Modelling the accidental oil spills at potentially hazardous facilities in the Arctic zone of Krasnoyarsk Krai

Y Grebnev1,2, A Moskalev1

1Siberian Federal University, Krasnoyarsk, Krasnoyarsk, Svobodny Pr., 79m Russia
2Forecasting Department of the Central Office of the Russian Ministry of Emergency Situations in Krasnoyarsk Krai, Krasnoyarsk, Mira Pr., 68, Russia

yaroslav.grebnev@gmail.com, ak_moskalev@mail.ru

Abstract. Intensified human activity in exploiting the natural resources leads to increasing technogenic load on Arctic’s fragile ecosystem. The boost in industrial facilities is associated with a growing number of stationary fuel reservoirs poorly monitored due to their considerable remoteness and extreme weather conditions. The 2020 emergency in the Arctic zone of Krasnoyarsk Krai exposed the lack of adequate methods for risk assessment and behaviour in case of accidents at potentially hazardous facilities. The existing methodologies for assessing the area of spill following an accidental depressurisation present significant limitations. Most methodologies are based on analytical models not taking into account the physics of processes. This work uses modelling with neural networks of oil spill at the potentially hazardous object located in the Arctic territory of the Krasnoyarsk Krai. The software used was neural network simulator NeuroPro, developed in the Institute of Computational Modelling of Krasnoyarsk Scientific Centre of SB RAS. For training the neural network there were used daily operational data on fourteen main vectors affecting the propagation rate. The neural network modelling of the accidental oil spill during the depressurization of one of the fuel tanks at potentially hazardous facilities in the Arctic zone in 2020 correlated perfectly with the real data.

1. Introduction

The Arctic is a unique natural ecosystem that requires special attention and approaches for the development of its rich resources. Intensification of extraction of natural resources in the Arctic region results in greater anthropogenic pressure on the ecosystem. There happen more and more man-made accidents, leading to ecological disasters. An example of such an impact is the emergency situation that occurred on the territory of TPP-3 in Norilsk, where depressurization of a reserve tank with diesel fuel accounted for pollution of land and water bodies with a total area of more than 16 km² (along the Dal'nyak and Ambarnaya rivers alone, 2.93 km² and 13.18 km², respectively). This caused irreparable damage to the ecology of a particularly sensitive Arctic area. Oil and oil product spills resulting from such man-made accidents have a significant impact on the environment, and restitution for such accidents requires costly in terms of environmental measures technologies for land remediation and ecological rehabilitation of the area which suffered from such spillage.

One of the state functions of the Russian Federation regulating nature management in the Arctic is protection of the population and nature there from the impending threats of natural and man-made accidents; provision of scientific and technical support for timely forecasting, development and
implementation of preventive measures, which is born out by the normative acts of the Russian Federation.

Assessing risks accompanying natural and man-made accidents implies longitudinal processing of monitoring data concerning hazards; in addition, climatic conditions, geographical location, hydrography and other indicators must be taken into consideration as well. The methodologies applied now for assessment of spillage areas in case of accidental depressurisation reveal a series of restrictions. For this reason, the methodology generally accepted in the scientific community, which would give the assessment and calculation of mandatory means for liquidation of accidents related to oil products spillage, has not been accepted so far.

In this connection the urgent scientific and technical task is to estimate territorial risks of ecological catastrophes and to create models of forecasting possible events in their dynamic development.

The problem of assessing the risk of man-made disasters requires the use of modern methods of forecasting and mathematical modelling [1]. The development of environmental monitoring systems, inexpensive and accessible computational systems, and environmental monitoring devices has resulted in large volumes of data that need to be processed. To solve the problems of processing large amounts of data, machine learning methods are now being extensively used [2].

Numerous works are devoted to the analysis of consequences of environmental pollution [3-7]. The problems of regulating management of polluted lands and water bodies were covered by a number of researchers [8-11]. It is worth mentioning that countless normative-legal acts and methodological documents regulate rational nature management and ecology, and also normalize the activity of monitoring systems in various departments, determine the procedure of information exchange for the purpose of “preventive activities in terms of disasters and emergencies of natural and technogenic character” [12].

The problem of emergency forecasting is a crucial and complex scientific task, whose solution lies in the integration of scientific directions and research at the intersection of such sciences as physics, mathematics, ecology, biology, geology, etc. It also demands for uniting the monitoring information of various departments and organizations into a single database and organization of operational information exchange in real time. Adoption of this approach will be able to generate a decision-making support system based on mathematical models with physical parameters of the environment and include formalized scenarios of events development with an algorithm of actions on predicted risks in order to minimize them. The system of decisions support makes it possible to eliminate errors associated with incorrect assessment of the situation due to incomplete data or lack of experience in assessing such data. This can bring trouble for decision makers who supervise preventive, rescue and other urgent works. At present, the approach that includes generic analysis of risks of emergencies and operational monitoring data and statistical methods of their processing is considered the most reasonable one for creating forecasting systems [13]. Individual man-made accidents can be predicted with methods of catastrophe theory and nonlinear mechanics [14]. Not to mention that in practice the described approaches and methods have not yet found application in forecasting agencies.

2. Materials and methods
Analysis of regulatory documents dealing with prevention and liquidation of emergencies at aggrieved enterprises, examination of statistical data on natural and man-caused accidents that have occurred in the Arctic territory of Krasnoyarsk Krai over the past 20 years demonstrates the low efficiency of the present approaches based on average statistical indicators of emergencies for the region as a whole. Thus, we needed to apply an approach that considers realistic estimates of the probability of emergency situations at facilities which due to their situation in specific areas can be hazardous.

The previously used approaches, in principle, have not met the requirements set. To solve the above-described problems and to prognose man-caused emergencies at such facilities located in the Arctic zone, in this work we applied the method of forecasting with neural network algorithms, as this method allowed us to neutralize the aforementioned disadvantages of other forecasting methods.
The neural network forecasting method is a powerful and flexible tool for solving problems of modelling and forecasting behavior of complex systems. In this paper we modelled the emergency situation of May-June 2020 at OJSC Norilsk-Taimyr Energy Company. The task of modelling by a neural network is reduced to training and testing the network with predetermined characteristics. To solve the task aimed at projection, we selected the NeuroPro 0.25 neural network simulator developed by V.G. Tsaregorodtsev at the Institute of Computational Modelling, KSC SB RAS, under the supervision of A.N. Gorban [15].

For the study we used multilayer neural networks which apply a sigmoidal function:

$$f(x) = \frac{x}{c+|x|}$$

(1)

where $c$ is neuron’s characteristic;

$x$ – a set of input parameters.

The neural network training algorithm was as follows (Figure 1):

![Figure 1. Neural network training algorithm](image)

(& is a sign for “if”: a process repeats if the percentage of valid results is low, and the process is to be analysed if the percentage of valid results is sufficient).

The parameters used as inputs were chosen empirically. The dimensions of the input layer varied according to the number of input parameters, which differed from experiment to experiment. Notably,
that all parameters were taken from the nearest weather station at the date of spill detection. Interpolation of meteorological data and use of weather forecast in calculations is a separate complex problem, the solution of which cannot be given here. While preparing for training the neural network, we compiled a database with parameters (data) about an oil spill that occurred in Norilsk. The data were collected from the Main Department of the Russian Ministry of Emergency Situations for Krasnoyarsk Krai, Agency of Krasnoyarsk Krai for the Civil Defense, Emergency Situations and Fire Safety. The following feature vectors were generated and taken to the input of the neural network:

1. Time passed from the start of the oil spill.
2. Longitude.
3. Latitude.
4. Mass of oil spilled.
5. Area of oil slick, sq km.
6. Mass of oil dispersed into water, tonnes.
7. Wind speed, m/s.
8. Speed of water flow, m/sec.
9. Type of oil product.
10. Wind direction.
11. Air temperature at the start date of the spill.
12. Ice phenomena (some rivers have ice remaining).
13. Amount of precipitation.
14. Volume of oil products in the oil reservoir, tonnes.

Dimensions of the feature values mentioned above were set empirically, the whole number reached fourteen (it stands to mention that experiments were conducted with other number of features as well). The multilayer neural network with 8 layers and the number of neurons at the hidden layer equal to 112 show good results in practice. Our calculations showed that the percentage of reliability of the obtained results fell in the range of 87-92%. The resulting values form training vectors, which were compared with the area of oil spill spread in the Daldykan River area in Norilsk.

3. Results and discussion
An accidental oil product spill occurred in May 2020 as a result of depressurisation of a reserve tank with diesel fuel (total tank volume was 30,000 m3) on the territory of Thermal Power Plant No. 3 of OJSC Norilsk-Taimyr Energy Company. This ended in land contamination with diesel fuel entering Bezymyannyi Creek, which flows into the Daldykan River, and further into the Ambarnaya River and Lake Pyasino. Using data of daily monitoring on spreading of oil products, data on polluted area and other parameters described above, we performed neural network training and modelling of the situation development. The end results were compared with the real monitoring data in the area suffered from emergency.

Our findings based on the neural network results and the real values of the oil spillage area are shown in Table 1 and in Figure 2.

| Date       | Real area, m² | Projected area, m² | Deviation |
|------------|---------------|--------------------|-----------|
| 31.05.2020 | 4400          | 4640               | 240       |
| 03.06.2020 | 8100          | 8460               | 360       |
| 06.06.2020 | 10300         | 10360              | 60        |
| 09.06.2020 | 12000         | 13820              | 1820      |
| 12.06.2020 | 13500         | 13460              | -40       |
| 15.06.2020 | 14800         | 14860              | 60        |
Figure 2. Comparative graph of real and simulated oil distribution.

The oil spillage rate during this period was relatively constant, indicating a relatively steady rate of spreading of oil products on the surface of the Daldykan, Ambarnaya and Pyasino Rivers. On June 6, 2020, they started to apply sorbents and containment booms with such a pace that brought an error in the model of oil slick spread (point of maximum deviation). After the application of sorbents and booms, the rate of the oil slick spread began to decrease significantly, which corresponds to the actual data and simulated values. A generalised model of development is presented in Figure 3.

Figure 3. A generalised model for oil products spread.

June, 18, 2020 marked the end of engineering works to create an artificial stream “Bezymyanny” to divert water from the main polluted channel. Further spillage was prevented. The results obtained
illustrate the possibilities of applying models using neuroarchitecture for the tasks to forecast oil spill in the Arctic zone.

When performing risk forecasting of possible accidental spills, one should also take into account their causes. Having investigated all possible scenarios of events, we estimated the most probable scenarios of accidents at three objects of the fuel and lubricant storage No. 2 of the OJSC Norilsk-Taimyr Energy Company, which were not subjected to emergency oil spill on May, 29, 2020.

Undoubtedly, actual values of spills should be expected to be lower than those described, due to the fact that possible spills were calculated for the entire volume of oil products.

\[ F_p = f_sV_l, \]

where \( f_s \) – spill coefficient, m-1 (in the absence of data it can be taken as 20 m-1 for spillage on ground surface, 150 m-1 for spillage on concrete or asphalt surface);

\( V_l \) is the volume of liquid that came into the environment when the tank was depressurized, m3.

Scenario 1. Sudden emergency depressurization of an above-ground vertical steel storage tank RVS-400. Complete depressurization of above-ground storage tank with a 400 m3 maximum volume and “arctic” diesel.

The storage of oil products necessitates using above-ground metal tanks made of carbon steel.

The tanks are installed in a tank farm with a bund wall, which is 0.8 m high and 1.5 m wide.

The interior of the tank farm is unpaved ground. The surface outside the tank farm is unpaved ground.

Residual oil product layer height within the tank farm bund after pumping out oil products is calculated based on the accepted average value of the spill residual layer thickness equal to 0.053 m.

Scenario 2. Oil product emergency spillage when a tanker truck with oil product (diesel fuel, oil) is located at a tanker loading/unloading site for tankers with the volume of 12 m3.

Scenario 3. Sudden emergency depressurization of the above-ground horizontal steel storage tank RGS-8. Complete depressurization of the above-ground storage tank with 8 m3 maximum volume for storing oil products (oil).

For the storage of oil products, the use of horizontal metal tanks made of carbon steel is prescribed. The tanks are installed in a container, in the lower part of which there is a pallet divided into sections. The height of the pallet walls is 0.5 m.

The container area is 14.6 m2. In the event of a sudden depressurization of the tank, the actual spill area would be 14.6 m2 (within the container).

The residual oil product layer height within the container after pumping out the oil is calculated based on the assumed residual spill height equal to 0.55 m.

After describing 3 scenarios of event development at the potentially hazardous facility at OJSC Norilsk-Taimyr Energy Company in the Arctic zone, where an emergency oil spill has already occurred, a calculation was performed using previously trained neural network to identify maximum oil product spills and maximum contaminated area under these scenarios. Projected maximum volumes, volume of spilt oil products and spill areas in case of accidents at the site facilities are presented in Table 2.

| Scenario | Site | Character of spill | Max volume of spill, m³ | Spill area, m² |
|----------|------|--------------------|-------------------------|--------------|
| 1        | Above-ground storage tank RVS-400 | Diesel fuel spill when the tank is 100% depressurized | 400          | 76000        |
| 2        | Tanker loading/unloading | Gasoline spill when the tanker is 100% | 12           | 720          |
The calculated values indicate the need for preventive measures at the site of the RVS-400 tank calculated under Scenario 1 and the organization of continuous monitoring, as the spill area is quite high and will lead to contamination of water bodies (the Daldykan River, Pyasino Lake and the Ambarnaya River) of the Arctic zone and may cause serious ecological consequences in the already disturbed ecosystem of these water bodies.

4. Conclusion
This article outlined using neural network algorithms to build a situation model of emergency development with sudden and complete destruction of a diesel fuel tank with the volume of 3,000 tonnes, which took place in May 2020. Possible scenarios of emergency situations at OJSC Norilsk-Taimyr Energy Company were also considered in the article. The results of the present work are proposed to be used for planning measures to prevent emergencies and developing effective methods for dealing with man-made accidents at potentially hazardous facilities located in the Arctic zone.

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