Analysis of the Implementation Process of Rail Transport for Oversized Loads Using FlexSim Software: Current Status and Prospects for the Use of Artificial Intelligence

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Abstract— **The development of a concept for the transport of oversized cargo by rail and road constitutes an essential element of logistics planning, particularly in relation to military equipment. This article presents a simulation model developed in FlexSim software for the loading, transportation, and unloading of a tank platoon and compares rail transport with road transport using low-loader trailers. In addition to identifying the limitations of the proposed model, the paper discusses future research directions related to the application of artificial intelligence, including machine learning for predicting operation times and delay risks, reinforcement learning for multimodal route selection, and resilience modeling for contested logistics environments. The study also addresses the role of human oversight in AI-supported decision-making and outlines potential directions for further development in this field.**

Keywords— **rail transport, modeling, simulation, artificial intelligence, military logistics, contested logistics**

I. INTRODUCTION

Rail transport has remained one of the most important components of the country's transportation system for many decades. Its rapid development took place during the second half of the 19th century and the first half of the 20th century, when rail became one of the most effective means of transporting people and materials. Today, despite the rapid growth of road and air transport, rail continues to play a significant role in the transport of heavy and oversized cargo, particularly over medium and long distances. Rail transport is of particular importance for the movement of oversized and over-dimensional cargo. This category includes, among other things, heavy military vehicles, specialized industrial machinery, components of transportation and energy infrastructure, bridge structures, tunnel segments, offshore platform components, and turbines used in the power industry. Transporting this type of cargo requires compliance with numerous technical and organizational requirements stemming from the cargo's weight, dimensions, and transportation infrastructure limitations. It also requires the use of appropriately selected rolling stock, specialized loading and unloading equipment, and precise planning and coordination of all stages of the logistics process.

In addition to transporting heavy equipment and large structural components, railways also play a significant role in the transport of strategic raw materials. From the perspective of national energy security, the ability to transport fuel oil using specialized tank cars is of particular significance. This solution offers an alternative to pipeline and marine transport, increasing the flexibility of the national logistics system. In Poland, this type of transport is carried out, among other means, using tank cars owned by the Orlen Group, which enables the efficient movement of raw materials between transshipment terminals, warehouses, and refineries (Piękoś & Czyrny, 2026, pp. 145-147).

In the military environment, oversized transport operations are a crucial component of the armed forces' logistical support. Their efficient execution impacts the ability to rapidly deploy troops, equipment, and supplies both within the country and as part of allied operations. The significance of this issue is growing, particularly in the context of contemporary security challenges, where there is an increasing emphasis on the need to ensure the resilience of logistics systems and their ability to function under conditions of infrastructure and operational

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disruptions.

The increasing complexity of logistics processes means that traditional planning methods are no longer sufficient for analyzing multiple operational scenarios and evaluating their effectiveness. The solution to these challenges lies in the use of simulation tools that enable the modeling of real-world logistics processes in a virtual environment. One of the solutions used in this area is FlexSim software, which allows users to build discrete-event models and analyze the flow of transportation, warehousing, and transshipment processes. This makes it possible to identify bottlenecks, evaluate resource utilization, and seek solutions to increase the efficiency of operations.

The purpose of this article is to analyze the potential for using rail transport to move oversized cargo using FlexSim software and to present ways to optimize this process based on the results of computer simulations. An additional objective is to identify directions for the development of simulation models based on artificial intelligence methods, which can support the decision-making process and enhance the predictive capabilities of modern logistics systems.

The objectives set allowed us to formulate the main research problem as follows: How can oversized cargo shipments be effectively planned and carried out using rail transport and FlexSim simulation tools, and what artificial intelligence methods can expand the analytical capabilities of classical discrete-event models?

To resolve the research problem, a set of complementary research methods was employed. In the theoretical section, a critical analysis of the literature was conducted, covering topics such as rail transport, military logistics, computer simulations, and the applications of artificial intelligence in logistics systems. In the empirical section, computer modeling and simulation were used in the FlexSim environment to replicate the process of loading, transporting, and unloading oversized cargo. This was supplemented by a case study approach, observation, and expert analysis of the results obtained during the simulation experiments. This approach made it possible to assess the impact of selected organizational and technical parameters on the efficiency of the transportation process and to identify potential areas for improvement.

The structure of this article comprises four main sections. The first section presents selected theoretical issues related to the rail transport of oversized cargo, taking into account its significance for military logistics, allied cooperation, and the concept of contested logistics. The second section provides an overview of the FlexSim software and analyzes its potential applications in modeling logistics processes. The third section presents a practical example of modeling the process of loading, transporting, and unloading oversized cargo, along with an analysis of the results obtained. The final section discusses the prospects for the development of computer simulations supported by artificial intelligence solutions, with particular emphasis on their potential application in military logistics and transportation planning.

II. SELECTED THEORETICAL ISSUES RELATED TO TRANSPORTATION

Every day, enormous quantities of goods are transported by rail in Poland and the European Union. Although most of these goods are subject to standard logistics procedures, certain types of cargo-due to their specific characteristics-require special attention and specialized transportation solutions. These include perishable goods, oversized cargo, and hazardous materials, the transport of which involves increased risk (Piękoś & Piękoś, 2025, p. 14).

In terms of military transport, rail transport is used to quickly move equipment and materiel whose dimensions exceed the rail gauge. Such transports are organized infrequently and are one-off in nature the military is the largest organizer of such transports in Poland, including for the transport of equipment to maintenance facilities or training grounds, and during crises and wars for the movement of forces as part of NATO or European Union operations. Transport is understood as a process involving movement from a point of origin to a destination, as well as activities such as loading, unloading, transshipment, and handling operations. (Kurasiński, 2014, pp. 40-41).

Equally important in the context of transportation is the financial settlement of fees for the rail transport of troops, which is carried out on the basis of so-called settlement agreements concluded between the Garrison Support Unit and the rail transport service provider usually the state-owned rail carrier, PKP Cargo S.A.

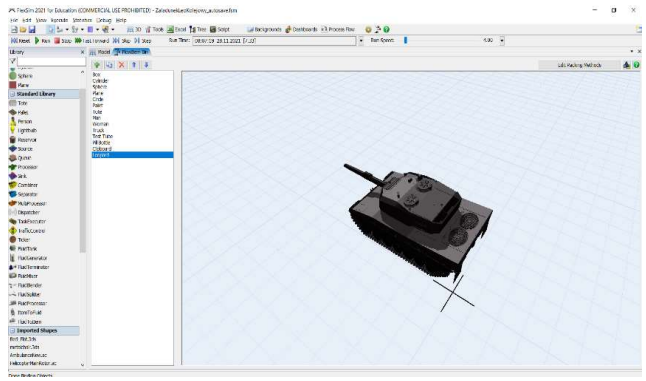
From the perspective of military rail transport, PKP Cargo is the key player. PKP Cargo's main tasks include, above all, providing bulk freight services and maintaining low freight rates for medium- and long-distance shipments. The company also focuses on utilizing an extensive rail network that corresponds to the locations of key distribution markets (Piękoś et al., 2024, pp. 5-18). Transport can also be defined as the provision of a service for a fee, the purpose of which is to move people and equipment, as well as to provide ancillary services, using dedicated resources and means. The transport parameters are generally data concerning volume, time, and distance (Pawlisiak & Piękoś, 2019, pp. 133-134). Knowledge of transport needs based on these parameters is crucial for the effective and efficient operation of transport by various modes of transportation. In analyzing the theoretical aspects related to the potential use of rail transport, it is essential to pay attention to the condition of the rail infrastructure network (Pawlisiak, 2016, pp. 2-4). Traditional transport theory assumes relatively stable conditions and predictable transit Times (Forbes, 2026). However, the contemporary security environment the experiences of the war in Ukraine, as well as the formal technological priorities of the U.S. and NATO require supplementing this model with the concept of "Contested Logistics," i.e., the possibility of deliberate disruption of infrastructure (sabotage, cyberattacks on rail traffic control systems, network overload). The U.S. Department of Defense has identified "Contested Logistics" as one of six critical technology areas, and NATO DIANA has designated "Responsive Logistics" as the alliance's official innovation challenge, confirming the priority character of this topic.

The above-mentioned theoretical aspects can be summarized by stating that there are opportunities to make use of rail transport for both military and civilian shipments (DefenseScoop, 2026). The key to identifying quantitative, qualitative, and temporal aspects of transportation efficiency is to conduct research under real-world operating conditions. Undoubtedly, the transportation process can be optimized and appropriately regulated through the use of computer simulation. By entering appropriate values, parameters, and variables, it is possible to adjust the timing of delays in such transportation; ultimately, these solutions would serve as an illustrative and training tool, as well as a factor influencing critical decision-making by relevant decision-makers. This requires analytical tools that go beyond classical discrete-event simulation, as discussed in Chapter 4.

III. FEATURES AND CAPABILITIES OF THE FLEXSIM SOFTWARE

To create a simulation of a military unit's transport, it was necessary to select software that would allow the logistics process to be analyzed in terms of time, quantity, and cost, while maintaining simplicity and clarity. FlexSim version 2021 was selected because it provides a clear user interface and facilitates programming by allowing simulations to be created not only in the classic way for programming environments by entering code but also by designing algorithms for specific elements that are graphically represented on the user's model (Beaverstock et al., 2019). Not only in this section of the article but also in subsequent sections, tanks-as loads that extend beyond the railcar's end serve as the point of reference. However, the methodology presented is identical to that applied to oversized objects on the civilian rail network.

FIGURE 1. A GRAPHICAL MODEL OF THE LEOPARD 2A5 TANK



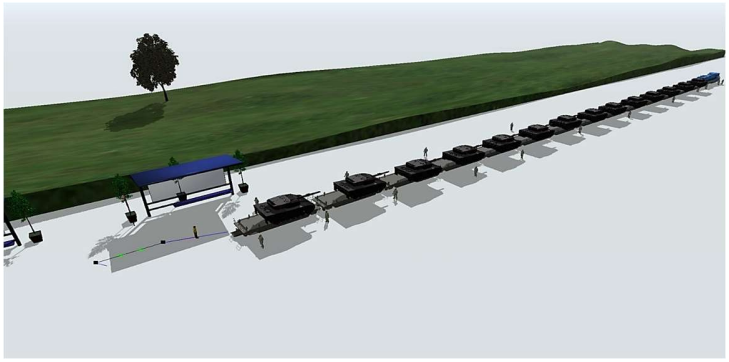
Source: Own elaboration.

FlexSim software enables simulations by adding graphical objects to the "workspace" whose parameters can be modified before running the simulation, allowing users to customize the simulation and better replicate real-world situations. The Process Flow module allows users to program the process logic algorithmically-using decision rules analogous to "if," "switch case," or "when," generate tokens (object instances, in this case: tanks), and create SubFlows (algorithms executed asynchronously with the main process, e.g., loading/unloading). In addition, FlexSim enables the simulation of air transport using map elements. The Dashboard module enables real-time and post-simulation analysis of simulation results in graphical form including operator occupancy charts, distance traveled over a given time period, and Gantt charts. The results can be exported to a CSV file and further analyzed in Excel. An important, though rarely used, feature of FlexSim is its ability to integrate with external analytical tools via data exchange mechanisms (CSV export/import, external scripts). In the current model, the Process Flow logic is entirely programmed manually in the form of conditional rules. An alternative is to replace part of this logic with a learning component a predictive model that feeds simulation parameters (e.g., loading time) or a reinforcement learning agent that learns the optimal sequence of decisions instead of following a pre-programmed rule. FlexSim then serves as the "physical engine" that models the actual process constraints, while the decision-making layer is fed by an external model - this approach is explored in Chapter 4.

IV. PRACTICAL EXAMPLE OF USING FLEXSIM TO MODEL A LOADING PROCESS

The loading process simulation assumes that the operator moves from point A to point B, where the appropriate number of transport vehicles have been made available, and then the operator picks up one of them and transports it to the designated location within the specified time frame.

FIGURE 2. LOADING PROCESS SIMULATION



Source: Own elaboration.

Compared to the processor's execution time, this process is not significant and does not substantially affect the loading time or the duration of the simulation, as it takes less than 3 seconds (which results in a delay of less than one minute in the overall simulation). In the actual loading process, the time required to load a single tank is not a constant but a fluctuating value; therefore, assuming a one-minute delay for loading the entire convoy is not a gross error, since according to standard DU-4.4.1 (B), the total loading time for tank subunits is considered to be 4 hours and 30 minutes. In the scenario under

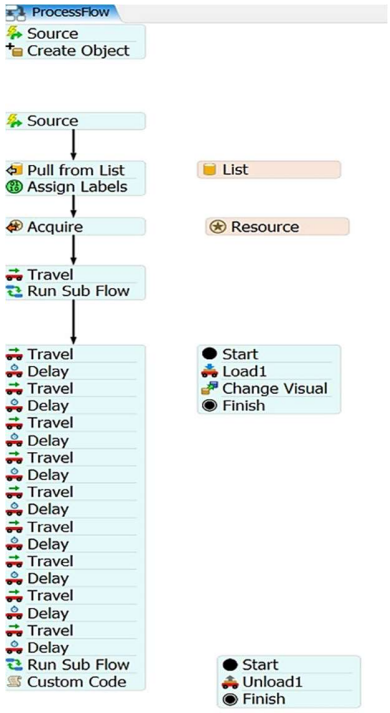
consideration, loading takes exactly that long, including the delay resulting from the schedule. When analyzing this process, the following conclusions should be drawn: the loading completion time depends largely on the time required to load a single oversized vehicle (tank) onto the ramp. By increasing the number of exercises, we enhance the experience of the personnel involved in the loading process; by familiarizing them with the vehicle being loaded, we can effectively reduce the time needed to load the entire convoy. Another factor that would help increase the speed of vehicle loading is the expansion of infrastructure. The next element subjected to computer simulation is the entire logistics process of rail transport, which includes loading, the movement of the unit, and unloading.

The algorithm for the transport simulation was developed using the "Process Flow" module:

1. The loading algorithm calls for the generation of a queue of 18 oversized loads, along with a locomotive, which will depart from Point A.
2. The loading process was simulated by attaching a ramp with a loaded tank to the locomotive. In this case, the tanks are generated by inserting the appropriate block into the "Process Flow" algorithm. Military vehicle equipment is generated on the ramp model.
3. After loading the military equipment, the train—which acts as the operator responsible for moving the convoy (in this case, 18 railcars, according to an individual schedule)—carries out its task by moving through the objects that the software defines as a network of connections—"Network Node." The logic of these objects allows for the determination of appropriate travel parameters, such as changes in virtual distance, the setting of maximum speeds on specific sections, and traffic volume in a given direction along the route. This enhances the realistic representation of the process under consideration and facilitates its analysis.
4. The rail transport of military equipment depends on many variables, which necessitates the introduction of delays that affect the total duration of the process.
5. When the train arrives at point B—the training ground—unloading begins. According to the standard, unloading takes a maximum of 2 hours and 30 minutes, which was also assumed in the simulation.

Another type of Dashboard object used in this study was the relationship between the distance traveled by the operator and the number of hours. Based on this relationship, it is possible to determine the vehicle's average speed over specific time intervals, which allows for an analysis of how the transport was carried out. The area under the graph represents the total distance, i.e., the distance from the permanent base to the land forces' training range or the destination station (recipient) of the oversized cargo. In the case of the route under examination, the graph indicates two time intervals during which the journey is interrupted: starting at 6:00 p.m. and starting at 9:00 p.m. During these time intervals, the operator has scheduled a stop or is unloading military equipment, respectively. In addition, simulations of transporting a military subunit by road were considered in order to compare methods of carrying out the troop transport process. The algorithm was analogous to the rail variant, with differences in loading time, route, and unloading time in accordance with road transport standards. It demonstrated a shorter operation time; however, a financial analysis over longer distances shows it to be less cost-effective than rail transport.

FIGURE 3. ALGORITHM FOR RAIL TRANSPORT USING THE "PROCESS FLOW" MODULE



Source: Own elaboration.

The use of FlexSim software in the field of transportation to conduct a detailed analysis requires keeping in mind that the model has significant limitations, which set the direction for further research as presented in Chapter 4: the loading time was assumed to be a constant value, whereas in reality it fluctuates; the model does not account for disruption scenarios (failures, sabotage, network overload, as discussed in Chapter 1). Nevertheless, the simulation confirms that the conclusions drawn from the military model can also be applied in a civilian environment.

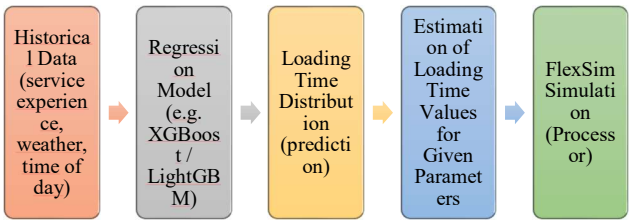
V. PERSPECTIVES FOR THE USE OF COMPUTER SIMULATIONS

The modeling process presented in Chapter 3 is based on classical discrete-event simulation (DES). This is a modeling technique in which all changes in the model's state occur exclusively at strictly defined moments, determined on the basis of previously entered data called events. The selected modeling process, within the scope of the example discussed, is sufficient but is limited in terms of the use of methods from the field of artificial intelligence (AI). The following outlines the potential applications of computer simulations, which include:

1. predicting the duration of individual operations using machine learning,
2. estimating the risk of delays for the entire trip using time-series models,
3. reinforcement learning (RL) directly integrated with the FlexSim model for route selection and sequencing of activities,
4. scenario-based testing of the model's resilience to disruptions (contested logistics), and guidelines for human oversight of the transport system in question,
5. anomaly detection,
6. a decision-making assistant based on Large Language Models (LLM).

In the model from Chapter 3, the loading time for a single vehicle was assumed to be a constant (15 min), even though in reality it depends on a number of factors, primarily the experience of the operators. Machine learning (ML) allows us not only to describe this relationship qualitatively but also to estimate its value. The core of this approach is a regression model from the Gradient Boosting family (a machine learning algorithm that builds a sequence of simple decision trees, each of which learns to correct the errors made by the previous trees). The most widely used software implementations are the XGBoost and LightGBM libraries (Chen & Guestrin, 2016, pp. 1-5). The model is trained, among other things, on historical data in which, for each recorded loading operation, both its duration and the accompanying conditions are known—for example, the type of equipment, the experience level of the operators, weather conditions, and the time of day. Crucially, the trained model returns an estimated numerical value for the loading time for a given combination of conditions.

FIGURE 4. LOAD TIME PREDICTION ALGORITHM



Source: Own elaboration.

Instead of using a fixed loading time value, in this approach to using AI methods in FlexSim simulations, the value of this parameter is calculated each time the process is run, thereby reflecting the natural variability of the process—rather than artificially ignoring it. In other words, the classic, manually programmed simulation parameter is replaced by a parameter learned from the data—without changing the structure of the FlexSim model itself.

TABLE 1. THE SAMPLE INPUT DATA FOR THE PREDICTION MODEL (ILLUSTRATIVE DATA)

Experience	Weather	Time of Day	Time [min]
low	good	day	19
medium	good	day	15
medium	rain	night	21
high	good	day	11
high	rain	night	16

Source: Own elaboration.

The parameters described above reflect the factors identified in Chapter 3, including the standards and regulations of loading oversized equipment. In the context of AI methods, these are contextual variables that indirectly influence the pace of work. Even with this small, illustrative set of variables, ML methods can identify correlations between them and the loading time. A linear regression model formalizes this relationship numerically and allows it to be applied in a simulation instead of using a single average value.

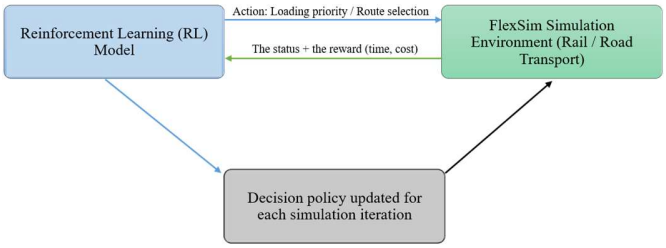
In contrast to the previously described model, which estimates the duration of a single operation, delay prediction applies to the entire trip and answers a different question: what is the probability that the transport will not arrive on time due to factors beyond the control of the Staff-such as network congestion, prioritization of passenger traffic, or weather conditions. For this purpose, time-series models are better suited than point regression; they analyze data organized chronologically (i.e., a sequence of values measured sequentially, such as hourly or daily) to identify patterns-such as trends, seasonality, and cyclicality-and use these to predict future values. A prime example of a model that decomposes a time series into trend and seasonality is the Prophet model, which breaks down a complex time series into several distinct components and then combines them to produce a result that is easier to interpret (Taylor & Letham, 2018, pp. 37-45).

Another example is the Long Short-Term Memory (LSTM) recurrent neural network -an architecture capable of "remembering" information from distant, earlier time steps-which can capture sequential relationships in railway traffic data collected over time. Models of this type, trained on historical data regarding congestion and delays, can return not a single number but a probability curve for delays depending on the planned travel time. The result of the analysis is the output of the calculations. The practical implication of such a prediction is straightforward: a planner can intentionally avoid scheduling a loading and transport window in a high-risk zone or consciously include an appropriate time buffer in the schedule. The models described above are predictive in nature; they provide decision-makers with information to anticipate the risk of delays depending on the time of travel, but they do not make decisions on the decision-maker's behalf.

The third step is reinforcement learning (RL), which differs fundamentally from regression-based approaches: the model does not learn from a predefined set of examples with "correct answers," but rather through trial and error—by performing actions in a simulated environment, observing their effects, and receiving a reward signal. This approach is particularly useful where the "correct" decision changes over time along with the conditions of the environment under study; for the example discussed here, this applies to the problem of choosing a mode of transportation, described in Chapter 1 as a continuous

decision-making task (Sutton & Barto, 2018, pp. 2-10).

FIGURE. 5. REINFORCEMENT LEARNING LOOP CONNECTED TO A FLEXSIM MODEL

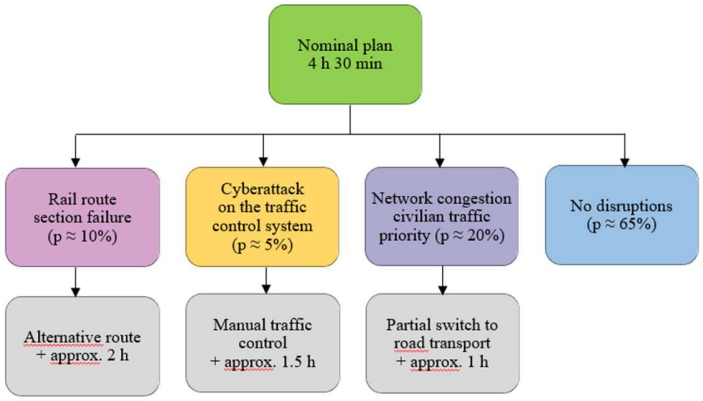


Source: Own elaboration.

Figure 5 illustrates the concept as a feedback loop integrated with the FlexSim environment, rather than as a one-time algorithm. The RL model observes the state of the simulation environment (including rail network load, the previously described forecasts of delay times and risks, and the availability of low-floor trains) and, based on this, selects an action-such as the order in which vehicles are loaded or the decision to switch to low-floor trains. FlexSim simulates the consequences of this decision and returns a reward to the agent consisting of the turnaround time and the cost of the operation. The agent's decision-making policy is updated after each such iteration, and the entire cycle is repeated multiple times until the desired outcome is achieved. It is important to note that the entire learning process takes place within the simulation, not in actual transportation operations-the commander can "practice" thousands of low-risk scenarios before the system is authorized to support real-world decision-making.

The models presented so far assume that the transportation network functions properly, and that only its parameters (time, risk of delay) are variable. In contrast, contested logistics under disputed conditions, as presented in Chapter 1, assumes that the infrastructure itself may be intentionally or randomly taken out of service, and that the transportation plan should be tested for resilience, not just for efficiency under nominal conditions. In practice, this means building a generator for disruption scenarios and running FlexSim simulations multiple times for each scenario, rather than a single run assuming no problems. Below is an example scenario tree for a nominal plan (4 hours 30 minutes, in accordance with standard DU-4.4.1(B)). The adopted disruption categories are not chosen arbitrarily but correspond to three distinct types of risk documented in the literature: technical failure of a section of a given route, a cyberattack on the rail traffic control system, and network overload, i.e., the phenomena already observed in the simulation from Chapter 3. The assigned probabilities are illustrative; each scenario has also been assigned a separate mitigation strategy (alternative route, manual mode, or partial shift to road transport) along with an estimated time overhead.

FIGURE. 6. EXAMPLE OF A DISRUPTION SCENARIO TREE



Source: own study - the illustrative data is used to illustrate the structure of the scenarios and is not based on actual statistics.

The result of running the simulation multiple times according to such a decision tree is not a single completion time, but a distribution of possible times, taking into account both the no-disruption scenario and other variants. This makes it possible to assess the extent to which standard DU-4.4.1(B) remains realistic under conditions of limited predictability andcrucially from the perspective of advance planning to prepare time buffers and alternative procedures in advance, rather than improvising them only when a disruption occurs.

The methods presented above differ in their degree of autonomy: predictive models merely provide information; the RL model can make and implement decisions on its own; and testing disruption scenarios supports strategic decision-making. The higher the level of autonomy, the more critical the question becomes of who bears responsibility—and to what extent—for a decision made with the involvement of an AI system, and at what stage of the process a human retains a real ability to intervene. In NATO C2COE documents dedicated specifically to the issue of human oversight of artificial intelligence systems in defense applications, a three-tiered classification of oversight is used for this purpose (NATO Command and Control Centre of Excellence, 2026).

TABLE 2. LEVELS OF HUMAN OVERSIGHT OF AI FUNCTIONS IN THE TRANSPORTATION PROCESS

Level	Characteristics	Example function
HITL (human-in-the-loop)	The human makes every decision	Decision on an alternative route in the event of a disruption
HOTL (human-on-the-loop)	The system operates, the human supervises	Prediction of loading time and delay risk
HOOTL (human-out-of-the-loop)	The system operates autonomously	Updating the RL environment policy between simulation iterations

Source: Own study based on - (NATO Combined Joint Centre Of Excellence, 2026).

Determining the appropriate level of oversight is not the same for every system; it depends on the scale of the consequences of a particular decision. An error in a predictive model is usually reversible and does not directly threaten safety, provided it is subjected to a parallel analysis by a team of specialists. The overarching rule remains consistent: AI should

serve as a support for decision-makers, not as a replacement for them, and the system's growing autonomy must go hand in hand with a clearly defined and documented scope of human responsibility.

VI. CONCLUSION

The theoretical considerations presented and the simulation model developed confirm that the use of discrete-event simulation allows for the identification of constraints in the transportation system, the assessment of resource utilization, and the analysis of various options for organizing the transportation process. This makes it possible to reduce organizational risk, shorten task completion times, and rationalize the use of available transportation and transshipment resources. An analysis of trends in digital technology indicates that the next stage in improving simulation models will be their integration with artificial intelligence methods. The use of machine learning algorithms, decision support systems, or optimization methods may enable the automatic generation of optimal transport schedules, the prediction of bottlenecks, and the dynamic adaptation of transport plans to changing operational conditions. As a result, it can be concluded that combining classical computer simulation methods with artificial intelligence-based solutions represents a promising direction for the development of modern logistics systems. In the future, this approach could significantly increase the efficiency of planning and executing oversized transport operations, in both civilian and military applications, thereby contributing to the reliability and resilience of the entire transportation system.

VII. REFERENCES

Armed Forces General Command, Doctrine DU-4.4.1(B). Principles of military rail transport, Ministry of National Defence, Warsaw, 2014.

Banks, J., Carson, J.S., Nelson, B.L., Nicol, D.M. Discrete-Event System Simulation. Upper Saddle River, 2005.

Beaverstock, M., Greenwood, A., Nordgren W., Applied simulation. Modeling and analysis using FlexSim, InterMarium Publishing, Kraków, 2019.

Chen, T., Guestrin, C., XGBoost: A Scalable Tree Boosting System, ACM SIGKDD, San Francisco, 2016.

Fajczak-Kowalska, A., Rail Transport in Logistic Processes of the Polish Economy, University of Lodz Publishing House, Łódź, 2013.

Harper, J. Pentagon looks to AI, other tech to help tackle contested logistics challenges. Available online: https://www.defensescoop.com

Hochreiter, S., Schmidhuber, J., Long Short-Term Memory, Neural Computation, Cambridge,1997.

Kirichenko, D. Ukraine's AI Drones Are Hunting Russian Supply Lines. Available online: https://www.forbes.com/sites/davidkirichenko/2026/05/12/ukraines-ai-drones-are-hunting-russian-supply-lines/

Kurasiński, Z., Compendium of a Military Logistician, Warsaw, 2014.

NATO DIANA. Responsive Logistics, Challenge Document. Available online: https://www.diana.nato.int/resources/site1/general/challenges/challenges2027/challenge_pdf/2027_responsive_logistics.pdf (accessed on 25 September 2026).

Pawlisiak M., Piękoś D., Needs and possibilities of using rail transport in military transport, Military Logistics Systems Volume 51 (2019), p. 133.

Piękoś D., Piękoś A., Economic and legal aspects of using rail transport for the carriage of dangerous goods, Scientific Journal of Bielsko-Biala School of Finance and Law, Vol. 29, No. 2; Bielsko-Biała, 2025, p. 14, DOI:10.19192/wsfip.sj2.2025.2.

Piękoś D., Ściborek Z., Alomar I., Assessment of the logistics service provider PKP Cargo using indicator analysis, Military Logistics Systems Volume 61 (2024), ISSN 1508-5430, pp. 5-18, DOI: 10.37055/slw/203433.

Piękoś D., Suduł P., Augustyn S., Expansion of logistics infrastructure in the oil sector as a form of improving Poland's energy security, Scientific Journal of Bielsko-Biala School of Finance and Law, Vol. 27, No. 2; Bielsko-Biała, 2023, p. 13-14, DOI: 10.19192/wsfip.sj2.2023.2.

Scherrenburg, M. Human Oversight in AI-Driven Defence – at what positions do we need the Human in the Loop. Available online: https://c2coe.org/new-article-human-oversight-in-ai-driven-defence/

Sutton, R. S., Barto, A. G., Reinforcement Learning: An Introduction, Cambridge, 2018.

Van der Horst, M. R., de Langen, P. W., Coordination in Hinterland Transport Chains: A Major Challenge for the Seaport Community, Maritime Economics & Logistics, 2008, 10(1–2), pp. 108–129.