Modeling environment intelligent transport system for eco-friendly urban mobility

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Abstract

The research in this paper focuses on developing a modeling environment for urban mobility systems and traffic flow services. A modeling environment for urban mobility systems and traffic flow services has been developed, focusing on both scientific research and practical implementation. This initiative aimed at optimizing traffic flow, reducing congestion, and enhancing the efficiency of urban mobility systems. The separation of the modeling environment and program basis allows for flexibility, adaptability, and scalability, accommodating diverse software solutions. Active agent modeling was incorporated to optimize traffic systems by enabling autonomous, adaptable, and distributed decision-making. In an experiment conducted in Khmelnytskyi, optimizing traffic light durations yielded significant reductions in CO_2 emissions, showcasing the potential to enhance environmental sustainability in urban transport. Thus, the use of the optimization target function in the model environment allows to reduce CO_2 emissions in the best case by 7.4% when controlling the traffic of vehicles. The modeling environment and program basis demonstrated effectiveness in conducting experiments, refining parameters, and optimizing traffic scenarios. The results emphasized the importance of continuous research and implementation of traffic optimization strategies to improve the environmental friendliness of urban transport systems. Overall, the developed modeling environment and program basis, coupled with active agent modeling, provide valuable tools for achieving sustainable and efficient urban mobility systems.

Keywords

intelligent transportation systems, emissions reduction, urban mobility, modeling environment, active agents

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1. Introduction

Road transport is the main element of domestic transportation for most countries, acting as a key component of the transportation system and playing a significant role in ensuring economic growth and social development. The growth of the car fleet is accompanied by negative consequences in the field of road safety, ecology and the use of natural resources [1]. Continuing to study the issues of road transport, it should be noted that the presence of cars on the roads is accompanied by other negative consequences. Among them are traffic jams that occur in large cities and on cross-country routes, which lead to increased fuel consumption and time for road users [2].

Despite its obvious advantages in terms of mobility and economic development, road transport also creates a set of problems related to road safety, environmental pollution, and infrastructure costs that require attention and systematic work to address.

In most megacities, automobile exhaust emissions account for a significant share of total atmospheric emissions. This factor seems to be particularly critical in the context of air pollution, which leads to serious consequences for human health and the ecological balance. The negative impact on the atmosphere caused by road transport requires immediate measures to reduce toxic emissions and ensure sustainable use of natural resources.

This situation indicates the need for active reorganization and improvement of the transport system, given the high level of impact of road transport on the social, economic and environmental aspects of modern society. It should be noted that managing the formation of toxic substances in exhaust gases requires a systematic approach and the implementation of evidence-based strategies. The key contribution to total emissions is made by chemical processes in the engine combustion chamber. Taking into account the impact of driving mode on emissions emphasizes the need to regulate these processes depending on the operating conditions of the vehicle.

The main contributions of this study are:

- A modeling environment has been developed that allows creating realistic models and experimenting with various parameters to optimize traffic in an urban environment.
- The concept of separation of the modeling environment and the software base was introduced to ensure flexibility and adaptability. This allows the use of different technologies to optimize different aspects of urban mobility.
- Active agents have been researched and implemented to optimize traffic flow management. Agents provide autonomy, adaptability, and distributed decision-making, which increases the efficiency of traffic management.
- Experimental studies of the application of the model environment on the example of the city of Khmelnytskyi aimed at optimizing the duration of green light at traffic lights in order to reduce CO_2 emissions have been carried out. The results obtained indicate significant improvements in environmental performance.
- The importance of improving the parameters of the transport infrastructure to achieve a more sustainable and environmentally friendly urban transport system has been revealed.

The structure of the paper is as follows. Section 2 analyzes previous research related to intelligent transportation systems and urban mobility management. Section 2 provides a detailed description of the method used in the research aimed at optimizing traffic flows and urban mobility systems. The presentation of the model in the modeling environment is investigated, including a description of the model display in a specialized modeling environment for experiments and optimization. Section 4 presents an experiment to evaluate the effectiveness of the proposed approaches in real-world conditions. The Discussion section includes an analysis of the experimental results and their further discussion with regard to possible applications. The Conclusions section summarizes the research and identifies the main conclusions arising from the results of the work.

2. Related Works

Traffic's environmental impact includes emissions of harmful substances, air and water pollution, acoustic pollution, loss of natural habitats, resource consumption, energy consumption, and climate change. The solution to these problems includes the development of efficient transportation systems and the use of more environmentally friendly technologies. A number of scientific studies have been devoted to solving problems from a range of complex solutions as intelligent transportation system [3-5]. The scientific community pays considerable attention to the problems of reducing the impact of transport on the environment in order to reduce environmental impact. Thus, research is being conducted in terms of optimizing traffic flows using modern capabilities with indirect measurements of traffic density. Although intelligent transportation systems have a wide range of challenges [6, 7], the development of individual components is yielding positive results. The analysis is extended to geographic areas, including intersections and road infrastructure, to provide adequate solutions for traffic optimization, especially at intersections [8, 9]. Methods of improving neural networks are actively developing and achieving good results, at the same time, practical application is of great importance [10-12]. Various graph neural networks, such as convolutional graphs and attention graphs, are used to solve traffic forecasting problems in the context of traffic. These methods are used in various forecasting tasks, including traffic forecasting, speed forecasting, and passenger flow forecasting in urban transportation systems [13].

The main aspect of such research is the data-driven approach, which involves the use of historical data for forecasting. The problem of traffic forecasting turns out to be extremely complex, as it involves large amounts of data with high dimensionality and multiple dynamics. This is compounded by the consideration of emergencies, such as road accidents, repair work, periodic traffic jams, etc. Spatial and temporal dependence is recognized as an essential feature of traffic conditions. It takes into account the influence of not only neighboring areas, but also temporal fluctuations, including seasonal variations. Traditional linear time series models, such as regression models, are ineffective in addressing such spatial and temporal forecasting challenges. Machine learning and deep learning techniques are widely used in the traffic management industry to improve forecasting accuracy. For example, convolutional neural networks are successfully used to model the entire city in the form of a grid. For tasks where traffic is represented in the form of a graph, such as in road networks, graph neural networks are widely used [14].

In many cases, existing methods of spatio-temporal modeling do not provide sufficient attention to the dynamic characteristics of the relationships between points in the road network. In particular, most works based on recurrent neural networks have limited efficiency due to the repetitive nature of their structures. In addition, the lack of proper comparison of different methods on the same data sets remains a problem [15-16]. Modern traffic forecasting experts mainly use heuristically constructed static traffic graphs, which may not accurately reflect traffic dynamics. Previous attempts to use dynamically generated traffic graphs also face problems such as long model training time and a decrease in model quality in terms of a number of characteristics [14, 17].

In order to fully automate the network, which can be a likely tool in solving current challenges related to traffic forecasting in urban environments, detailed data analysis is required [18]. The use of machine learning models based on historical data is a common practice for traffic forecasting. This helps to develop solutions for optimizing traffic flows and facilitates the forecasting of passenger traffic. Research on real-time data, despite the randomness of traffic flow trajectories, demonstrates the possibility of predicting user movement [19, 20]. Among these methods, the use of Markov chain-based methods along with graph neural networks stands out, as it is characterized by its lower complexity [21, 22]. A special place is occupied by papers that determine the trustworthiness of decisions made by AI [23-25], since vehicles are means of increased danger.

It is important to note that in order to achieve full network automation and address the current challenges of traffic flow forecasting, it is necessary not only to take into account historical data but also to focus on the dynamics of traffic. Some studies, based on real-time data, try to predict user movements while taking into account a high degree of uncertainty in traffic flow trajectories.

In particular, when studying movements that determine the trajectories of users from source to destination at different intervals, it is important to use comprehensive mobility forecasting studies. Experts also study various methods for predicting user mobility patterns [26]. A set of studies in the field of traffic flow and passenger movement forecasting using machine learning and deep learning methods is a relevant and important area of development for further optimization and automation of transport systems in urban environments. However, an environment for adaptive traffic management and meeting objective functions is important for simulation modeling of urban mobility systems and optimization of environmental impact on the environment. The simulation environment should correspond to the urban implementation environment for specific operating conditions and be able to reproduce the scenarios of the adaptive control system and the likely traffic context.

It is important to note that successful modeling of the urban mobility system and optimization of the environmental impact on the environment largely depends on the quality of the simulation environment. This environment must be specifically adapted for effective traffic management and meet the target functions of the system. It is also important to ensure that the simulation environment is adaptable so that it can effectively respond to changes in traffic conditions and urban dynamics. This includes the ability to take into account various traffic management strategies, accident prevention, traffic signal optimization, and other aspects that affect the efficiency of the urban mobility system and environmental sustainability. Simulation modeling and adaptive traffic management are key to such tasks. Successful implementation of algorithmic solutions in a real-world environment requires experimental testing of the relevant models.

This study focuses on creating an analytical environment for effective simulation modeling. The main goal is to thoroughly analyze the impact of various traffic signal control methods on exhaust gas emissions and noise generation during road traffic. The study is based on specific practical observations and the use of a simulation model that reflects realistic traffic conditions.

3. Research method

Building a modeling environment for urban mobility systems and traffic flow services has an important scientific and practical justification. Research in this area is aimed at developing and improving algorithms, methods, and models that will optimize traffic flow, reduce congestion, and maximize the efficiency of urban mobility systems.

However, in addition to the scientific aspect, building such an environment also solves specific problems for the practical implementation and support of real traffic flow systems. The modeling environment should be able to optimize traffic. The development and implementation of traffic signal control algorithms, public transportation routes, and coordination systems help to effectively regulate traffic, reducing travel time and congestion. Be able to use predictive models to anticipate and adapt to changes in traffic flows, events, or emergencies. Efficient use of resources, which means that vehicle distribution models are developed and public transport operations are optimized to use resources efficiently and reduce emissions. Be able to interact with the real world. Apply realistic modeling of interaction with existing infrastructures, including roads, traffic lights, parking lots, and other elements that affect traffic flow. Support real-time decisions. Develop systems that can provide recommendations and make decisions in real time to effectively manage traffic flows.

Thus, building an environment for traffic flows should not only improve scientific research, but also create a basis for the practical implementation and optimization of real systems in the field of urban mobility.

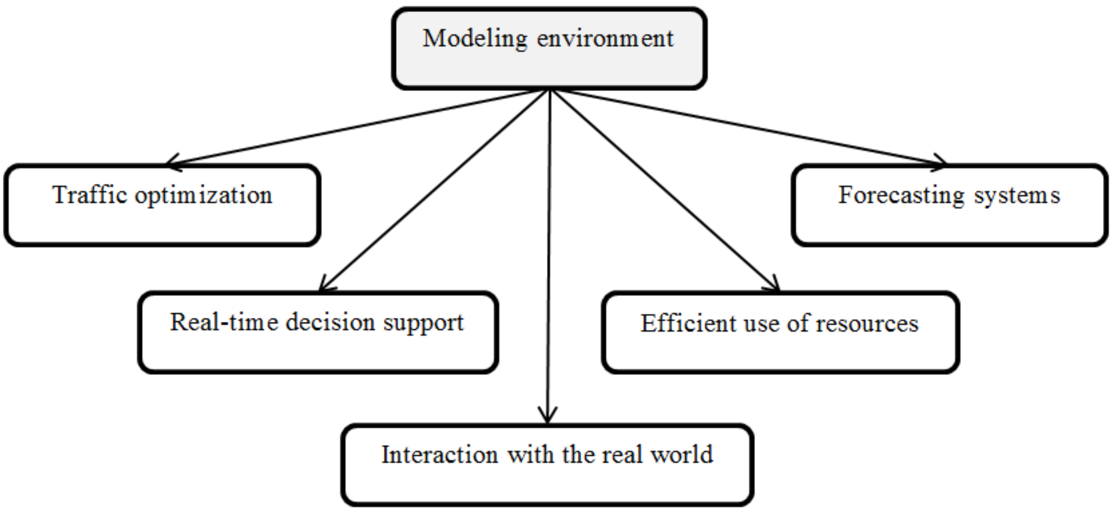

Figure 1: Main aspects of the modeling environment for traffic flows.

The functionality of the modeling environment and the program basis in the context of scientific research and practical application must interact harmoniously for effective modeling and optimization of urban mobility systems. This means that the modeling environment should provide the ability to create realistic models and flexible parameter configuration for conducting various experiments. The main aspects of the interaction between the functionality of the modeling environment and the program basis are presented in the Table 1.

Table 1
Interaction between the functionality of the modeling environment and the program basis

№	Category	Environment	Description
1	Modeling real-world conditions	Modeling environment	Enabling the creation of realistic models that reflect the conditions of urban mobility with all its complexity and dynamics
		Program basis	Developing tools that allow agents and systems to interact in a virtual environment, taking into account a variety of conditions.
2	Effective agent modeling	Modeling environment	Development of user-friendly interfaces for defining and configuring agents with different characteristics.
		Program basis	Development of algorithms for modeling the behavior and interaction of agents, taking into account their autonomy and adaptability.
3	Flexibility and adaptability	Modeling environment	Easy modification of parameters and conditions for various experiments.
		Program basis	Development of flexible algorithms and data structures that allow for efficient interaction with different models and conditions.
4	Data collection and processing	Modeling environment	Include mechanisms for collecting and processing data from experiments and modeling.
		Program basis	Development of tools for efficient collection, storage, and processing of data from various sources.
5	Experiments and analysis of results	Modeling environment	Support for conducting experiments and analyzing the results to draw conclusions.
		Program basis	Development of tools for statistical analysis and visualization of modeling results.
6	Optimization and scenario modeling	Modeling environment	The ability to conduct optimization experiments and scenario modeling.
		Program basis	Developing algorithms to automate the optimization process and select the best strategies.

The program basis, in turn, should be developed taking into account the needs of the modeling environment, ensuring efficiency and flexibility of interaction with agents and systems. This includes creating user-friendly interfaces for agent configuration, developing algorithms for modeling their behavior and interaction. It is also important to ensure the ability to collect, process, and analyze data, as well as integrate with real-world data collection technologies. The program basis should support experiments, analysis of results, and optimization tests.

The main goal is to create such a relationship between the modeling environment and the program basis that would ensure effective modeling, analysis, and improvement of urban mobility systems in a real urban environment.

The separation of the modeling environment and the software base in traffic flow modeling systems is due to several important aspects. First, it provides flexibility and adaptability in research, allowing the use of different software solutions for different aspects of research. This approach allows choosing the best technologies and integrates different tools to maximize the efficiency and accuracy of the results.

The second aspect is scalability. Large and complex studies may require the use of different tools, and the modeling environment can serve as a platform for efficiently managing the interaction of different software bases. This approach helps to optimize the use of resources and ensures scalability of research.

The third aspect is data integration. The modeling environment can serve as a platform for data integration and processing, and the program basis can be used to analyze and display results. This helps to optimize information processing and facilitates the collaboration of different tools. In general, the separation of the modeling environment and the program basis is a key strategic approach aimed at ensuring flexibility, efficiency, and adaptability in traffic modeling. The functionality of the modeling environment in the context of scientific research and practical application should closely interact with the functionality of the software base for effective modeling and optimization of urban mobility systems.

The functionality of the modeling environment in scientific research and practical application should be based on the functionality of the program basis. Accordingly, this can be represented as follows. Let M be a modeling environment and P be a program basis. The functionality of M is based on the functionality of P from the main categories given in the Table 1.

$$M = f(P), \tag{1}$$

where f is a function that defines the relationship between the modeling environment and the program basis.

This function may include such aspects as:

– modeling of conditions

$$M_{\text{conditions}} = f_{\text{conditions}}(P_{\text{modeling}}, P_{\text{data}}); \tag{2}$$

– effective agent modeling

$$M_{\text{agents}} = f_{\text{agents}}(P_{\text{modeling}}, P_{\text{algorithms}}); \tag{3}$$

– flexibility and adaptability

$$M_{\text{flexibility}} = f_{\text{flexibility}}(P_{\text{modeling}}, P_{\text{configuration}}); \tag{4}$$

– data collection and processing

$$M_{\text{data}} = f_{\text{data}}(P_{\text{simulation}}, P_{\text{tools}}); \tag{5}$$

– experiments and analysis of results

$$M_{\text{experiments}} = f_{\text{experiments}}(P_{\text{analysis}}, P_{\text{visualization}}); \tag{6}$$

– optimization and modeling of scenarios

$$M_{\text{optimization}} = f_{\text{optimization}}(P_{\text{modeling}}, P_{\text{algorithms}}). \tag{7}$$

It can be noted that the set of functions of the modeling environment M is absorbed by the set of functions of the program basis *P*:

$$M \subseteq P. \tag{8}$$

The program basis should provide the ability to implement all the necessary functionality of the modeling environment and not limit research and practical use. At the same time, the program basis should be beta extensible and have sufficient flexibility to be extended to meet the needs of scientific research and development. Such an approach reflects the complex interaction between the functionality of the modeling environment and the program basis, which allows to effectively solve the problems of scientific research and practical use in the field of urban mobility systems.

3.1. Application of active agents in the intelligent transportation system

The use of active agents in modern systems and technologies has sound reasons and important advantages. The use of active agents has a set of advantages, especially when they are used in systems to optimize their performance according to quality criteria.

Active agents can act autonomously and independently, making decisions without constant intervention from centralized management. This ensures more efficient and flexible management in different scenarios. Agents can adapt to changes in the environment and operating conditions. Their adaptive capabilities allow for more flexible and effective solutions in variable environments. Active agents are based on a distributed architecture where different agents can work in parallel and independently. This makes the system less vulnerable to failures and allows expanding functionality by adding new agents. Agents have the ability to work based on local knowledge, which allows them to make decisions based on limited information. This is especially useful in distributed and dynamic systems. Active agents can use machine learning techniques to improve their performance on their own and make optimal decisions based on experience. The distributed nature of active agents contributes to the efficient use of resources, as they can work in parallel and dynamically respond to current conditions.

Combining these advantages, active agents are an effective tool in the development of systems and technologies where flexibility, efficiency, and adaptability are important. Let us consider the model of the active influence system from the point of view of an active agent in the context of optimizing the model parameters in the model environment built into the program basis (Fig. 2). In this case, the active agent can perform a number of functions and interact with elements of the modeling environment and the program basis.

In the process of the modeling environment, the active agent can contribute to the optimization of model parameters by interacting with various elements of the environment. This may include changing parameters by agents to influence modeling conditions and algorithm performance. The agent may also interact with algorithms to facilitate the implementation and optimization of algorithms in the simulation environment. This may include selecting and adapting algorithms depending on the needs of the model.

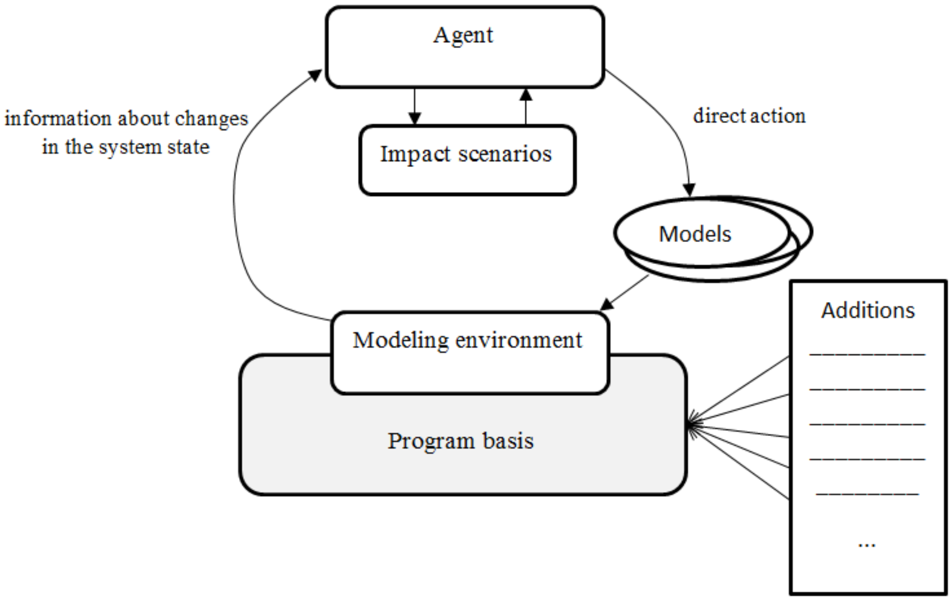

Figure 2: Main aspects of the modeling environment for traffic flows.

The active agent can detect dynamic changes in model parameters and independently adapt them in real time to optimize model performance in changing conditions. Interaction with the configuration of the program basis is also important, and the agent can adjust the parameters of the program basis to achieve optimal interaction with the modeling environment. The agent can also participate in data collection and analysis, determining which model parameters or properties should be measured and analyzed to achieve better performance.

The agent also has the ability to select impact scenarios. This feature allows the active agent to define specific situations or conditions to which it should direct its influence as part of the model parameter optimization. The agent can analyze the current state of the model environment and identify potential influence scenarios that can improve or optimize the model performance. The choice of a particular scenario may depend on various factors, such as changes in traffic conditions, weather conditions, or specific user requirements.

This feature allows the agent to be flexible and adaptive to various situations that arise during the modeling process. Choosing the optimal impact scenario can significantly improve the efficiency of parameter optimization and the model's performance in general. In addition, the active agent constantly adapts to new conditions and requirements of the modeling environment to ensure the effectiveness of parameter optimization. This approach allows the modeling environment and the program basis to interact and optimize in real time, responding to changes in the input data, modeling conditions, and user requirements.

This approach provides interaction between the modeling environment and the program basis for the effective use of the agent-based approach in research and practical applications of urban mobility systems.

3.2. Model representation in the modeling environment

Let's consider the formal representation of the model that will be used in the modeling environment in order to achieve the effectiveness of the objective function. Let's define the objective function in terms of reducing environmental impact within urban mobility by optimizing traffic flow regulation.

The objective function for optimizing traffic flow management within urban mobility with a focus on reducing environmental impact can be formulated with the identification of factors that take into account various aspects of sustainability, comfort, and environmental performance. The general objective function is presented in the form:

$$\phi_{opt} = \langle Eco, Comf, Sust \rangle, \tag{9}$$

where ϕ_{opt} – the target optimization function;

Eco – environmental indicator (CO_2 emissions or other pollutants);

$Comf$ – comfort (average speed, waiting time, etc.);

$Sust$ – sustainability of traffic flows.

The challenge is to find the optimal traffic management that maximizes comfort and sustainability while minimizing environmental impact. This is a simple example, and there may be more parameters and constraints in real-world conditions. Optimizing the objective function may involve the use of mathematical optimization methods.

The model for the environmental impacts of traffic flows in urban mobility is defined as follows:

$$Eco = \langle Trf, Emis, VihT, EmisSt, TtfPat, RdTopl, CondAtm \rangle, \tag{10}$$

where Trf – traffic or traffic volume;

$Emis$ – emissions per unit of traffic;

$VihT$ – types of vehicles by fuel consumption;

$EmisSt$ – emission standards and approaches for determining transport emissions;

$TtfPat$ – parameters of transport movement, such as speed and other factors;

$RdTopl$ – road topology;

$CondAtm$ – atmospheric conditions.

Each of these factors represents an additional level of detail to account for different aspects that affect vehicle emissions. More complex dependencies with additional factors may be used in the specification of studies and models, depending on the specific data and research objectives. On the basis of the presented models, we will conduct experimental studies of the performance and efficiency of the active agent modeling system.

4. Experiment

Let's define the real-world environment for modeling the traffic control system. The real-world environment for modeling of the traffic control system in the city of Khmelnytskyi includes various infrastructure and organization aspects of the transportation system. The city has different road types, such as main, arterial, and local roads, which connect different parts of the city. Intersections and interchanges regulate traffic using traffic lights and roundabouts.

The city is also served by public transportation, such as buses and trolleybuses, which provide transportation to the different parts of the city. Pedestrian zones, central squares, and bicycle lanes contribute to pedestrians and cyclists' safety.

The infrastructure also includes parking lots and parking garages, while electronic traffic control and monitoring and management systems help to optimize traffic. Environmental aspects are taken into account through green areas and alleys aimed at reducing emissions and improving air quality.

For this purpose, let's use the urban road system of Khmelnytskyi, which is shown in Fig. 3.

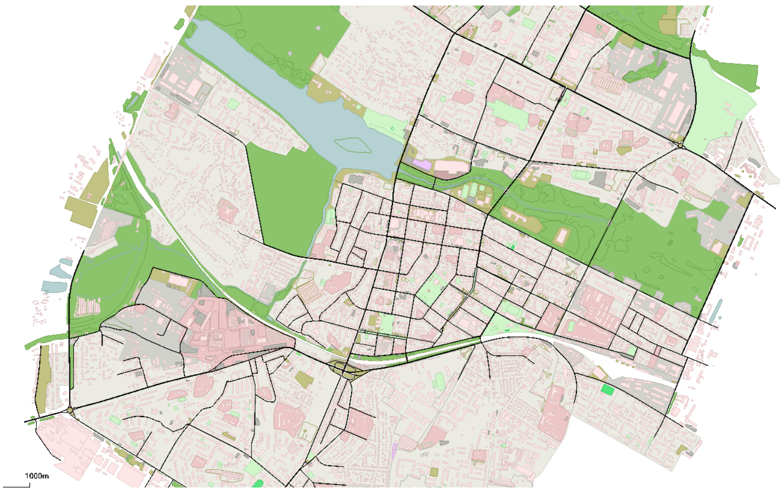

Figure 3: Map of transport roads in the city of Khmelnytskyi.

When analyzing the traffic flows of districts in the city of Khmelnytskyi, traffic lights are identified as key points of intervention in urban mobility, which have a decisive impact on the efficiency of the transport system. The a priori analysis identified the following critical points.

Traffic lights are located in the central areas where main and arterial roads are intersected. Traffic lights are also important at the entrances to the city from highways and main thoroughfares. A separate category is the traffic lights at the intersections of bus and trolleybus routes.

Traffic lights are also identified in areas with heavy pedestrian traffic, such as around shopping centers or educational institutions. Particular attention is paid to the traffic lights in areas where traffic congestions often occur, as well as at bottlenecks and overpasses. In addition, traffic lights in the areas of transfer to different types of transport are considered, as these are key nodes of citizens' mobility and movement between different vehicles.

Identification of these critical points of traffic signal control allows us to set up an optimal traffic management regime, direct efforts to improve urban mobility and reduce traffic congestion. After analyzing the traffic flows of the districts in terms of urban mobility, we will determined the set of traffic lights, which, according to the a priori analysis, have the most significant impact on the functioning of the transport system Fig. 4.

Figure 4: Map with marked traffic lights.

The city of Khmelnytskyi is divided into different districts with defined vehicle routes. In the central business district, which covers the city centre, there are main and arterial routes with marked traffic lights at intersections. Residential areas have their own road routes, with traffic lights at main streets and at the entrances to residential areas. Industrial zones also include designated routes with their own traffic signal control points for traffic efficiency.

The city of Khmelnytskyi has a set of notable traffic zones, each with its own characteristics and dynamics. Green zones are the starting points of traffic, defined as places where vehicle depart. This scenario describes the typical traffic in the morning. The vehicles in these zones go to their destinations, represented by the purple zones Fig. 5.

The purple zones are the final destinations where the vehicles are headed to. Each of these zones represents a separate direction or area of the city. Thus, vehicle from the green zones are directed to purple zones, making trips from one end of the city to the other. In addition to the planned traffic, 30% of random traffic was included in the emulation. This random traffic has no specific directions, and is "fixed" – it moves randomly on each run of the emulation, but with a fixed direction on each run.

This approach allows simulating the vehicle movement in the city, with taking into account the main directions of departure and arrival, as well as additional elements of unpredictability characterized by the random traffic. We initialized the sets of green light durations for traffic signals and conducted experimental studies to determine whether it is possible to optimize the objective function, which we defined as CO_2 emissions, according to this criterion. We set up the parameters of green light duration for the traffic lights and conducted experimental studies to determine the possibility of optimizing these parameters with respect to the CO_2 emissions criterion. This criterion will act as an objective function in the optimization process.

a)

b)

Figure 5: Map with characteristic traffic zones (1 – Clothing market; 2 – City Centre; 3 – Ozerna; 4 – Lezneve; 5 – Rakove; 6 – Dubove; 7 – Ruzhychna; 8 – Southwestern; 9 – Hrechany; 10 – Okruzhna): a – zones with starting and ending points for traffic movements; b – zones with starting and ending points for traffic movements and marked traffic lights.

By varying the duration of the green light at traffic lights, we determined the impact of this parameter on CO_2 emissions. This allowed us to find the optimal mode of traffic lights operation that reduces CO_2 emissions while ensuring efficient traffic flow.

Experimental studies will help to determine the optimal values of green light duration for each traffic light, taking into account the traffic intensity in specific areas of the city and the impact on CO_2 emissions (Table 2).

The results of the experimental studies indicated that significant improvements in CO_2 emissions can be achieved by optimizing the duration of the green light at traffic signals. These results indicated that the introduction of optimal parameters for the duration of the green light leads to a systematic reduction in CO_2 emissions at city intersections (Table 3, 4). Negative values indicate a positive impact of optimization on environmental indicators.

Table 2
Sets of traffic lights duration by green color

№	Crossroads	Traffic lights			
		Set 1		Set 2	
		Green light for str. 1, s	Green light for str. 2, s	Green light for str. 1, s	Green light for str. 2, s
1	Prospekt Myru str. – P. Myrnoho str.	42	42	48	36
2	Zarichanska str. - Starokostiantynivske str.	39	39	32	44
3	Prybuzka str. - Starokostiantynivske str.	39	39	34	40
4	Tolstoy str. - Hrushevskoho str.	39	39	50	20
5	Kamianetska str. - Gagarin str.	40	40	46	36
6	Kamianetska str. - Instytutska str.	42	42	42	32
7	Kamianetska str. - Ternopilska str.	42	42	42	32
8	Ternopilska str. - Molodizhna str.	42	42	42	32
9	Kamianetska str. - Prospurivskoho Pidpillya str.	42	42	42	32
10	Svobody str. - Prybuzka str.	42	42	46	36
11	Kamianetska str. - Prybuzka str.	39	39	44	34
1	Prospekt Myru str. – P.Myrnoho str.	52	32	42	32
2	Zarichanska str. - Starokostiantynivske str.	30	48	20	40
3	Prybuzka str. - Starokostiantynivske str.	32	44	22	22
4	Tolstoy str. - Hrushevskoho str.	54	16	50	20
5	Kamianetska str. - Gagarin str.	48	32	40	20
6	Kamianetska str. - Instytutska str.	46	30	40	20
7	Kamianetska str. - Ternopilska str.	46	30	40	20
8	Ternopilska str. - Molodizhna str.	46	30	30	20
9	Kamianetska str. - Prospurivskoho Pidpillya str.	48	25	30	20
10	Svobody str. - Prybuzka str.	48	32	40	20
11	Kamianetska str. - Prybuzka str.	48	30	40	20

Table 3
Results of optimization by transport movement time

№	Name of the route	Average time, s						
		Set 1	Set 2	Set 2 comp. to Set 1, %	Set 3	Set 3 comp. to Set 1, %	Set 4	Set 4 comp. to Set 1, %
1	Dubove (6) – Cloth. market (1)	534.7	497.0	-7.0%	610.8	14.2%	488.5	-8.6%
2	Dubove (6) - City Centre (2)	654.9	642.7	-1.9%	648.6	-1.0%	580.7	-11.3%
3	Hrechany (9) – Cloth. market (1)	789.8	769.4	-2.6%	778.4	-1.4%	783.0	-0.9%
4	Hrechany (9) - City Centre (2)	619.4	672.9	8.6%	612.0	-1.2%	681.1	10.0%
5	Lezneve (4) – Cloth. market (1)	1516.0	1574.8	3.9%	1657.6	9.3%	1358.3	-10.4%
6	Lezneve (4) - City Centre (2)	1086.3	1055.5	-2.8%	1024.9	-5.7%	994.6	-8.4%
7	Okruzhna (10) – Cloth. market (1)	1645.7	1504.1	-8.6%	1325.4	-19.5%	1451.7	-11.8%
8	Okruzhna (10) - City Centre (2)	1241.0	1266.1	2.0%	987.0	-20.5%	1135.7	-8.5%
9	Ozerna (3) - Clothing market (1)	1524.7	1588.8	4.2%	1399.6	-8.2%	1419.9	-6.9%
10	Ozerna (3) - City Centre (2)	1079.4	1101.6	2.1%	948.3	-12.1%	1004.2	-7.0%
11	Rakove (5) - Clothing market (1)	856.0	918.1	7.3%	1094.9	27.9%	786.8	-8.1%
12	Rakove (5) - City Centre (2)	719.0	740.1	2.9%	755.3	5.0%	695.7	-3.2%
13	Ruzhychna (7) – Cloth. market (1)	541.6	507.3	-6.3%	503.9	-7.0%	497.8	-8.1%
14	Ruzhychna (7) - City Centre (2)	1394.8	1082.3	-22.4%	1079.7	-22.6%	1084.4	-22.3%
15	Southwest. (8) – Cloth. market (1)	279.1	277.5	-0.6%	277.1	-0.7%	282.3	1.1%
16	Southwest. (8) - City Centre (2)	1731.6	1381.7	-20.2%	1479.5	-14.6%	1279.5	-26.1%
Average value				-2.6%		-3.6%		-8.2%

Table 4
Results of optimization by CO_2 emissions

№	Name of the route	CO_2 (carbon dioxide), mg/s						
		Set 1	Set 2	Set 2 comp. to Set 1, %	Set 3	Set 3 comp. to Set 1, %	Set 4	Set 4 comp. to Set 1, %
1	Dubove (6) – Cloth. market (1)	1798684	1666014	-7.4%	1997063	11.0%	1658273	-7.8%
2	Dubove (6) - City Centre (2)	1890698	1858510	-1.7%	1881219	-0.5%	1696336	-10.3%
3	Hrechany (9) – Cloth. market (1)	2414845	2368731	-1.9%	2390072	-1.0%	2402114	-0.5%
4	Hrechany (9) - City Centre (2)	1773678	1913029	7.9%	1763632	-0.6%	1931617	8.9%
5	Lezneve (4) – Cloth. market (1)	4748542	4900473	3.2%	5135955	8.2%	4329591	-8.8%
6	Lezneve (4) - City Centre (2)	3187835	3105637	-2.6%	3033354	-4.8%	2958399	-7.2%
7	Okruzhna (10) – Cloth. market (1)	5031908	4613073	-8.3%	4227391	-16.0%	4462352	-11.3%
8	Okruzhna (10) - City Centre (2)	3569611	3655976	2.4%	2993131	-16.1%	3307579	-7.3%
9	Ozerna (3) - Clothing market (1)	4543093	4724013	4.0%	4263580	-6.2%	4302850	-5.3%
10	Ozerna (3) - City Centre (2)	3012558	3073883	2.0%	2698130	-10.4%	2824703	-6.2%
11	Rakove (5) - Clothing market (1)	2675660	8004042	4.7%	3296908	23.2%	2459465	-8.1%
12	Rakove (5) - City Centre (2)	2035853	2090915	2.7%	2122065	4.2%	1973621	-3.1%
13	Ruzhychna (7) – Cloth. market (1)	1592326	509868	-5.2%	1495647	-6.1%	1478103	-7.2%
14	Ruzhychna (7) - City Centre (2)	3748523	2932195	-21.8%	2914679	-22.2%	2934932	-21.7%
15	Southwest. (8) – Cloth. market (1)	913744	906388	-0.8%	908556	-0.6%	918846	0.6%
16	Southwest. (8) - City Centre (2)	9809964	4125978	-17.2%	4364836	-12.4%	3860718	-22.5%
Average value				-2.5%		-3.1%		-7.4%

5. Discussions

The results of the experimental studies conducted indicate a great potential for optimizing traffic in terms of environmental impact. This indicates the possibility of improving the traffic control system to reduce emissions and improve the environment of urban space. The proposed system of modeling environment and program basis on the example of application indicates the presence of the necessary flexibility and adaptability to the needs of experimental research.

The results obtained indicate the importance of improving the parameters of traffic lights and other elements of transport infrastructure to achieve more sustainable and environmentally friendly urban transportation systems. The enormous potential in this area points to the need for further research and implementation of optimized traffic strategies to ensure more efficient environmental friendliness of urban transport. Thus, in comparison with the most undesirable set of green traffic lights, the integrated indicator of improving the time of transport movement is respectively Set2 - 2.6%, Set3 - 3.6%, Set4 - 8.2%. If we choose the volume of CO_2 emissions as the optimization criterion for the same data sets, we get the following results: Set2 - 2.5%, Set3 - 3.1%, Set4 - 7.4%. The conducted studies indicate that the proposed approach to the formation of the model environment and program basis has significant potential, especially in terms of using an active agent to adapt the conditions of traffic management in urban areas. The goal of the research was achieved and the results showed that the program basis should have sufficient flexibility in relation to the research tasks and be able to properly meet the research objectives in the process of active scientific research. The proposed approach to the delineation of environments from the standpoint of design solutions indicates good prospects for further research on the development of a system of active and adaptive influence on traffic flows. Accordingly, the proposed system of research environment structure structures the research environment and does not limit the possibilities of scientific research, but rather stimulates its flexibility and adaptability, allowing to focus on the process of scientific research.

The study was limited to optimizing traffic light duration and measuring the impact on CO_2 emissions. Also, the study concerned only the city of Khmelnytskyi. This limitation is justified by the fact that the application problem is considered, since general methods under specific application conditions leave many aspects out of consideration. And these aspects can have a decisive influence on the final result

6. Conclusions

The conclusions of the experimental studies on optimizing the duration of green light at traffic lights in Khmelnytskyi confirm the significant potential for reducing CO_2 emissions and improving environmental performance in urban transport.

The experiment showed that the introduction of optimal parameters for the duration of traffic lights led to a significant reduction in CO_2 emissions at various intersections in the city. The proposed system of modeling environment and program basis, based on the example of application, demonstrates the necessary flexibility and adaptability to the requirements of experimental research. The flexibility of the system lies in the ability to adapt the parameters of traffic lights and other elements of urban infrastructure to identify optimal decision to reduce CO_2 emissions. Optimizing traffic lights reduced CO_2 emissions by 2.5-7.4% compared to non-optimized light durations, showing potential to improve air quality.

The study was conducted with the limitation that the objective function was CO_2 emissions as an environmental impact. This limitation is due to the fact that the effectiveness of the proposed method was determined within the scope of this study, with the aim of obtaining a positive result. Therefore, including more parameters in the model, such as speed limits, lane configuration, public transport routes, etc., will bring the model closer to real conditions. Also, measuring other pollutants besides CO_2, such as NO, solid particles, VOCs will allow a more objective look at the study results.

To summarize, optimization of urban traffic lights is a promising area for improving environmental performance and creating more sustainable transportation systems, and the use of a modeling environment approach and program basis are effective tools for applying active agents to influence the modeling environment.

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