Risk Management Methodology for Transport Infrastructure Security

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The development of transport infrastructure is associated with risks, expressed in the likelihood of harm to the road users' health during road accidents and their consequences. The risk management process is aimed at reducing the influence of factors that contribute to the occurrence of an accident and increase the consequences' severity after it.

Keywords: road safety ; road accident ; risk analysis ; risk assessment ; risk management

1. Introduction

Ensuring road safety is one of the priorities of state policy. Road accidents pose a serious threat to the sustainable functioning of the transport complex and cause significant social and economic damage. The number of deaths as a result of road accidents globally has already exceeded 1.35 million people a year and, unfortunately, by 2030, this indicator is predicted to triple in growth due to the countries that do not pay much attention to this problem.

To reduce the road accident rates, first of all, it is necessary to conduct scientific research aimed at developing a comprehensive mechanism for preventing accidents as well as analyzing, assessing, and managing the risks of road safety.

Since many traffic parameters (flow intensity in the first place) are stochastic in nature, and the functioning of the transport system is associated with risks (material, human, timing), any change in the traffic situation can lead to the system's malfunction (deterioration of the traffic situation, and in the most serious cases—to a transport collapse). Therefore, any actions to change the infrastructure or the management system must be scientifically justified. In such situations, it is always important to calculate the possible risks of road safety, their probable harm to the road users' health and material losses during road accidents and their consequences as well as also have risk management tools.

2. Risk Management Methodology for Transport Infrastructure Security

The assessment of transport and social risk and their predictive values are defined in the Federal Target Program "Improving Road Safety in 2013–2020." [1], however, the list of factors causing risks is incomplete.

To classify the road safety risks, the author developed a concept in [2]. According to this concept, road traffic is a complex socio-technical system consisting of three subsystems (levels): (1) a subsystem, the functioning of which directly ensures the satisfaction of the transport need, namely the spatial movement of people and goods; (2) a subsystem for the traffic preparation and maintenance; and (3) a subsystem formed by executive authorities that implement the functions of state administration of a sectoral and intersectoral nature in relation to the subsystems of the first and second levels. Each level has its own risks. He classified the risks of each group in accordance with the selected criteria: risk cause (kind); place of risk; risk subject and source; objects to which the risks are directed; and the size and extent of the damage [3].

An important direction in ensuring road safety, as the author notes in his work [4], is the management of road safety risks, which are expressed in the likelihood of causing harm to road users from the road accidents and their consequences. The process of traffic safety risk management, in his opinion, can be defined as reducing the influence of factors that contribute to the appearance of the accidents' causes. These factors are risk factors, circumstances that affect the risk likelihood or consequences, but are not their direct cause. A group of researchers [5] developed characteristics by which risks were classified in accordance with the road safety requirements.

The authors of [6] analyzed an approach to calculate the car collision probability (collision detection assessment) in the context of their prevention. The authors proposed a study of the collision probability without temporary collision measures as an intermediate or necessary value, which makes it possible to obtain the collision probability over a long period of time by integrating it over time. According to the authors in [7], rapid prediction of the accident severity allows trauma and emergency centers to assess the potential damage from an accident and, accordingly, send the appropriate emergency rescue units to provide appropriate emergency care. The authors proposed a two-level ensemble machine learning model to predict the crash severity. The first level combined four basic machine learning models: the k-nearest neighbor, decision tree, adaptive boost, and support vector machine; the second layer classified the accident severity based on a feed-forward neural network model. The authors used as input data only those accident signs that could be obtained instantly and easily. In [8], to predict the occurrence of accidents, vehicle failures, and driver errors, a fuzzy cognitive model was built. This allowed them to take into account a large number of heterogeneous factors. The predictive model to estimate the transportation duration was based on the results of the expert survey, and fuzzy logic was used to formalize the expert estimates.

The authors of [9] pointed out that compared to vehicle collisions, collisions with pedestrians were less studied due to insufficient data, but the development of image processing technology contributed to solving this problem through the use of video data. They used video data to analyze pedestrian–vehicle conflicts.

The study in [10] was devoted to a risk-based analytical framework to estimate the number of fatalities in a crash. It combined the probabilities of both an accident and the fatalities in the event of an accident. It was assumed that the frequency of crashes between the different road users was proportional to their roadway usage. The authors estimated the fatality rates for various combinations of vehicles and pedestrians and concluded that in the absence of road safety measures, there was first an upward trend and then a downward trend in mortality. The lowest road death rate was observed in the bus-dominated scenario. At the same time, it was also necessary to take into account the risks of a long-term period, when the consequences of accidents manifest themselves with a delay in time. This approach to assessing risks in manufacturing was developed by the authors in [11].

Although public transport is considered the safest, assessing the risk of accidents on bus routes can improve the safety of transport operators. In [12], the authors corrected the existing methods for assessing the safety of bus networks by integrating the safety factors, predictive models, and risk assessment methods. The experiment showed that transport managers can use this methodology to accurately analyze safety on each route.

Infrastructure is also an important component. In [13], the authors assessed the relationship between the infrastructure deficiencies and the frequency of crashes and severity and found that a high density of access roads strongly affected the collision frequency.

To manage and minimize risks, researchers have offered various methods. In [14], the authors developed a method for using subjective video annotations to assess the risk likelihood in avoiding a vehicle collision as well as to characterize the dynamics of a vehicle and the events in classifying the accident risks. The authors in [15] developed a unified approach to substantiate the requirements for an automated traffic control system as a system of “measuring equipment—identification—vehicle traffic control”. They showed that it is advisable to use multi-criteria optimization. In the article by [16], the authors discussed topical issues of vehicle traffic control when using operational and technical control systems. The authors substantiated promising directions to improve the traffic control system using automated means of monitoring compliance with traffic rules. Thus, in [17], it was found that the installation of speed cameras in various sections showed a decrease in the total number of accidents by 70%, accidents with property damage by 53%, a decrease in accidents with injuries by 84%, and a complete absence of fatal accidents.

The relevance of research on road risk management is increasing due to the possible emergence of autonomous vehicles (AV) on public roads. The authors of the study in [18] calibrated and evaluated the responsibility-sensitive safety (RSS) model developed by Intel using possible crash situations where the minimum time to collision was less than 3 s. In each scenario, the human driver was replaced by an AV controlled by the adaptive cruise control (ACC) system based on the model predictive control (MPC) built into the RSS model. They evaluated and compared three types of safety performance: human driver, ACC model, and ACC model with built-in RSS. As a result, they found that the third one optimally improved safety performance in emergency situations. The driver has a great influence on the intention to adopt, use, and adapt AV. The study in [19] proposed an objective method to assess and predict driver confidence in AV technologies. Data on the frequency of use of advanced driver assistance systems (ADAS) and self-reported confidence ratings were collected and combined to classify driver confidence levels as low, medium, and high based, which found that the driver’s hand position during ADAS activation (which means during lane departure warning and lane keeping assist) was closely related to their confidence level.

Increasing intellectualization helps to solve the problems of road safety. The growth data collected in transport systems can greatly improve the mobility research and provide valuable mobility insights for commuters, data analysts, and transport operators. In this case, it is advisable to use machine learning methods [20][21][22].

Despite the diversity and extensiveness of the research on risk assessment in various aspects, there is a need to develop a comprehensive methodology for managing the transport system risks. The analyzed research did not consider the risks as a complex, highlighting one or more sides. First of all, they singled out a person or the influence of other factors through them indirectly. Without excluding the dominance of human factors, it is necessary to remember the importance of the vehicle technical condition, infrastructure, and organizational measures. Several studies have fully presented the classification of risks, sources, and consequences, but did not provide mechanisms by which the root causes of accidents can be influenced. At the same time, the growing array of the initial information about the accident rate requires appropriate powerful processing methods. Therefore, this study was aimed at developing a comprehensive multi-stage methodology to manage the transport system risks, based, among other things, on the modern methods of machine learning and simulation, which ensures road safety.

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