DEVELOPING ENVIRONMENTALLY ADAPTED SIMULATORS FOR AUTONOMOUS MINING DUMP TRUCKS: A MULTI-CRITERIA APPROACH TO ENHANCE SUSTAINABILITY AND ECOLOGICAL SAFETY

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ABSTRACT

The study explores the selection and development of simulators tailored for autonomous mining dump truck control systems, with a focus on sustainability and environmental adaptation. Mining operations pose unique challenges due to extreme weather conditions, varied terrain, and restricted visibility, which necessitate specialized simulators to ensure effective and eco-friendly solutions. By leveraging multi-criteria analysis, this research evaluates simulator capabilities to optimize resource use, minimize ecological risks, and enhance operational safety. The use of simulation environments mitigates real-world risks such as emissions, environmental contamination, and damage to ecosystems, while enabling efficient training and testing of autonomous systems. Additionally, the study underscores the importance of integrating ecosystem-specific parameters into simulation models to address climate variability and reduce the carbon footprint of development processes. The findings provide actionable insights for designing sustainable and environmentally conscious autonomous control systems in the mining industry.

Keywords: environmental adaptation in simulation, safety in autonomous operations, multi-criteria decision analysis.

INTRODUCTION

Currently, there is significant progress in the development of autonomous vehicles designed to ensure safety for people when traveling on public roads (Akhmetshin et al., 2024; Bazhina, 2023; Rozhko et al., 2024). Creating autonomous vehicles requires the installation of a large amount of additional equipment, which can be divided into two groups: equipment for sensing the environment and equipment for processing incoming information and making independent decisions during driving (Auyelbek et al., 2022; Ilyushin and Martirosyan, 2024; Jassim et al., 2024; Pankratova, 2003). The first group includes various radars, lidars, and cameras (Nurhidayat et al., 2024), while the second includes computing units based on personal or industrial computers (Dubinkin et al., 2020, 2023a; Voronov et al., 2022; Voronov et al., 2024).

When developing software for autonomous vehicle control systems, errors always arise, preventing the installed equipment from performing its functions. These errors must be detected and eliminated (Poorani and Krishnan, 2024). During direct control of an autonomous vehicle, software errors can lead to disastrous consequences, which is unacceptable (Rozhko et al., 2024). Additionally, most autonomous control systems are based on artificial intelligence algorithms, such as neural networks (Abdullayev et al., 2024; Ilyushin and Afanaseva, 2020). For these neural networks to function correctly, they must be trained to perform specific tasks (Syrkin et al., 2023b). Training neural networks is a time-consuming process that requires using large amounts of data (e.g., images of numerous road signs) (Terekhova and Zubova, 2020).

One of the tasks in developing autonomous vehicle control systems is creating a module for perceiving road conditions (Akhmetshin et al., 2023). The basic elements of this module are neural networks of various architectures that, based on sensor data, can identify types of objects surrounding the autonomous vehicle and their relative positions (VISTA Simulator, 2023). Despite the well-known problem and the availability of large datasets for training (Dataset) provided by various companies in open access, no data exist for training neural networks specifically for mining dump trucks (Best Open-Source Autonomous Driving Datasets, 2023). Therefore, a tool is needed to create such datasets for the preliminary training of neural networks in the perception module. In addition to creating such datasets, research on mining dump truck control systems based on reinforcement learning requires a simulation environment to assess system behaviour (Ananyev et al., 2021; Dubinkin et al., 2023b; Elallid et al., 2022; Zhao et al., 2020).

Training and tuning control systems can be done in real-world road conditions. However, potential software errors make this process unsafe in real conditions (Vasyukov and Khisamova, 2021). Additionally, a large dataset is required to train neural networks (Abdullaev et al., 2023; Gallese Nobile, 2023). Thus, the developer must drive the autonomous vehicle over a long distance, which, during the initial development stages, is completely unsafe (Boashash et al., 2015; Polovchenko, 2021). This creates a vicious circle—training the control system requires covering many kilometers, but this cannot be done due to the risks of unsafe autonomous driving. Since driving is impossible, the necessary data for training neural networks cannot be collected.

This circle can be broken using additional tools—autonomous vehicle simulators. A simulator allows the control system to make errors without causing critical consequences—for example, after a simulated crash, the simulator can be restarted, and no vehicle or pedestrian will be harmed. A virtual vehicle can be launched in a wide range of road scenarios, including various terrains, weather conditions, and visibility restrictions. Using simulators allows for the creation of an autonomous vehicle control system in a short time and in complete safety for the surrounding world (Auyelbek et al., 2022).

Despite the structural and visual similarities between an autonomous mining dump truck and any other autonomous vehicle, there are unique features in the design of the vehicle and its area of operation. The main features include the large size of the mining dump truck, the construction of the dump truck's load-bearing system (which significantly differs from the body of a passenger car), and its operation in a mining enterprise (Ananyev et al., 2021; Dubinkin et al., 2023a).

The design features of the mining dump truck's load-bearing system determine the differences in sensor placement compared to a passenger car. The surrounding environment in a mining site also differs from that of passenger vehicles (Ali et al., 2024).

These distinctions determine several requirements for simulators used to study autonomous control of mining dump trucks:

- Flexibility in defining autonomous vehicle models.
- Availability of a wide range of sensor models and the ability to flexibly configure their parameters.
- Dynamic management of additional objects on the terrain (other vehicles, people, etc.).
- Simulation of various weather conditions, including changing lighting conditions, fog, rain, and snow.
- Flexible creation of terrain maps, including functional generation.
- Generation of photorealistic images transmitted to a virtual camera sensor.
- Availability of an API (programming interface) to integrate simulation results with the mining dump truck control system (SIL, software-in-the-loop).
- Support and development of the software by developers.
- Use of modern hardware capabilities (processors, video cards).

- Availability of an open license allowing simulator modification.
- If the product is paid, it must be available in the Russian Federation.

The identified features and developed requirements allowed us to formulate the goal of this work: to justify the choice of a simulator for studying the work and interaction of autonomous mining dump truck control systems based on multi-criteria analysis (MCDA).

To achieve the set goal, the following tasks were formulated:
- Select at least ten options for autonomous vehicle simulators.
- Formulate the requirements for the simulator based on the design features and operating conditions of the mining dump truck.
- Compare the simulator's compliance with the requirements using the multi-criteria analysis method (Syrkin et al., 2023a).

Overview of Existing Simulators
To achieve the set goal, it was necessary to identify existing simulators that would meet the requirements for the autonomous control system of a mining dump truck. The research conducted to search for various simulators identified several popular programs used for training neural networks:
- SVL simulator;
- CARLA simulator (Dosovitskiy et al., 2017);
- Simcenter Prescan (Simcenter Prescan software, 2023);
- AutonoVi-Sim (Best et al., 2018);
- VISTA Driving Simulator (VISTA Simulator, 2023);
- Gazebo simulator (Koenig and Howard, 2004);
- Flow simulator (Wu et al., 2017);
- AVSandbox (AVSandbox, 2023);
- COGNATA (COGNATA, 2023);
- Ansys Autonomous Vehicle Simulation (Ansys Autonomous Vehicle Simulation, 2023) ;
- MORAI (MORAI, 2023).

Below are the capabilities of the listed simulators.

Since LG simulator is a paid product, testing it was not possible.
CARLA simulator is a traffic simulation program. It is based on the Unreal Engine, which generates a three-dimensional image of the surrounding world. A plugin for the engine provides the ability to interact between the user's control programs for autonomous vehicles and the game world (Zhao et al., 2020). The user has two operating modes with the simulator. In the first mode, the user takes on the role of an autonomous vehicle control system developer. The second mode of working with the simulator is the mode of modifying three-dimensional models of maps, vehicles, and other objects.
SVL Simulator is a simulation platform used for the development of autonomous vehicles and robotic systems. The program allows simulating a virtual environment where one or more vehicles or autonomous systems and their sensors are located. The simulation software provides an integrated and customizable interface with the user's test system. This allows the developer to debug, perform modular testing, and conduct integration testing.
Simcenter Prescan is a physics-based simulation platform used for the development and testing of ADAS (Advanced Driver Assistance Systems) and autonomous vehicles (Elallid et al., 2022). A distinctive feature of Siemens Prescan is its modular system architecture, consisting of a scenario editor, simulation system, and MATLAB interaction system. The advantage of Prescan over CARLA is the visual adjustment of the parameters of the sensors installed on the vehicle and the visualization of their "field of view." Despite this advantage, an important drawback for solving the set tasks is the limited number of objects that can be placed on the map.
AutonoVi-Sim is a set of high-level extensible modules that allow for the quick development and testing of vehicle configurations and simplify the creation of complex traffic scenarios (Boashash et al., 2015). Despite many advantages, a significant drawback of this software product is its unavailability for download, as it is an internal development of the University of North Carolina, USA.

VISTA Driving Simulator differs from other simulators in that it is a data-driven simulation mechanism. By accepting real-world data as input, VISTA strives to recreate this world and synthesize new viewpoints of the environment. Since VISTA is built on real-world data, it avoids typical problems related to photorealism and model-to-reality transfer (Syrkin et al., 2023a).
Gazebo simulator was created as a simulation environment for robotic systems to study the basics of robotics and serves as the official simulator for DARPA robotics competitions. This simulator has advanced APIs and integrates well with the ROS system, which is the basic software product for developing robot control systems for research purposes (Goodwin et al., 2004; Koenig and Howard, 2004). The drawbacks of this simulator, according to the specified requirements, include low-quality graphics and the inability to create photorealistic images.
Flow simulator is a platform for traffic management comparative analysis, providing a set of traffic management scenarios (tests), tools for developing custom traffic scenarios, and integration with reinforcement learning and micro-simulation traffic libraries. Since this system simulates traffic only, its application for solving the set tasks is inappropriate.
AVSandbox is a platform for modeling and testing the behavior and characteristics of autonomous vehicles and ADAS systems. The platform supports photorealistic images and allows the creation of custom vehicle models and terrain maps. The main disadvantages of the platform include the closed information about the built-in API and the fact that it is paid software produced in the United Kingdom.
COGNATA is a platform for accelerating the development of autonomous transport systems in the automotive, agriculture, construction, and mining industries (Bryukhovetsky et al., 2023; Skrypnikov et al., 2021). It supports various simulation models, including "Hardware in the Loop," "Driver in the Loop," and ADAS system simulation, and supports photorealistic imaging. This simulator has similar disadvantages to AVSandbox—the absence of detailed documentation in open access and the fact that it is produced by a U.S.-based company.
Ansys Autonomous Vehicle Simulation provides a comprehensive solution specifically designed to support the development, testing, and verification of safe autonomous driving technologies (Alkhanova et al., 2021; Wang et al., 2022). The main drawback is the unavailability of the software in Russia.
MORAI simulator allows the creation of digital twins of the environment and features a realistic model of both the vehicles and sensors. Moreover, the software is certified according to the ISO 26262 standard, which is the international standard for functional safety of road vehicles. The main drawback is the unavailability of the software in Russia.

MATERIAL AND METHOD

Methods

To analyse how well the capabilities of the reviewed simulators meet the specified requirements, the TOPSIS method was employed. The TOPSIS method is one of the multi-criteria decision-making (MCDA) methods.
The TOPSIS method involves five stages of calculations. In the first stage, the performance of the selected options is evaluated based on the requirements. The obtained characteristics are normalized in the second stage. The normalized indicators are then compared to the best results. Afterward, the proximity of each option's indicator to the ideal and anti-ideal indicator is calculated. Finally, the relative closeness coefficient is determined for each simulator option (Ananyev et al., 2021).
The initial data for selecting a simulator using the TOPSIS method is a decision matrix (Table 1), which includes the evaluations of alternatives (na) based on criteria (ki), as well as the weight of the criteria (wi).

Table 1. Decision matrix.

Alternatives	**Criteria**			
	k_1	k_2	k_3	k_i
	Weight of Criteria			
	w_1	w_2	w_3	w_i
n_1	x_{11}	x_{12}	x_{13}	x_{3i}
n_2	x_{21}	x_{22}	x_{23}	x_{2i}
n_a	x_{a1}	x_{a2}	x_{a3}	x_{ai}

In this case, the alternatives are the options of simulators being reviewed, and the criteria represent the requirements for them.

To simplify, the simulators are labeled as follows:

- SVL simulator – "A1"
- CARLA simulator – "A2"
- Simcenter Prescan – "A3"
- AutonoVi-Sim – "A4"
- VISTA Driving Simulator – "A5"
- Gazebo simulator – "A6"
- Flow simulator – "A7"
- AVSandbox – "A8"
- COGNATA – "A9"
- Ansys Autonomous Vehicle Simulation – "A10"
- MORAI – "A11"

The criteria are labeled as follows:

- Flexibility in defining autonomous vehicle models – "B1"
- Availability of a large number of sensor models and flexibility in configuring their parameters – "B2"
- The ability to dynamically manage additional objects on the map (other vehicles, people, etc.) – "B3"
- The ability to simulate various weather conditions, including lighting changes, fog, rain, snow – "B4"
- Flexibility in creating terrain maps, including functional generation – "B5"
- The ability to generate photorealistic images transmitted to a virtual camera sensor – "B6"

Availability of an API for integrating simulation results with the mining dump truck control system (SIL, software-in-the-loop) – "B7"
Support and development of the software by developers – "B8"
Use of modern hardware capabilities (processors, video cards) – "B9"
Availability of an open license for modifying the simulator's software – "B10"
If the product is paid, it must be available in the Russian Federation – "B11"

RESULT AND DISCUSSION

A summary decision matrix is compiled (Table 2), including the weights of the criteria and expert evaluations.

Table 2. Summary decision matrix.

Alternatives	Evaluation Criteria										
	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
	Weight of Criteria w_i										
	0,9	0,9	0,6	0,6	0,8	0,8	0,7	0,6	0,8	0,5	0,9
A1	5	6	7	5	4	4	1	6	5	5	6
A2	7	7	6	6	8	8	6	7	6	8	8
A3	6	5	4	6	8	6	4	7	4	6	6
A4	5	6	5	5	7	1	1	3	5	4	3
A5	6	6	5	4	5	7	2	6	4	6	3
A6	4	5		5	4	1	1	3	5	4	5
A7	7	8	3	6	7	2	2	4	4	4	4
A8	1	6	4	6	2	3	4	4	4	4	5
A9	1	5	4	5	7	6	2	3	3	3	2
A10	4	3	1	5	7	5	5	1	1	1	1
A11	5	4	1	5	1	4	5	1	1	1	1

The indicator weights were determined using a rating scale from 1 to 9 during testing of the demo version of each software product, which is subjective in nature. For comparing different alternative assessments, the method of ideal normalization is used.
At the normalization stage, the evaluations are divided by the maximum value in each column (1).

$$r_{ai} = x_{ai}/u_{ai} \quad (1)$$

where uai=max(xai) for a = 1,..., n.

The calculated values are summarized in Table 3.

Table 3. Calculated values r_{ai} under ideal normalization.

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
A1	0,71	0,75	1,00	0,83	0,50	0,50	0,17	0,86	0,83	0,63	0,75
A2	1,00	0,88	0,86	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00
A3	0,86	0,63	0,57	1,00	1,00	0,75	0,67	1,00	0,67	0,75	0,75
A4	0,71	0,75	0,71	0,83	0,88	0,13	0,17	0,43	0,83	0,50	0,38
A5	0,86	0,75	0,71	0,67	0,63	0,88	0,33	0,86	0,67	0,75	0,38
A6	0,57	0,63	0,43	0,83	0,50	0,13	0,17	0,43	0,83	0,50	0,63
A7	1,00	1,00	0,43	1,00	0,88	0,25	0,33	0,57	0,67	0,50	0,50
A8	0,14	0,75	0,57	1,00	0,25	0,38	0,67	0,57	0,67	0,50	0,63
A9	0,14	0,63	0,57	0,83	0,88	0,75	0,33	0,43	0,50	0,38	0,25
A10	0,57	0,38	0,14	0,83	0,88	0,63	0,83	0,14	0,17	0,13	0,13
A11	0,71	0,50	0,14	0,83	0,13	0,50	0,83	0,14	0,17	0,13	0,13

At the third stage, weight coefficients are calculated with (2) by multiplying r_{ai} with their corresponding weights wi (Table 4).

$$v_{ai} = r_{ai} \cdot w_i \quad (2)$$

Table 4. Weighted normalized decision matrix.

	B1	**B2**	**B3**	**B4**	**B5**	**B6**	**B7**	**B8**	**B9**	**B10**	**B11**
A1	0,64	0,68	0,60	0,50	0,40	0,40	0,12	0,51	0,67	0,31	0,68
A2	0,90	0,79	0,51	0,60	0,80	0,80	0,70	0,60	0,80	0,50	0,90
A3	0,77	0,56	0,34	0,60	0,80	0,60	0,47	0,60	0,53	0,38	0,68
A4	0,64	0,68	0,43	0,50	0,70	0,10	0,12	0,26	0,67	0,25	0,34
A5	0,77	0,68	0,43	0,40	0,50	0,70	0,23	0,51	0,53	0,38	0,34
A6	0,51	0,56	0,26	0,50	0,40	0,10	0,12	0,26	0,67	0,25	0,56
A7	0,90	0,90	0,26	0,60	0,70	0,20	0,23	0,34	0,53	0,25	0,45
A8	0,13	0,68	0,34	0,60	0,20	0,30	0,47	0,34	0,53	0,25	0,56
A9	0,13	0,56	0,34	0,50	0,70	0,60	0,23	0,26	0,40	0,19	0,23
A10	0,51	0,34	0,09	0,50	0,70	0,50	0,58	0,09	0,13	0,06	0,11
A11	0,64	0,45	0,09	0,50	0,10	0,40	0,58	0,09	0,13	0,06	0,11

The weight coefficients are used to compare each indicator with the highest and lowest coefficient. For this, Table 5 is created.

Table 5. Matrix of highest and lowest coefficients.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**
v_i^+	0,90	0,90	0,60	0,60	0.80	0,80	0,70	0,60	0,80	0,50	0,90
v_i^-	0,13	0,34	0,09	0,40	0,10	0,10	0,12	0,09	0,13	0,06	0,11

The proximity of each indicator in Table 5 to the highest and lowest coefficients is calculated using formulas (3) and (4).

$$d_a^+ = \sqrt{\Sigma_i (v_i^+ - v_{ai})^2}, where\ a = 1, \ldots, m \qquad (3)$$

$$d_a^- = \sqrt{\Sigma_i (v_i^- - v_{ai})^2}, where\ a = 1, \ldots, m \qquad (4)$$

These calculated values are summarized in Table 6. The relative proximity coefficient for each option to the highest coefficient is calculated using formula (5).

$$C_a = \frac{d_a}{d_a^+ + d_a^-} \qquad (5)$$

Table 6. Proximity of indicators.

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11
d_a^+	0.948	0,141	0,654	1,229	0.930	1,301	1,052	1,300	1,372	1,541	1,651
d_a^-	1,296	1,965	1,507	1,125	1,292	0,938	1,319	0,925	0,938	0,947	0,771
C_a	0,578	0,933	0,697	0,478	0,582	0,419	0,556	0,416	0,406	0,381	0,318

Based on the analysis of the results presented in Table 5, the CARLA simulator (Option A2) was found to best meet the requirements for creating autonomous mining dump trucks.

CONCLUSIONS

- To justify the choice of a simulator necessary for conducting scientific research in the development of autonomous mining dump truck control systems, requirements for the simulator were formulated, and eleven existing and available simulator options were identified.
- Based on the formulated requirements and the simulator options, an analysis using the TOPSIS method was conducted. As a result, CARLA simulator was determined to be the most suitable simulator among the existing options and will serve as the foundation for conducting scientific research in the field of mining dump truck control system development. It is important to note that CARLA simulator offers the possibility to create terrain maps that simulate the working conditions of a mining dump truck at a mining enterprise.
- Future research directions include the use of CARLA simulator to solve tasks related to the development of an autonomous mining dump truck control system.
- This includes studying the impact of the number and placement of sensors on the truck's surrounding view and preparing data for training neural networks and the perception subsystem of the autonomous mining dump truck.

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