. These results highlight the potential of applying the proposed genetic algorithm to improve the parameters of intelligent transport systems aimed at minimizing the environmental impact and optimizing traffic flow in urban infrastructure conditions.

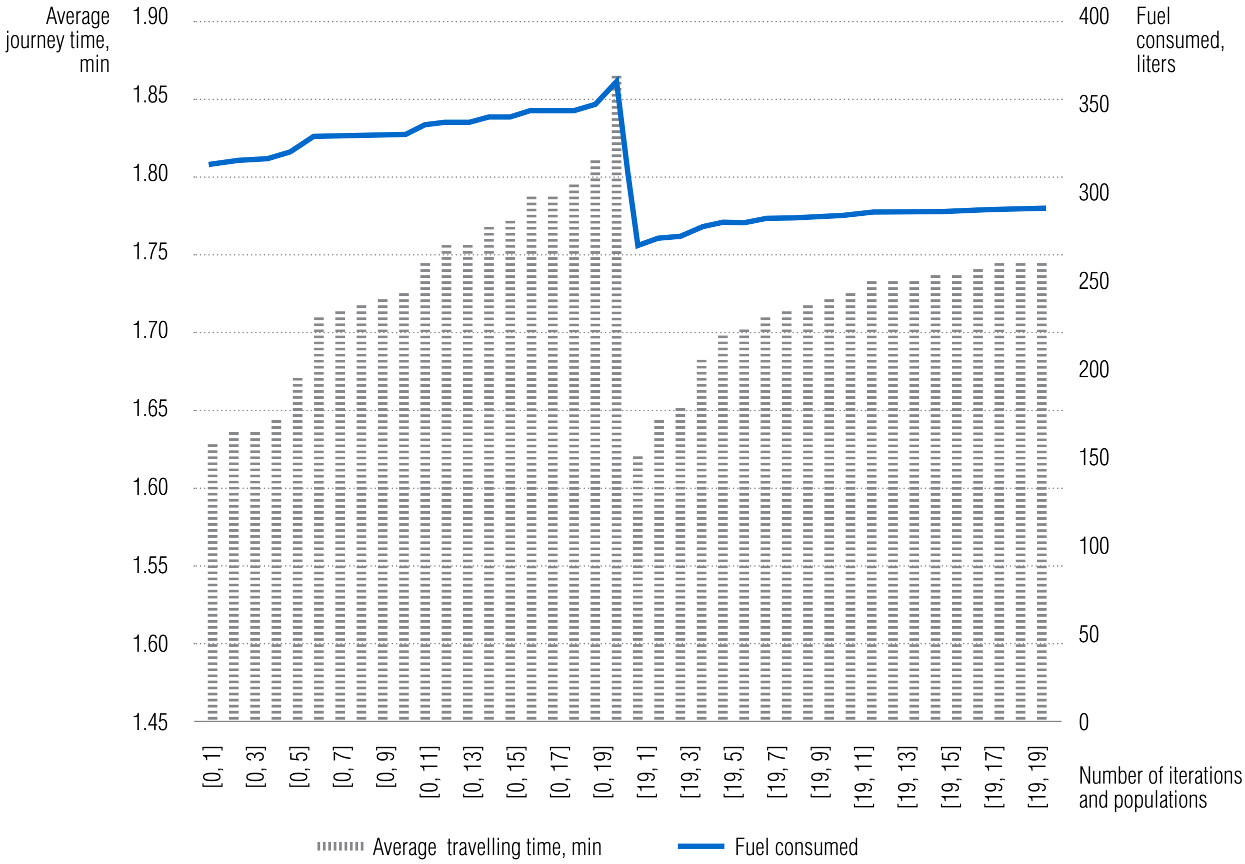

Fig. 7. Average travelling time and fuel consumption for a set of 10 000 vehicles that successfully traversed a given.

In *Fig. 9*, the ordinate on the left corresponds to the average travelling time in minutes. At the same time, there is a decrease in the value of this indicator over a series of iterations, which indicates the efficiency of the optimization process (convergence of the genetic algorithm). Meanwhile, the ordinate on the right reflects the amount of fuel consumed for ten thousand vehicle units, and this value of this indicator also decreases with the iterations of the genetic algorithm. Consequently, the dynamics of both dependencies in the graph indicate a positive change in the key metrics: a reduction in the time cost of travelling and the corresponding fuel consumption. At the initial stage of the optimization, the maximum value of the average travel time is fixed, while at the final cycle the maximum does not exceed the thresholds reached during the optimization process. The consistent reduction in fuel consumption is the result of two determining factors: minimization of travel time through the considered section of the street network and reduction of fuel load.

Figure 10 shows the average journey time at different iterations of the genetic algorithm. The consistent improvement of the value of this target indicator from the first to the twentieth iteration indicates the convergence of the genetic algorithm and the possibility of minimizing the travel time of vehicles through optimizing the duration of the phases of traffic signals. Such dynamics confirm the increase in the capacity and efficiency of the urban road network,

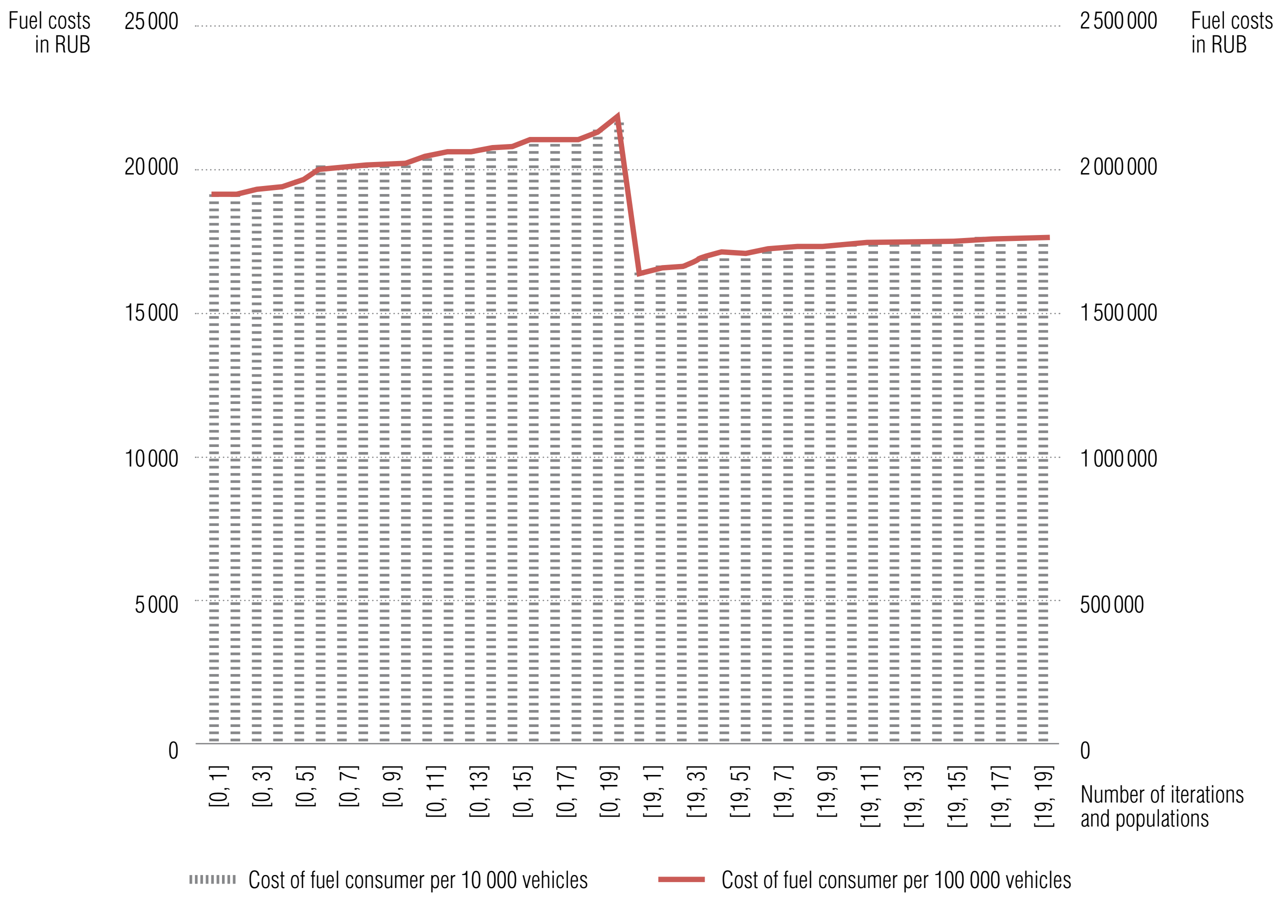

Fig. 8. Average fuel costs at RUB 60 per liter and total fuel costs for 100 000 vehicles travelling the route.

demonstrating the advantages of applying evolutionary methods in the optimization of urban transport systems. The process of decreasing the average travelling time observed over a series of iterations reflects the improvement in the quality of traffic regulation due to the fine-tuning of traffic light operating cycles. The effectiveness of the genetic algorithm in this context is reinforced by its ability to search for optimal solutions in the multi-parameter space of management decisions, taking into account the diversity of conditions and dynamics of urban traffic. The evolutionary improvement of the traffic light control system is based on selection, crossing and mutation mechanisms that facilitate iterative refinement and optimization of parameters based on an assessment of their impact on the overall efficiency of the transport system. The genetic algorithm, demonstrating stable convergence, enables adaptive traffic light control to reduce the time costs of road users and improve the overall efficiency of transport infrastructure utilization.

Adaptive control of traffic lights using the proposed genetic algorithm contributes to a significant reduction in travel time and fuel costs, as demonstrated by the results of optimization experiments. This is manifested in the reduction of the average travel time (for the ensemble of agents – vehicles) from 1.86 minutes to 1.62 minutes, i.e., by 14.8%, which is also accompanied by a noticeable reduction in fuel consumption by 33.6%, i.e., from 363.98 to 272.49 liters for every 10 000 vehicle units. This indicates the effectiveness of

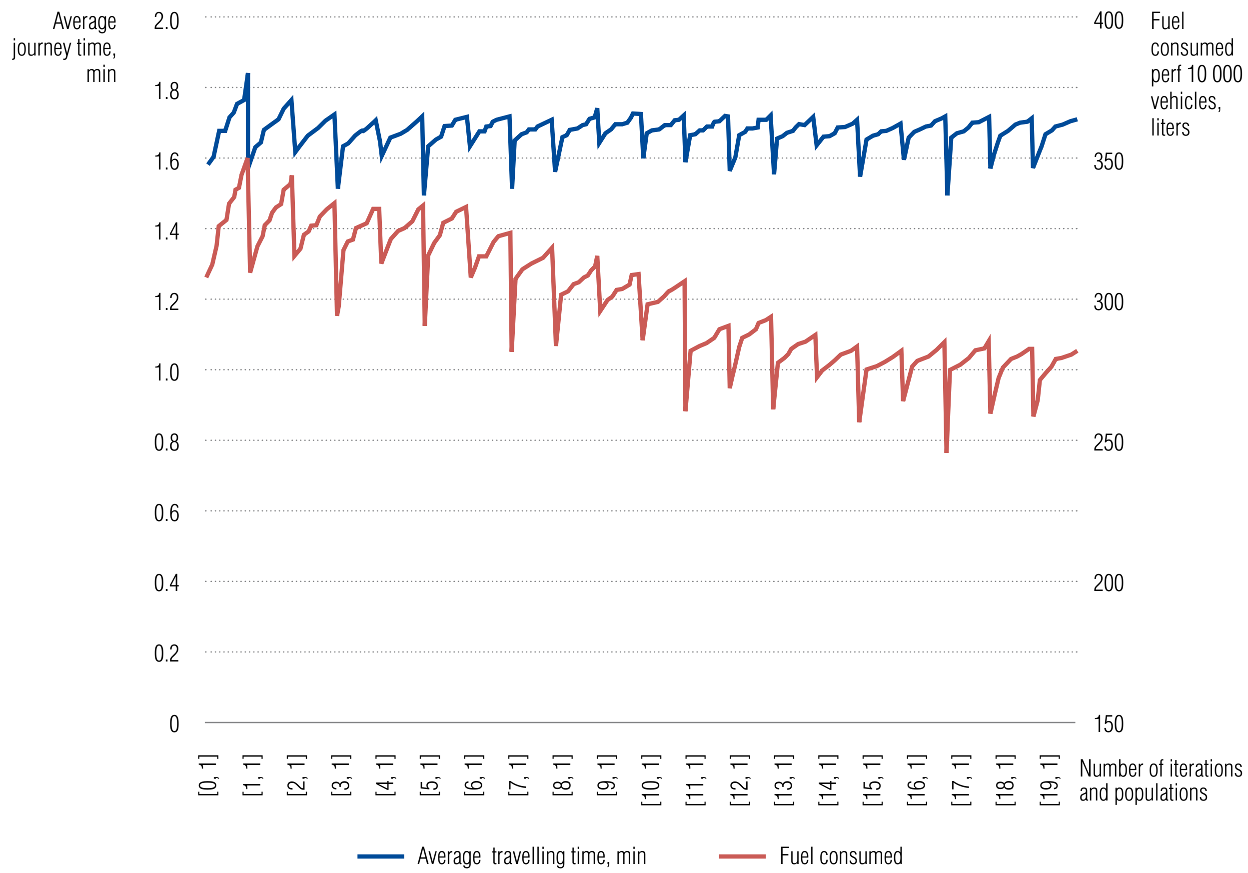

Fig. 9. Average travel time in iterations of genetic optimization of traffic flows.

the algorithm and its validity for integrated transport optimization in a metropolitan environment.

Considering the scalability and multi-parameter adaptability of the genetic algorithm we developed, it is reasonable to integrate it with modern ITS, which will contribute to the improvement of traffic in the city (elimination of traffic congestion, increased level of social comfort of road users, fuel cost savings, etc.).

On the other hand, in the future, it is necessary to take into account additional ITS characteristics, such as traffic intensity and meteorological conditions, to improve the accuracy and adaptability of the optimization algorithm. Such integration could be the next step in developing strategies to improve environmental sustainability and quality of life in urban settings, including attracting investments in urban infrastructure and tourism.

Optimizing the phase duration of traffic signals contributes not only to fuel savings but also to the reduction of pollutant emissions, contributing to a clean and comfortable urban environment. This increases the attractiveness of the city, both for its residents and tourists, and contributes to the overall urbanization of the space.

Thus, the system we developed provides new opportunities for the creation and improvement of ITS products, offering efficient solutions for municipalities and private operators of urban infrastructure. Further research and development in this area can contribute

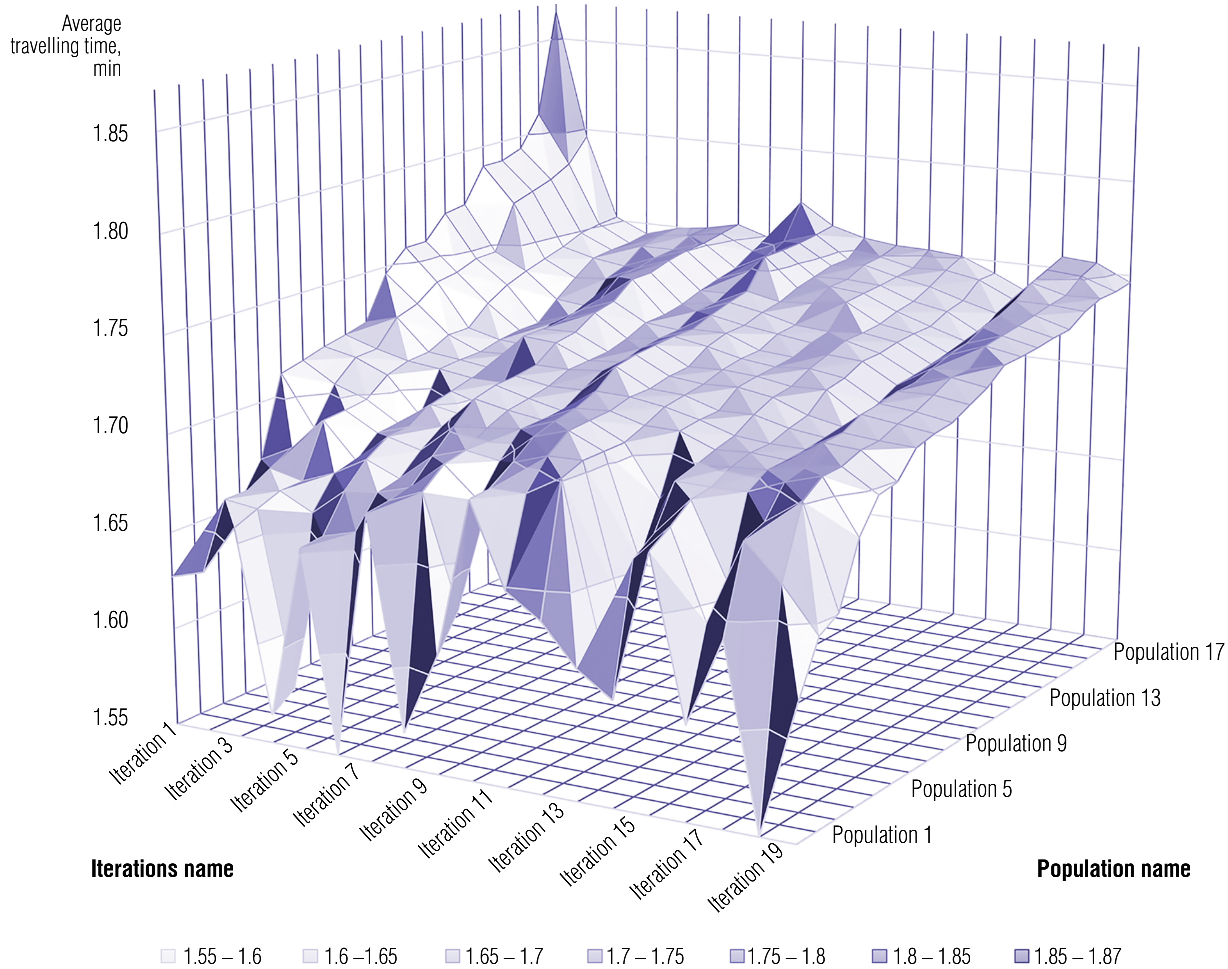

Fig. 10. Average travel time in iterations of genetic optimization of traffic flows.

to the evolutionary transformation of transport infrastructure, ensuring its maximum compliance with the increasing needs of modern urban society.

Conclusion

In conclusion, the study should emphasize the significance of the approach we developed for optimizing traffic flows in an urban environment and its applicability in decision support systems for municipal and state enterprises responsible for the evolutionary development of transport infrastructure. The implementation of such an approach in relation to a real section of the Moscow road network, based on the use of the proposed genetic optimization algorithm, allowed us to significantly improve the efficiency of traffic and pedestrian flow regulation, contributing to the reduction of vehicle waiting time at regulated intersections.

The application of our genetic algorithm aggregated with the proposed ITS simulation model implemented in AnyLogic demonstrates the importance of integrating state-of-the-art algorithmic and modeling approaches in ITS design and improvement. The study confirmed the hypothesis that it is possible to significantly improve the efficiency of traffic control through adaptive regulation of the duration of traffic light phases taking into account the state of current traffic. An important result of the work was the identification of promising directions for further research, including analysis and optimization of transport infrastructure at the macro level, development of multifunctional traffic management models capable of adapting to changes in the road network and the needs of different road users.

Further research will focus on the study of ITS with more complex (multi-level, multi-link) configuration of street road networks at the scale of a smart city and the application of hybrid algorithms using swarm intelligence, genetic optimization and machine learning techniques. ■

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