Differential neural network approach in information process for prediction of roadside air pollution by peat fire

V Lozhkin\(^1\), D Tarkhov\(^2\), V Timofeev\(^1\), O Lozhkina\(^1\) and A Vasilyev\(^2\)

\(^1\) St. Petersburg University of State Fire Service of EMERCOM of Russia, 196105, Moskovsky, 149, St. Petersburg, Russia
\(^2\) Peter the Great St. Petersburg Polytechnic University, 195251, Polytechnicheskaya, 29, St. Petersburg, Russia

E-mail: olojkina@yandex.ru

Abstract. The paper presents a novel differential neural network model estimating the dispersion of CO emissions from a peat fire near a highway. We have developed approaches for the optimization of the model on the base of simulated and experimental measurements of CO concentrations in the area of dispersion of the smoke cloud. The numerical solutions of the problem are presented in the form of neural network approximations by the Gaussian model and in the form of neural network approximate solutions of partial differential equations. The trained neural network model can be used for the prediction of emergency when wind speed and direction and other fire parameters are changing. The method is also recommended for the development of air quality monitoring and predicting information systems.

1. Introduction

Peat deposits are found in many places around the world, but the world's largest peatlands are the West Siberian Lowland, the Hudson Bay Lowland, and the Mackenzie River Valley [1]. The peat ecosystem is the most efficient carbon sink on the planet, for that reason, peat fires are significant sources of carbon dioxide, other greenhouse gases, carbon oxide and other pollutants, which may be a serious human health concern [1, 2]. Peat can burn deep underground for meters, even in damp conditions and in winter time under the snow layer. Peat fires are difficult to extinguish, and severe fires in peatlands can last for months. Winter peat fires are often smoldering fires that create a lot of smoke because of incomplete combustion and result in greater emissions of carbon monoxide and other harmful substances [3-6]. If a peat fire develops near a motorway, the smoke from the burning peat-bog reduces the visibility, makes the breathing difficult, affect human nervous and cardiovascular systems and may finally result in traffic accidents or in an emergency. Such an emergency, caused by a peat fire, lasted in Irkutsk Region (situatated in Siberia) near the Federal Motorway P-255 “Siberia” from 26.10.15 to 15.01.16.

Atmospheric chemical transport models are widely used for developing air quality management strategies [7-13], however, the temporal and spatial estimates of emissions from wildfires, including peat fires, are problematic because of uncertainties in the size and location as well as their temporal and spatial variability [7].

Development of functional information systems allowing modeling of such situations without resolving differential equations in partial derivatives for different sets of input parameters is of great interest. The capability of neural network models to learning and optimization using the results of
observations and numerical calculations as the problem parameters (e.g. wind speed and direction, the area of the fire, the intensity of emissions, etc.) is their important advantage [14-19]. Thus, the aim of the present study was to develop and investigate a neural network model for the prediction of CO concentration in the area of a peat fire considering heterogeneous information from simulated and experimental measurements for the Federal Motorway P-255 "Siberia".

2. Modeling methodology

2.1. K-theory approach

According to Berlyand [20], such parameters as instant concentrations of CO, pulsed deviations from these values and the velocity of the CO dispersion should be taken into consideration while developing an emission model of a peat fire near a motorway. The problem can be simplified by the application of the turbulent diffusion model [20-23]:

$$\frac{\partial q}{\partial t} + u \frac{\partial q}{\partial x} + v \frac{\partial q}{\partial y} + w \frac{\partial q}{\partial z} = \frac{\partial}{\partial x} \left( k_x \frac{\partial q}{\partial x} \right) + \frac{\partial}{\partial y} \left( k_y \frac{\partial q}{\partial y} \right) + \frac{\partial}{\partial z} \left( k_z \frac{\partial q}{\partial z} \right) - \alpha q,$$

(1)

where \( q \) is the concentration of pollutant (g/m\(^3\)); \( x \) and \( y \) are the horizontal axis (m); \( z \) is the vertical axis (m); \( t \) is the time (s); \( u, v, w \) are the components of the average CO transfer speed along the axes \( x, y, z \), respectively, (m/s); \( k_x, k_y, k_z \) are the components of the exchange coefficient; \( \alpha \) is the coefficient taking into account probable metabolism of CO in the atmosphere.

This dispersion approach is based on the analytical approximation of results of joint numerical integration of the equation of atmospheric diffusion and the system of equations of hydro thermodynamics for the atmospheric boundary layer and is described in the Russian normative document for the calculation of the dispersion of harmful substances in the atmospheric air – OND-86 [21] and other studies [20-23]. Using this approach, also known as K-theory, together with some approximations and assumptions [21-24], there was established that the concentration of the pollutant emitted from a non-regular superficial source, such as a peat fire, is as follow [21]:

$$C_M = \frac{AMF_{mn} \eta}{H^2(V\Delta T)^\frac{1}{3}},$$

(2)

where \( C_M \) is the concentration of CO (g/m\(^3\)); \( A \) is the coefficient considering the temperature stratification of the atmosphere; \( \Delta T \) is the temperature difference (°C); \( M \) is the emission of pollutant (g/s), \( F \) is the dimensionless coefficient considering the velocity of a probable CO metabolism in the atmosphere; \( V_1 \) is the smoke flow rate from the peat fire (m\(^3\)/s); \( m \) and \( n \) are the experimental coefficients; \( \eta \) is the dimensionless coefficient considering the influence of the terrain relief; \( H \) is the height of the steady smog cloud (m).

The authors of the present paper have a long-term positive experience in the application of this model for the estimation and the forecast of transport and fire-related air pollution [24-27]. At the same time, this approach is time-consuming and does not specify inaccurate problem parameters derived from measurements. To solve these problems, we offer to apply a neural network approach.

2.2. Neural network approach

On the base of the measurements, we developed an original neural network model with parameters (weights) tuned via optimization methods [14-19]. The RProp method and the combination of cloud and RProp methods were in use. The neural network model of the complex system can gather pieces of heterogeneous information – differential equations, conservation laws, equations of state, symmetry conditions, etc. The information exchange via neural network parameters between different levels of hierarchy makes computing less resource consuming.
3. Results and discussion

3.1 Case study 1
Turbulent diffusion loses importance when modeling the transfer of the smog from the peat fire over long distances. In addition, there may happen not only a smoldering peat fire but a burning peat fire followed by the emission of hot gases [27]. We have developed an original neural network model, based on the Gaussian dispersion to estimate these physical phenomena.

Let’s assume that the average cross-section of a peat fire smog, migrating towards of a motorway, is similar to the Gaussian distribution having a plume profile (Fig. 1).

\[ q(t, x, y, z) = \frac{Q \exp \left( \frac{1}{2} \frac{(x - x_0 - ut)^2}{(\sigma_x)^2 t} + \frac{(y - y_0 - vt)^2}{(\sigma_y)^2 t} + \frac{(z - z_0 - wt)^2}{(\sigma_z)^2 t} \right)}{\left(\sqrt{2\pi t}\right)^3 \sigma_x \sigma_y \sigma_z}, \]  
\[ (3) \]

where \( q \) is the concentration of pollutant (g/m³); \( Q \) is the emission rate of the pollutant (g m⁻¹ s⁻¹); \( t \) is the time (s), \( x_0, y_0, z_0 \) are the coordinates of the CO emission source (m); \( u, v, w \) are the components of wind speed; \( \sigma_x, \sigma_y, \sigma_z \) are the mean square deviations of the CO concentration at a time \( t \) by the axes OX, OY, OZ:

\[ \sigma_x^2 = \frac{2}{h} \int_0^h K_x(z)dz, \quad \sigma_y^2 = \frac{2}{h} \int_0^h K_y(z)dz, \quad \sigma_z^2 = \frac{2}{h} \int_0^h K_z(z)dz, \]  
\[ (4) \]

where \( h \) is the height of the surface layer with active turbulence, \( K_x, K_y, K_z \) are the numerical coefficients.

Using the principle of superposition, it is easy to obtain from equation (3) a formula for the concentration of CO released from a persistent peat fire:
The calculation of the integral is complex: on one hand, analytical methods will lead to huge formulas, on the other hand, numerical methods are time-consuming. To solve the problem, let’s substitute the integral by a finite sum:

$$ q(t, x, y, z) = \frac{Q \exp \left\{ -\frac{1}{2} \left( \frac{(x-x_0-ut)^2}{\sigma_x^2 t} + \frac{(y-y_0-vt)^2}{\sigma_y^2 t} + \frac{(z-z_0-wt)^2}{\sigma_z^2 t} \right) \right\}}{(\sqrt{2\pi t})^3 \sigma_x \sigma_y \sigma_z} d\zeta_0 $$

where $K_i$ are the numerical coefficients; $i = 0,1,2,3, \ldots, n$ are the integration points.

Figure 2 visualizes the joint results of experimental and simulated measurements of the peat fire-related CO concentrations (received according to formula (2)) near the Federal Motorway P-255 – “Siberia”. The concentrations of CO are expressed in terms of Limit Value Units: 20 minutes CO Limit Value is 5mg/m$^3$. The calculations were realized using the software program Ecolog 4 (Integral Co Ltd, St. Petersburg, Russia). The results of the measured and simulated CO concentrations were later used as input data to test the proposed neural network technique. Figure 3 shows the dynamic development of the pollution in this area at the wind in the direction to the motorway (4 neurons).

$$ q(t, x, y, z, u, v, w) = \sum_{i=1}^{N} K_i \left[ \frac{Q \exp \left\{ -\frac{1}{2} \left( \frac{(x-x_0-ut)^2}{\sigma_x^2 t} + \frac{(y-y_0-vt)^2}{\sigma_y^2 t} + \frac{(z-z_0-wt)^2}{\sigma_z^2 t} \right) \right\}}{(\sqrt{2\pi t})^3 \sigma_x \sigma_y \sigma_z} \right] $$

3.2. Case study 2

Equation (1) can be greatly simplified for the solution of the problem concerning peat fire. Changing the parameters of the problem (the wind speed, the radius of the fire, etc.), we suppose the process is quasi-stationary, in other words, the concentrations are stabilized faster than the parameters are changed. Thus, let us assume $\frac{\partial q}{\partial t} = 0$.

Figure 2. Visualization of the fields of CO concentrations (in terms of Limit Value Units) emitted from the peat fire near the Federal Motorway P-255 – “Siberia”.

Figure 3. Isolines of the level of CO at the wind in the direction to the Motorway P-255 – “Siberia” obtained by the neural network model (4 neurons).
Let us assume the z-axis pointed upward, so, \( w \) for heavy particles, having own sedimentation rate (with the sign ","), is equal to that rate, and \( w \) for light fractions is equal to 0. Let’s also assume that the average turbulent flow of pollutants at the earth’s surface is small and the exchange coefficients are constant. Let us suppose further that the concentration of CO satisfies the equation:

\[
\frac{u}{\partial t} \left( \frac{\partial q}{\partial x} \right) + v \left( \frac{\partial q}{\partial y} \right) - k \left( \frac{\partial^2 q}{\partial x^2} + \frac{\partial^2 q}{\partial y^2} \right) = Q, \quad (x, y) \in \Omega,
\]

(7)

where \( Q \) is constant in the area of peat fire (\( Q=0 \) out of the fire); \( k \) is the known parameter, \( u, v \) are the known wind speed components corresponding to the measurements.

We assume then the CO concentration tending to 0 zero at infinity, and we use this as boundary conditions. The solution of the problem can be simplified by the following conversions of the equation (7). Firstly, let us transfer the origin to the center of the peat fire, which we consider a superficial CO emission source of circular geometry. In the second place, let us direct the OX-axle in the direction of the wind by turning the coordinates. We eliminate the parameter \( k \) by scaling \( x \) and \( y \), and we eliminate the parameter \( Q \) by scaling the density of pollution. The actual value of \( Q \) can be determined by measurements.

Here there are left such parameters as the radius of the area of the fire and the wind speed. In the first version of the program, they are fixed and set at the beginning together with the other input data. They can be re-changed further by training the program.

Let us solve the equation (7) in the form of a neural network model:

\[
q(x, y) = \sum_{i=1}^{N} c_i \exp \left[ -a_i \left( x - x_i \right)^2 - b_i \left( y - y_i \right)^2 \right],
\]

(8)

whose parameters \( a_i, b_i, c_i, x_i, y_i \) can be found by minimizing the error:

\[
J = \sum_{j=1}^{M} \left( u \frac{\partial q(x_j^i, y_j^i)}{\partial x} - \frac{\partial^2 q(x_j^i, y_j^i)}{\partial x^2} - \frac{\partial^2 q(x_j^i, y_j^i)}{\partial y^2} - Q(x_j^i, y_j^i) \right)^2,
\]

(9)

where \( \{x_j^i, y_j^i\} \) are the test points in the area where the solution is built, they are updated through every 3-5 steps of the minimization \( J \); \( Q(x_j^i, y_j^i)=1 \) in the area of the peat fire and \( Q(x_j^i, y_j^i)=0 \) at other points.

Figure 4 shows the results of calculations for a peat fire with a radius of 1; N=20, M=200; u=1.

**Figure 4.** Lines of the gates of the neural network model \( q(x, y) \) in the entire area of variables change where the solution is sought (a), and in the area of the peat fire (b).

Moreover, we have built a parametric model considering wind speed as input data. In this case, the approximate solution is sought in the form of heterogeneous neural network function:
\[ q(x, y, u) = \sum_{i=1}^{N} c_i \exp \left[ \left( -a_i (x - x_i)^2 - b_i (y - y_i)^2 \right) \right] \exp \left[ d_i (u - u_i) \right], \quad (10) \]

whose parameters \( a_i, b_i, c_i, d_i, x_i, y_i, \) and \( u_i \) can be found by minimizing the error:

\[ J_2 = \sum_{j=1}^{M} \left| \frac{\partial q(x_j', y_j', u_j')}{\partial x} - \frac{\partial^2 q(x_j', y_j', u_j')}{\partial x^2} - \frac{\partial^2 q(x_j', y_j', u_j')}{\partial y^2} - Q(x_j', y_j') \right|^2, \quad (11) \]

where the points \( \{x_j', y_j', u_j'\} \) are periodically updated.

This parametric model allows predicting the level of peat fire-related air pollution at different wind directions.

Such models can be easily trained if there are measurement data in a set of points. In this case, there will be added an additional term to the error functional (9) or (11) equal to the sum of squares of the differences of the measured values and the neural network output. Likewise, data from numerical calculations are taken into account using standard methods or packages for individual parameter sets.

**Conclusions**

In this paper, an original self-learning neural network modeling technique is proposed that is capable of predicting dangerous roadside air pollution by carbon monoxide released from a nearby peat fire. The model was developed and tested by investigating a real peat fire happened in the Irkutsk region near atmospheric dispersion in the form of partial differential equations, calculation data (simulated measurements) obtained on the base of the Gaussian function; experimental data (real measurements) were used to build the neural network model. The results of the study show that the approaches developed here can be recommended as a useful tool for the air quality management and forecasting as well as for the prediction and prevention of such emergencies.

**Acknowledgements**

The investigations were supported by the grant of the Russian Foundation for Basic Research, project № 14-01-00733 А.

**References**

[1] Fraser L H, Keddy P A 2005 The World’s Largest Wetlands: Ecology and Conservation. Cambridge University Press, Cambridge, UK 488 p

[2] Biester H, Bindler R 2009 Modelling Past Mercury Deposition from Peat Bogs – The Influence of Peat Structure and \(^{210}\)Pb Mobility Working Papers of the Finnish Forest Research Institute 128 p 483

[3] De Groot W 2012 Peatland fires and carbon emissions. Natural Resources Canada. Canadian Forest Service. Great Lakes Forestry Centre, Frontline Express (GLFC - Sault Ste. Marie) 50 2p.

[4] Focheeva E V, Safronov A N, Rakitin V S, et al 2011 Investigation of the 2010 July–August fires impact on carbon monoxide atmospheric pollution in Moscow and its outskirts, estimating of emissions Izv. Atmos. Ocean. Phys. 47(6) 682-698

[5] Konecny K, Ballhorn U, et al 2016 Variable carbon losses from recurrent fires in drained tropical peatlands Global Change Biology 22(4) 1469–1480

[6] Gaveau D L A, Salim M A, et al 2014 Major atmospheric emissions from peat fires in Southeast Asia during non-drought years: evidence from the 2013 Sumatran fires Sc. Rep. 4 6112

[7] Pouliot G, Pierce T, et al 2005 Wildfire Emission Modeling: Integrating BlueSky and SMOKE Proc. 14th Int. Emission Inventory Conference "Transforming Emission Inventories - Meeting Future Challenges Today" (Las Vegas 11-14 April 2005) Ed EPA US
[8] Benson P 1992 A review of the development and application of the CALINE 3 and 4 models *Atmos. Environ.* 26 B (3) 379-390

[9] Berkowicz R 2000 OSPM – a parameterized street pollution model *Environmental Monitoring and Assessment* 65 (2) 323-331

[10] Hadjiiski L and Hopke P 2000 Application of artificial neural networks to modeling and prediction of ambient ozone concentrations *J. Air and Waste Manage. Assoc.* 50 894-901

[11] Feng X et al 2015 Artificial neural networks forecasting of PM2.5 pollution using air mass trajectory based geographic model and wavelet transformation *Atmos. Environ.* 107 118-128

[12] Kukkonen J, Partanen L et al 2003 Extensive evaluation of neural network models for the prediction of NO2 and PM10 concentrations, compared with a deterministic modeling system and measurements in central Helsinki *Atmos. Environ.* 37 4549-4550

[13] Lu H, Hsieh J et al 2006 Prediction of daily maximum ozone concentrations from meteorological conditions using a two-stage neural network *Atmos. Res.* 81 124-139

[14] Tarkhov D, Vasilyev A 2005 New neural network technique to the numerical solution of mathematical physics problems. II: Complicated and nonstandard problems *Optical Memory and Neural Networks (Information Optics)* 14 97-122

[15] Vasilyev A, Tarkhov D 2009 *Neural Network Modeling. Principles. Algorithms. Applications* (SPbSPU Publishing House, Saint-Petersburg) p 528 (in Russian)

[16] Vasilyev A, Tarkhov D 2014 *Mathematical Models of Complex Systems on the Basis of Artificial Neural Networks Nonlinear Phenomena in Complex Systems* 17 327-35

[17] Kainov N, Tarkhov D and Shemyakina T 2014 Application of Neural Network Modeling to Identification and Prediction Problems in Ecology Data Analysis for Metallurgy and Welding Industry *Nonlinear Phenomena in Complex Systems* 17 57-63

[18] Shemyakina T, Tarkhov D, Vasilyev A 2016 *Neural Network Technique for Processes Modeling in Porous Catalyst and Chemical Reactor* ed. L. Cheng et al (Switzerland Springer International Publishing) 547–554

[19] Haykin S 2008 *Neural Networks and Learning Machines* (Prentice Hall) p 936

[20] Berlyand M E 1991 Prediction and Regulation of Air Pollution 1991 *Atmospheric Sciences Library* 14 320 p

[21] Methodology for the calculation of the concentrations in the air of harmful substances contained in industrial emissions. OND-86 1987 Ed. Berlyand M E, Gasilina N K et al (Leningrad: Gidrometeoizdat) p 93 (In Russian)

[22] Genikhovich E L, Gracheva I G, Onikul R I, Filatova E N 2002. Air pollution modeling at urban scale - Russian experience and problems. *Water, Air & Soil Pollution: Focus* 2 (5-6) 501-512

[23] Genikhovich E L, Sciermeier F A 1995. Comparison of the United States and Russian complex terrain diffusion models developed for regulatory applications. *Atmos. Environ.* 29 (17) 2375-2385.

[24] Ložkin V, Ložkina O, Ušakov A 2013 Using K-theory in geographic information investigations of critical-level pollution of atmosphere in the vicinity of motor roads *World Applied Science Journal* 23 (13) 96-100

[25] Ložkina O, Nevmerzhitstsky N, Ložkin V 2016 Evaluation of air pollution by PM10 and PM2.5 on St. Petersburg ring road: mobile measurements and source apportionment modeling *Proc. 10th Int. Conf. on Air Quality: Science and Application (Milano 14-18 March 2016)* Ed S Finardi, A Farrow et al (Hertfordshire: University of Hertfordshire) p 176

[26] Ložkina O V, Ložkin V N 2015 Estimation of road transport related air pollution in Saint Petersburg using European and Russian calculation models *Transport. Res. Part D* 36 178-189

[27] Ložkin V, Sukhoivanov A 2000 Model for estimation of Impact of forest fires on Environment *Proc. Conf. on Improving operational performance of engines, tractors, and vehicles* Ed Nikolaenko et al (St. Petersburg: SPbGAU) 121-129.