PREDICTING AND MINIMIZING THE RISK OF RAIL TRANSPORTATION OF DANGEROUS GOODS IN THE CONDITIONS OF CLIMATE CHANGE

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Abstract

The article is devoted to the study of the natural risk impact on the operation of railway industry facilities using a Bayesian network model in the GeNIe Modeler software package. Statistics of railway accidents from floods over the past few years have allowed to identify the main parameters of the model, the network structure is based on the experience and expert opinion of railway industry workers and foreign researchers. The results show that natural and climatic factors can cause serious disruptions in the operation of railway transport, and in the case of dangerous goods, create conditions for developing cascading accidents. The developed Bayesian model can be used in integrated planning and railway system management during floods.

Keywords: railway transportation risk, Bayesian network, climate change, flood

I. Introduction

According to the estimates of the United Nations Intergovernmental Panel on Climate Change extreme climate events (fires, floods, intense rainfall) are a serious threat and will occur more often, leading to disruption of various infrastructures. Nowadays, the scale of natural disasters far exceeds the human capacity to cope with them.

Rail transport is a critical infrastructure. The railway failure leads to economic damage from the displacement of the delivery time of goods, the cost of restoring equipment, potential loss of life and environmental damage. When moving dangerous goods through the territory of urban agglomerations, there is a high risk of accidents, especially in combination with weather anomalies.

Thus, the flooding in Armenia caused by intense rains in May 2024 led to the death of 4 people, the evacuation of 300 people and the wash away of more than 2.5 km of railway tracks. In August 2023, 1000 m of the Baikal-Amur mainline and 10 power transmission towers were destroyed in Buryatia as a result of cloudbursts, more than 300 people were evacuated. In 2018, due to the heat at the Pskov-Tovarny railway station, sulfuric acid leaked from the tank, by chance no one was injured.

Natural risks cannot be managed; they can only be analyzed and quantified. Railway transport is more susceptible to natural risks compared to other modes of transport, because it is less flexible in spatial terms [3]. Measures to combat climate impacts are being developed on a global scale and may be useless at the regional and local levels, as they do not take into account socio-economic opportunities, limited resources, geographical and climatic features of a particular territory. The situation is aggravated by the negligence of the staff, and wear and tear of the equipment.

Many studies have been devoted to the problem of the nature influence on the engineering system functioning. Ostankovich I. et al. [15] conducted an analysis of the extreme temperatures and snowfall risks to assess the state of the Dutch railway network. Alabbad et al. [5] performed a spatial analysis of railway infrastructure facilities (marshalling yards, bridges and crossings) during seasonal floods in Iowa. Struzhkova et al. [17] investigated the influence of permafrost on the railway network functioning. The dependence of the working capacity of the Serbian railway personnel on weather conditions was studied in [1].These studies show that the assessment of natural risks in regions exposed to extreme weather conditions is of great importance for maintaining the operability of the railway network.

In this work, a prediction and detailed analysis of a railway accident as a result of the impact of a natural factor (flooding) was performed based on the previously developed hybrid Bayes network in the GeNIe Modeler software package for a railway accident (159 variables) [4] (Figure 1). The model was tested using the example of the spring leash of the Ural River in 2024 in Orsk, the city where the last flood occurred almost 70 years ago.

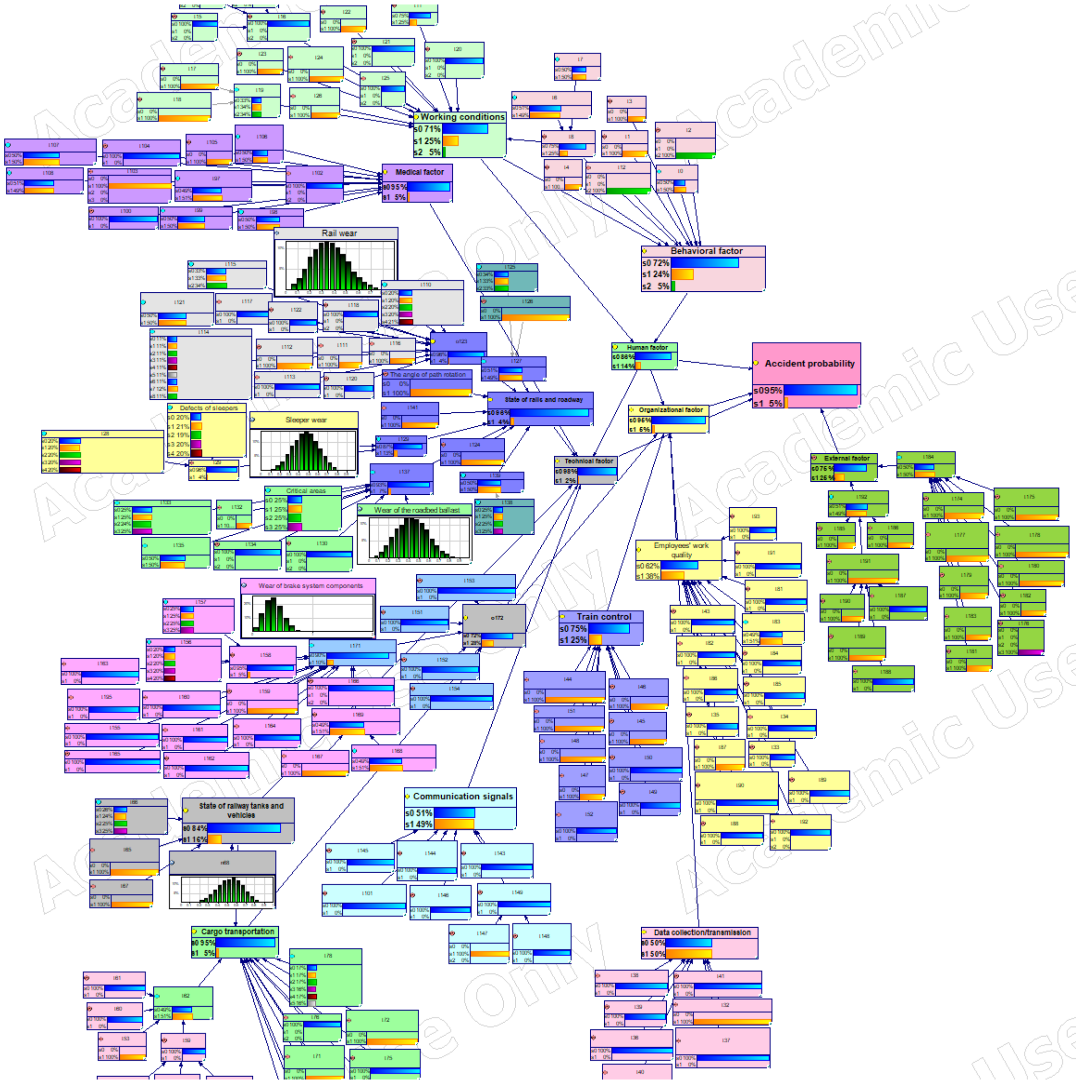

Figure 1: *The Bayesian model of a railway accident*
(the parameter names are hidden in order to preserve intellectual property)

II. Research methodology

2.1 Climate influence on the operation of railway infrastructure

The railway track is the most vulnerable element of the railway, because it is most affected by external factors. The most common meteorological factors are temperature and precipitation (snowfall, heavy rains, ice, etc.). Table 1 contains a list of possible impacts.

Table 1: *Natural phenomena and possible consequences for railway facilities [13]*

Natural hazards	Negative consequences
Geological Mudslides, landslides, flushing, subsidence, dust storms, avalanches, frost upheaval, waterlogging of territories, erosion (destruction of rocks by water, wind, man), abrasion (destruction of shores by waves)	Damage/destruction of railway tracks, embankments and slopes, falling power lines/trees, etc., blocking of railway stations
Geophysical Earthquakes, volcanic eruptions, karsts	Damage/destruction of railway tracks
Meteorological Storms, hurricanes, tornadoes, squally wind, whirlwinds, large hail, snowfall, showers, blizzard, fog, sleet, frost, drought, abnormal heat/frost, frequent change of warm/cold days, melting permafrost, lightning	Deformation and warping of railway tracks, sagging of power lines, overheating/electronic failures, fires on slopes, equipment failure, speed limitation, shortening of equipment life, the need for cooling equipment, damage to contact networks, power surges, breakdowns of alarm devices, centralization, blocking, falling of power lines/ trees, etc., freezing, icing, increased fragility of rails, freezing of switches, blocking of railway stations, accumulation of snow along railway tracks
Hydrological Flooding, high water, congestion, wind surges, rising groundwater levels, earthquake flood, typhoons, storms, changes in the strength and direction of waves	Inundation, damage to railway embankment and slope, erosion of bridge supports, railway tracks, contact networks, water penetration into underground structures, tunnels, flooding of coastal infrastructure
Wildfires Forest, peat, steppe, underground fires of combustible minerals	Thermal effects on all metal, combustible elements of railway equipment

Table 2: *Possible flood factors*

Natural and climatic	Non-climatic (organizational)
The amount of the winter precipitation, the water supply in the snow cover, the temperature condition before the start of spring melting, soil moisture in autumn, the snowmelt intensity, the terrain of the riverbed, the slope of rivers, the landscape of the area (forest belts, steppe or wooded soil with underlays), the presence of constrictions in the riverbed, the presence of obstacles to the flow, the earthquake impact, landslides, landslides, rising groundwater levels, deep freezing of the soil, snow reserves and its rapid melting, terrain.	The water level in the dam site, the technical condition of hydraulic structures, the distance from the dam, insufficient water discharges, design errors, poor-quality construction and maintenance, reduction of river capacity in the area of bridges, narrows, buildings in the floodplain, losses as a result of business activities, economic development, urban planning.

In this study, the focus is on floods, since the railway is the most vulnerable mode of transport to external influences [11]. In addition, floods occupy the first place among natural disasters in Russia in terms of frequency, area of distribution and total material damage [14]. The scale of floods depends on many natural and organizational factors (see table 2). It is necessary to take into account their synergistic effect, because in combination with each other, these factors increase the risk of an accident.

2.2 Data availability

The Bayesian approach makes it possible to combine frequency data with domain knowledge. Numerical values of probabilities can be extracted from databases, based on expert opinion, or determined by a combination of the above. Experts point out serious problems in collecting statistical information on the railway state due to climate impacts [5, 9, 11, 14]. This is due to the following factors:

- Complexity of meteorological observations, poor knowledge of the water regime of rivers, lack of hydrological observation posts, especially at the regional and local levels
- Lack of a clear algorithm for reporting railway accidents
- Deliberate misrepresentation of information by responsible persons in order to get away with it
- Inconsistency or inaccuracy of the data

Beyond that, the railway accident registration as a result of the effects of floods is not conducted anywhere. Therefore, this paper combines two sets of statistical data on floods and railway accidents [8] when creating two interconnected Bayesian networks. The first network is designed to calculate the probability of an accident as a result of flooding. The results of its calculates are partially used as input data for the launch of the second network, which determines the type of possible railway accident and the amount of possible damage.

2.3 Construction of model

The first data set contains more than 200,000 records on 50 features of past floods. The second data set includes more than 100,000 records of railway accidents abroad in 160 parameters from 1975 to 2022. These initial data were processed in the Python programming environment: cleared of omissions, invalid character and zero values, duplicates; all quantitative characteristics were given in the International System of Units, some of them are categorized for the convenience of building Bayesian models. After performing an Exploratory Data Analysis, only a few of the recorded data parameters were identified.

Flood data includes the following 19 features out of 50: relief drainage, drainage systems, river management, deforestation, urbanization, climate change, dam quality, siltation, incursions, effective disaster preparedness, vulnerability of coastal areas, landslides, deterioration of infrastructure, loss of wetlands, inadequate planning, political factors, probability of an accident.

Data on railway accidents include the following 18 features out of 160: month of accident, type of accident, dangerous cars, evacuated people, visibility, weather conditions, type of track, total tonnage, derailed loaded freight cars, derailed loaded passenger cars, cost of track damage (Figure 2).

The formatted data was imported into the GeNIe software package [10]. The columns in the data files correspond to variables (future nodes of the network), and the rows (records) correspond to various values of these variables. Continuous variables have been discretized. Based on the knowledge of the subject area [1, 2, 16, 17], the basic structures of Bayesian networks have been created. The Greedy thinning algorithm was used as the main algorithm for structural learning.

Report Year	Accident Month	Time	Accident Type	Hazmat Cars	Persons Evacuated	Temperature	Visibility	Weather Condition	Track Type	Maximum Speed
2017.0	6.0	2:14 PM	Derailment	0.0	149	65.0	Day	Clear	Yard	10.0
2017.0	6.0	2:14 PM	Derailment	0.0	0	65.0	Day	Clear	Yard	10.0
1981.0	4.0	7:20 AM	Side collision	0.0	0	28.0	Day	Snow	Yard	4.0
2007.0	1.0	7:10 AM	Derailment	0.0	0	56.0	Day	Cloudy	Industry	4.0
2017.0	10.0	3:55 AM	Hwy-rail crossing	7.0	0	66.0	Dark	Clear	Siding	0.0
2017.0	10.0	6:00 AM	Derailment	0.0	0	60.0	Dawn	Rain	Yard	3.0
2017.0	12.0	7:57 PM	Obstruction	0.0	0	62.0	Dark	Cloudy	Main	80.0
2016.0	12.0	6:30 AM	Other (describe in narrative)	0.0	0	16.0	Dark	Clear	Main	60.0
2017.0	3.0	8:45 AM	Derailment	23.0	0	44.0	Day	Rain	Industry	10.0
2017.0	4.0	10:40 AM	Derailment	0.0	0	38.0	Day	Clear	Yard	10.0
2006.0	10.0	5:10 PM	Derailment	0.0	0	70.0	Day	Clear	Yard	5.0
2010.0	6.0	10:00 PM	Derailment	1.0	0	55.0	Dark	Cloudy	Yard	6.0
2013.0	5.0	6:15 PM	Derailment	0.0	0	48.0	Day	Cloudy	Yard	7.0
2013.0	11.0	1:20 AM	Raking collision	0.0	0	0.0	Dark	Clear	Yard	3.0
2006.0	3.0	3:30 AM	Derailment	22.0	0	31.0	Dark	Clear	Yard	5.0
2006.0	3.0	9:55 AM	Derailment	3.0	0	45.0	Day	Cloudy	Yard	10.0
2014.0	3.0	6:00 PM	Derailment	0.0	0	40.0	Dusk	Cloudy	Industry	4.0
2011.0	4.0	6:15 AM	Derailment	0.0	0	42.0	Dawn	Rain	Yard	5.0
2007.0	7.0	10:25 AM	Derailment	0.0	0	75.0	Day	Clear	Siding	1.0
2006.0	10.0	4:50 AM	Derailment	4.0	0	40.0	Dark	Rain	Yard	10.0
2010.0	7.0	6:05 PM	Side collision	0.0	0	85.0	Day	Clear	Yard	6.0
2010.0	5.0	11:22 AM	Hwy-rail crossing	0.0	0	82.0	Day	Cloudy	Main	38.0
2010.0	5.0	5:45 AM	Other impacts	0.0	0	65.0	Dark	Clear	Yard	7.0
2012.0	5.0	6:00 AM	Other impacts	0.0	0	42.0	Dawn	Clear	Yard	6.0
2006.0	11.0	11:18 AM	Hwy-rail crossing	1.0	0	75.0	Day	Clear	Main	58.0
2016.0	8.0	5:30 AM	Other impacts	0.0	0	70.0	Dawn	Clear	Yard	16.0
2016.0	8.0	5:30 AM	Other impacts	1.0	0	70.0	Dawn	Clear	Yard	16.0

Figure 2: *Fragment of the data set on railway accidents*

As a result, two Bayesian models were obtained, including a number of factors described in Table 2. Figure 3 shows that climate changes do not directly affect the probability of an accident, but are significant with a low organization of services in case of an accident (see Figures 3 and 4).

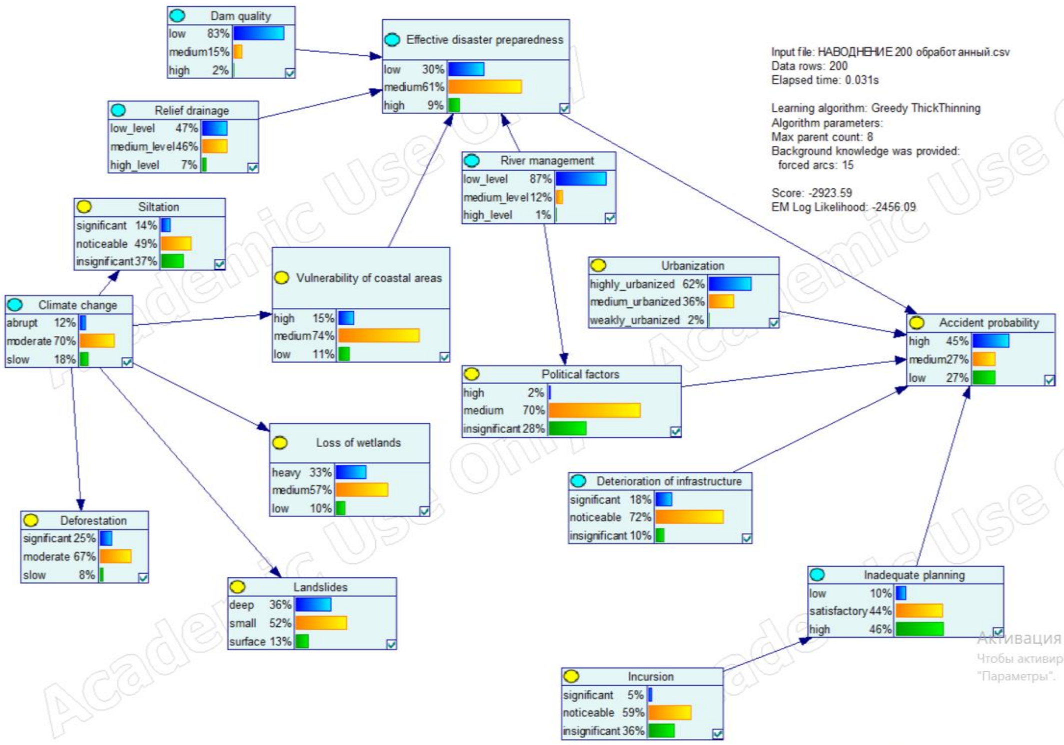

Figure 3: *Bayes network for calculating the probability of an accident*

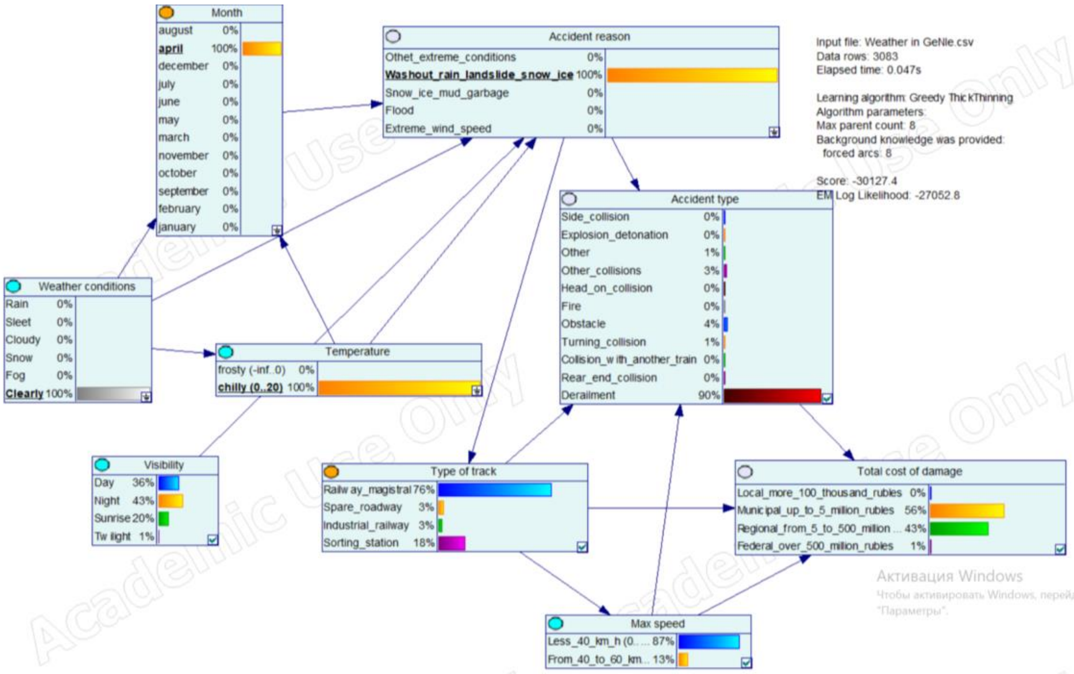

Figure 4: *Bayes network for determining the consequences of a railway accident*

2.4 Evaluation of model accuracy

The model accuracy was evaluated in two ways. Based on the first set of flood data, a new data file was generated to verify the accuracy of the first model with 200 records. The second model was evaluated by 10-fold cross validation. In this case, the original set of data on railway accidents was divided into 10 equal parts. The first nine parts participated in the training of the model, the last 10th part was used as a test sample. A graphical representation of the model accuracy is presented in the form of ROC curves with an overall accuracy of 89 and 75% for the main nodes of the network, respectively (Figure 5). Curves located above the diagonal and tending to the upper left corner represent good forecast results.

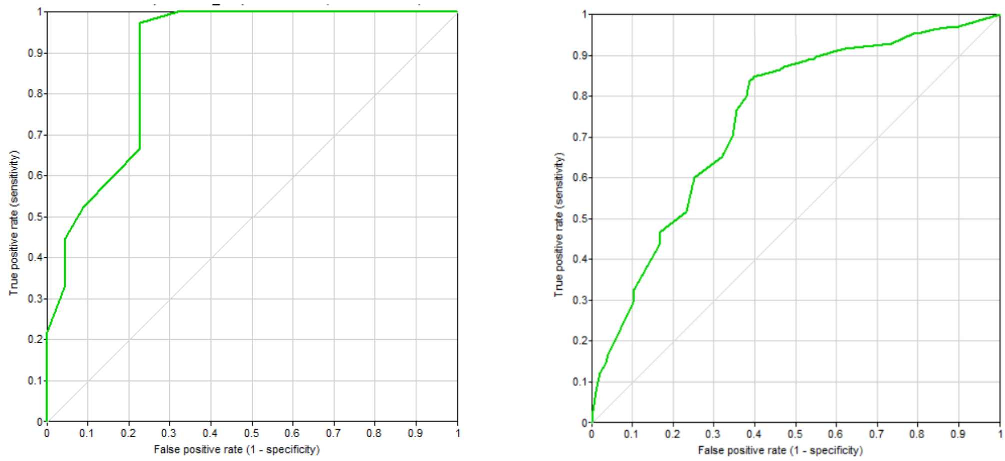

Figure 5: *ROC-curves for nodes ''Accident probability = high'' and '' Total cost of damage = Regional''*

II. Results

3.1 Case study

In April 2024, a number of Russian regions were exposed to catastrophic flooding caused by the spring flood on the Ural River. The city of Orsk in the Orenburg region suffered the most, for which flooding is a rather rare phenomenon. The last ones happened in 1922, 1942 and 1957. In Orsk, as a result of the destruction of the dam, about 6.6 thousand residential buildings, summer cottages and vegetable gardens were flooded (Figure 6). The total damage is estimated at more than 21 billion rubles. The flood led to the destruction of buildings and communications, the cattle death, the erosion of sewers, urban landfills, cemeteries and animal burial grounds, which created a threat of contamination of drinking water and human diseases. This real flood case was chosen to demonstrate the calculations of the resulting Bayesian networks.

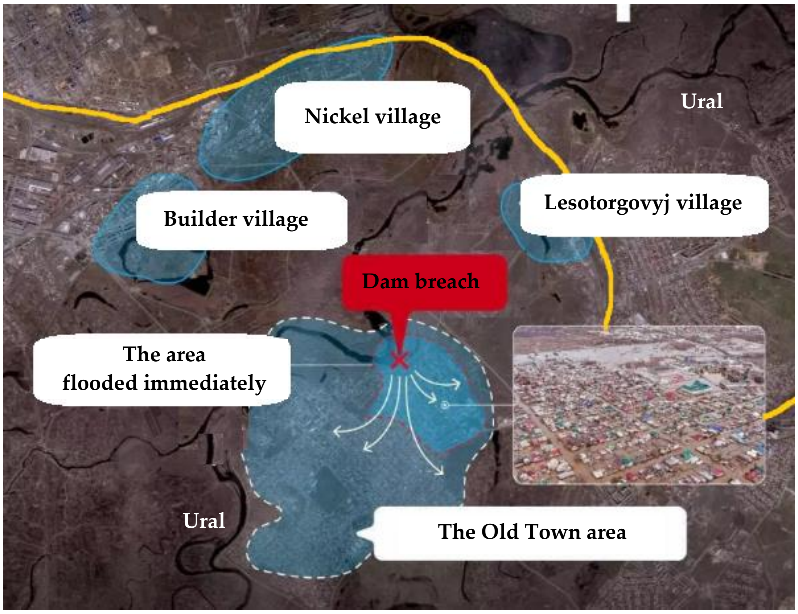

Figure 6: *Scheme of flooding in Orsk (the railway location is indicated in orange) [18]*

3.2 Analysis of calculation results

The probabilistic models have been edited for the case under consideration. The calculation of the networks showed updated posteriori probability distributions in the nodes of the networks. Further, the mutual influence of network parameters was analyzed.

Sensitivity analysis showed that the critical factors in flooding are "Disaster preparedness", "Level of urbanization", "Deterioration of infrastructure", which significantly affect the main target variable "Accident probability". This means that even minor changes in the colored nodes have a significant impact on the risk of an accident (Figure 7).

The ranking of flood factors showed that the most critical of them were "River management at zero level", "Poor quality of hydraulic structures", "Deterioration of infrastructure" (Figure 8). If the city's leadership had taken these factors into account, it would have been possible to prevent the developing of the spring flood up to a federal emergency.

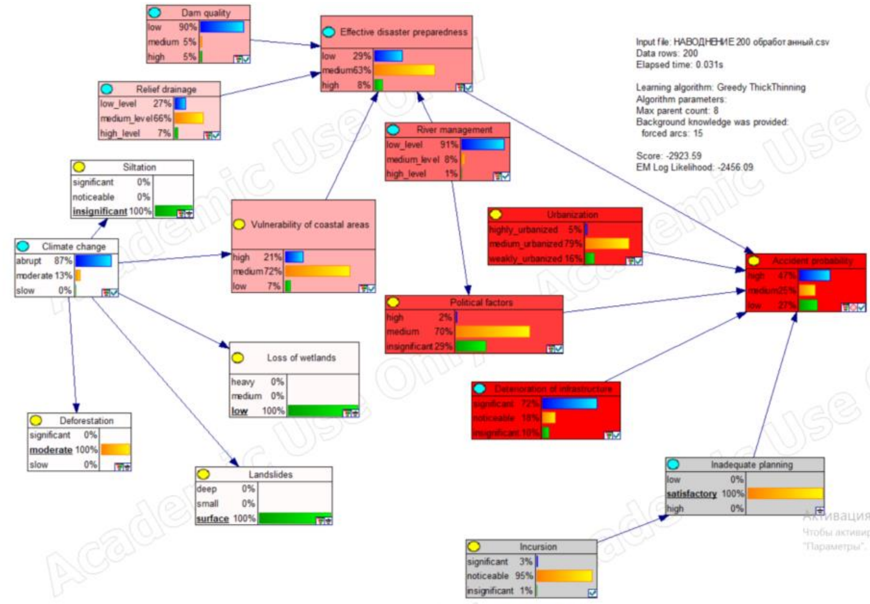

Figure 7: *Sensitivity analysis of the main node*

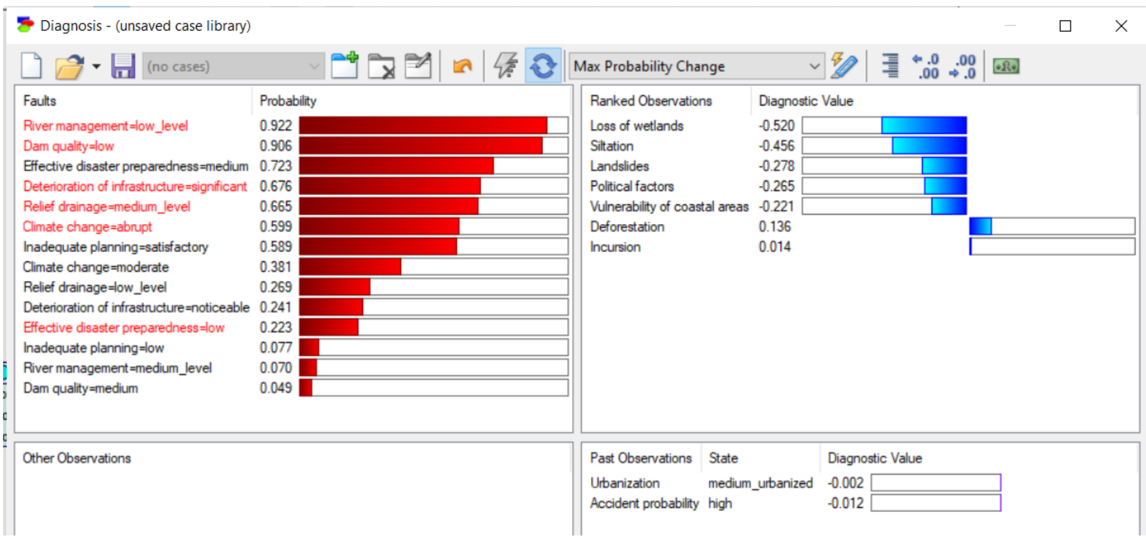

Figure 8: *Ranking of flood causes*

The developed networks are only an approximate model for predicting flood risk, since they are based on foreign statistics without taking into account the location of the area. At the moment, the accumulated scientific material is not enough to create a more complex and realistic flood model in the region under consideration. The study should be continued in the direction of collecting data covering a wider range of climatic factors and creating a database on accidents on domestic railways.

In the qualitative assessment of flood factors in Orsk, it is worth noting the following:

1. Features of the Ural River. The river has the largest water content among European rivers due to the uneven flow. The difference in river flow between high-water and low-water years can be 10 times. The depth of the river is small, but due to elevation differences in the source and mouth of the river, its speed can reach up to 10 km/h. [6]

2. High rate of urbanization. The massive construction of residential and commercial buildings, roads in the floodplain led to a 4-fold reduction in the natural floodplain.

IV. Conclusion

The article discusses the features of natural accidents on the railway due to floods in the context of climate change. The use of two thematic data sets (on floods and on railway accidents) is proposed. As a result, two Bayesian networks have been created to predict railway accidents in flood conditions. Using the example of a real flood in Orsk, the effectiveness of using the Bayesian approach for a comprehensive analysis of a railway accident as a result of a flood, including sensitivity analysis and ranking of flood causes with color visualization, is demonstrated.

The proposed probabilistic models can help in creating strategies for managing the consequences of natural risks on the railway, especially in cases of dangerous goods transportation. This will increase the reliability of the railway infrastructure in the face of climate change.

Among the preventive measures, the following should be highlighted:

- A ban on the construction and management of economic activities in floodplain areas and lowlands, which represent a permanent potentially dangerous area for urbanism
- Creation of a continuous monitoring system in vulnerable regions to collect climate data and take into account the impact of climate change in the design and operation of railway infrastructure

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References

[1] Aleksic, D., Markovic, M., Vasiljevic, M., Stojic, G., Pavlovic, N., Tanackov, I. (2017). Analysis of impact of meteorological conditions on human factors in estimating the risk of railway accidents. *Transport*, 33(5), 1-14. doi: 10.3846/16484142.2017.1332684

[2] Antonioni, G., Landucci, G., Necci, A., Gheorghiu, D., Cozzani, V. (2015). Quantitative assessment of risk due to NaTech scenarios caused by floods. *Reliability Engineering and System Safety*, 142, 334–345. doi: 10.1016/j.ress.2015.05.020

[3] Changnon, S. A. (2009). Impacts of the 2008 Floods on Railroads in Illinois and Adjacent States. *Transactions of the Illinois State Academy of Science*, 102, 181-190. URL: https://ilacadofsci.com/wp-content/uploads/2013/03/102-17MS2819-print.pdf. Accessed 30 Jan 2024

[4] Chikir, M.V., Poluyan, L. V. (2023). Bayesian Network Modeling for Analysis and Prediction of Accidents in Railway Transportation of Dangerous Goods. *Proceedings of the 6th International Conference on Construction, Architecture and Technosphere Safety ICCATS 2022*, 554-563. doi: 10.1007/978-3-031-21120-1_53

[5] Cikmaz, A.B., Alabbad, Y., Yildirim, E., Demir, I. A. (2024). Comprehensive Flood Risk Assessment for Railroad Network: Case Study for Iowa. Available via URL: https://www.research square.com/article/rs-4171938/v1. Accessed 21 Jun 2024

[6] Climate and waters, orensteppe.org. Available via URL: http://orensteppe.org/content/rek a-ural. Accessed 3 Mar 2024

[7] Cozzani, V., Antonioni, G., Landucci, G., Tugnoli, A., Bonvicini, S., Spadoni, G. (2014). Quantitative assessment of domino and NaTech scenarios in complex industrial areas. *Journal of Loss Prevention in the Process Industries*, 28, 10-22. doi:10.1016/j.jlp.2013.07.009

[8] Datasets, www.kaggle.com. Available via URL: https://www.kaggle.com/datasets. Accessed 1 Jun 2024

[9] Gang, Y., Dinghao, L., Jiayi, X., Ye. Ken, W. (2023). A Novel Approach for Modeling and

Evaluating Road Operational Resilience Based on Pressure-State-Response Theory and Dynamic Bayesian Networks. *Applied Sciences*, 13(7481), 1-33. doi: 10.3390/app13137481

[10] GeNIe 4.1, bayesfusion.com. Available via URL: https://www.bayesfusion.com/2023/09/15/genie-4-1/ Accessed 10 Jun 2024

[11] Gonzva, M., Barroca, B., Gautier, P. E. (2015). A modeling of disruptions cascade effect within a rail transport system facing a flood hazard. *Journal of Polish Safety and Reliability Association Summer Safety and Reliability Seminars*, 6(3), 53-60.

[12] Khakzad, N. (2018). Impact of wildfires on Canada's oil sands facilities. Natural Hazards and Earth System Sciences, 18(11), 3153-3166. doi: 10.5194/nhess-18-3153-2018

[13] List of possible effects of climate change for transport infrastructure facilities. Available via URL: https://mintrans.org/docs/Публикации/перечень%20повреждений%20ОТИ%202023.pdf. Accessed 10 Jun 2024

[14] Makhinov, A.N., Kim, V.I., Voronov, B.A. (2014). The 2013 *Amur Basin flood: causes and consequences. Vestnik* of Far Eastern Branch of Russian Academy of Sciences, 2, 5-14.

[15] Oslakovic, I.S., Maat, H., Hartmann, A., Dewulf, G. (2013). Risk assessment of climate change impacts on railway infrastructure. *Proceedings – EPOC 2013 Conference*, 1–16.

[16] Simonov, V., Osadchy, O. (2014). The nature of the occurrence of floods, inundations and the characteristics of their damaging factors. *Scientific and educational tasks of civil defence*, 1, 9-19.

[17] Struchkova, G.P., Kapitonova, T.A., Levin, A.I. (2019). Safety of Railway Transport Facilities Operating in Extreme Climatic Conditions. *Advances in Engineering Research*, 188, 328–332. doi: 10.2991/aviaent-19.2019.61

[18] Ural Flood 2024, commons.wikimedia.org. Available via URL: https://commons.wikimedia.org/wiki/File:Ural_Flood2024.jpg?uselang=ru. Accessed 10 Jun 2024