Solving a timber logistics problem using neural networks

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Abstract. This article examines application of neural networks to the timber water transportation logistics. Formulated are the key parameters required for estimating the near-sea environment. Defined are vectors for training the neural networks.

1. Introduction
Russia accounts for 22% of the planet's forest cover and half of the world's coniferous timber reserves. According to forecasts, by 2020 the world's demand for industrial timber will increase by around 100 million cubic metres and there is only one realistic source to meet this demand - Russia's reserves. Today these reserves amount to more than 82 billion m³.

The peculiarity of Russia's timber industry is that the most logging and timber processing enterprises are very distant from consumers, given the vast territory and underdeveloped transport infrastructure of the country. The vast territory determines the significant transportation costs and big losses of materials in the timber industry [1].

An important parameter determining the wood product transportation distance is the products range and degree of processing. The higher is the wood processing quality, the farther the products may be transported and exported. Ten countries account for the bulk of exports: China, Egypt, Tajikistan, Uzbekistan, Syria, Germany, Iraq, Denmark, Kyrgyzstan and Azerbaijan.

The second important factor in timber logistics is the method of the forest products delivery. Due to the geographical location of our country, water is the most common way of transport. For the safe timber delivery by an optimal route, pre-modelling needs to consider many factors [2].

2. Methods and Materials
2.1 Determination of parameters for the analysis of the spatial situation
The near-shore maritime zone (NSMZ) changes quite rapidly and requires constant assessment to ensure the safety of economic activities and the environmental situation. Traditionally, various geo-information tools have been used to display and analyse the spatial situation. Professional GIS is focusing on a wide range of different users. Narrow applications require creation of additional GIS software shells to address specific spatial analytical tasks.

The situation in the maritime zone is highly dynamic due to the large number of heterogeneous objects and phenomena. In this case it is appropriate to use artificial neural networks (ANN) model-methodological tool in GIS analysis. The ANN model contains significant analytical capacity for the classification and evaluation of large amounts of highly dynamic data [3].
Let us consider the operation of a neural network using the example of our task - transporting a load of timber from point A to point B. In order to do this we need to carry out an assessment of the near sea area zone for the subsequent safe passage of the vessel. In this case special attention will be paid to the depths to meet the technical features of the timber carriers.

In this example the key parameters will be: presence of potentially dangerous bottom topography (N1), distance to shore (N2), presence of military conflicts or exercises (A1), presence of transport route (A2), presence of ships in the area (A3), amount of rainfall (P1), presence of dangerous weather conditions (P2) and depth (S1). On the basis of the indicated parameters the vectors will be formed with which the considered neural network will work.

The further process is based on the cascade of artificial neural networks of the same architecture: the recurrent neural network. Vectors are only fed to the input of the first neural network. The second network receives the results of the first network, i.e. the transformed environment estimation map [4].

2.2 Model of the situation assessment

According to the input vectors listed above, it is necessary to solve the optimal control problem that simulates dynamics of the artificial neural network in the following notations. The dynamics of the network of n neurons is described by a system of differential equations with lag.

\[
\begin{align*}
\dot{x}_i(t) &= -\gamma_i x_i(t) + \sum_{j=1}^{n} (\omega_{ij}(t)g_j(x_j(t)) + u_i(t)); \quad i, j = 1 \ldots n; \\
\dot{z}_i(t) &= \sum_{j=1}^{n} \omega_{ij}(t)x_j(t) - h \\
g_i(z_i(t)) &= (1 + \exp(-\lambda \sum_{j=1}^{n} \omega_{ij}(t)x_j(t) - h))^{-1} \\
\dot{\gamma}_i(t) &= -\gamma_i x_i(t) + \left[1 + \exp\left(-\lambda \sum_{j=1}^{n} \omega_{ij}(t)x_j(t) - h\right)\right]^{-1} + u_i(t)
\end{align*}
\]

In terms of the biological prototype, i.e. the neural network, we can say that the equation describes the accumulated potential (electrical impulse) of the neuron at a given time, as well as its change over time [5]. The potential of a neuron is formed and altered by many factors:

- \(x_i(t)\) – the intrinsic potential of the neuron at a given point in time
- \(\gamma_i\) – the intrinsic attenuation of the i-neuron, describes the effect on the neuron of intrinsic forces that negatively affect the potential as well as the signal attenuation during transmission from one neuron to the others. The sum of \(\sum_{j=1}^{n} \omega_{ij}(t)x_j(t) - h\) can be called as the sum of potentials of ensemble of neurons. This sum of the effects of all neighboring neurons on the i-neuron.

The sum \(\sum_{j=1}^{n} \omega_{ij}(t)x_j(t) - h\) is the main element in the formation of the potential of the i-neuron, so this sum is called the body of the i-neuron \(\omega_{ij}(t)x_j(t)\).

\(x_j(t) - h\) – shows the signal lag of the neural network. Thus, the potential of the i-neuron is quite strongly influenced by the residual impulse of the neurons in the previous moment [3, 6].

Control function \(\omega_{ij}(t)\) describes neuron axons - an electrical or chemical impulse that is transmitted from one neuron to another. Thereby changing the potentials is the most important connecting element of the neuronal network. It is responsible for the interaction and performance of the entire network. In this case it is the impact on the i-neuron, the j-neuron.
Activation function $g_i(z_i(t))$ transforms the accumulated potential of a neuron according to some functional dependence. The prototype is the process taking place in the body of the neuron. It is caused, for example, by signals or impulses from the body’s peripheral nervous system (due to some change in the external environment).

The intrinsic capacity of neurons must not exceed the limits:

$$x_i(t) \leq B_i, \ i = 1, n.$$  \hspace{1cm} (2)

The characteristics of the neurons at the initial point in time are known:

$$x_i(0) = a_i, \ i = 1, n;$$
$$x_i(t) = q_i(t), t = -h, 0;$$  \hspace{1cm} (3)

Control function $u_i(t)$ describes an external impact on the $i$-neuron. This can be any change in the environment, to which the body reacts by changing the rate of transmission of electrical and chemical impulses of the nervous system. Restrictions on control functions are known:

$$|\omega_{ij}| \leq b, \ |u_i| \leq c$$  \hspace{1cm} (4)

The purpose of controlling neural network dynamics is to train the network, which implies the following objectives (criteria):

1. At a finite point in time, the characteristics of the neurons must match the input $A_i$.
2. During the process, the characteristics of the neurons must not exceed the specified range of values ($B_i$).
3. The control $u_i$ should aim for a minimum value for the process.
4. The control $\omega_{ij}$ should also aim for a minimum value for the process.

The control objectives can be formalised in terms of the following target function

$$I([x], [\omega], [u], [t]) = \sum_{i=1}^{n} x_i(t) - A_i)^2 + \sum_{i=1}^{n} \int_0^T M_i[\max(0; x_i(t) - B_i)]^2 dt +$$
$$+ L \sum_{i=1}^{n} \int_0^T u_i^2(t) dt + K \sum_{i=1}^{n} \sum_{j=1}^{n} \int_0^T \omega_{ij}^2(t) dt \rightarrow \inf; \ i = 1, n$$  \hspace{1cm} (5)

The main practical aim is to obtain optimum process controls by which a minimum of the target functional is achieved [7]. We obtain the optimum process control by gradient descent or, in ANN training terminology, by the method of backward error propagation. To solve the optimal control problem (2)-(5), we use the Pontryagin maximum principle:

$$H([x], [\omega], [u], [t]) = -\lambda_0 \sum_{i=1}^{n} M_i[\max(0; x_i - B_i)]^2 + L u_i^2(t) - \lambda_0 K \sum_{j=1}^{n} \sum_{i=1}^{n} \omega_{ij}^2 +$$
$$+ \sum_{i=1}^{n} p_i(t)(-y_i x_i + (1 + \exp(-\lambda \sum_{j=1}^{n} \omega_{ij}(t) x_j(t) - h) ))^{-1} + u_i), i, j = 1, n$$  \hspace{1cm} (6)

Let’s write down the maximum principle:

$$-\lambda_0 \sum_{i=1}^{n} M_i[\max(0; x_i - B_i)]^2 - \lambda_0 \sum_{i=1}^{n} L u_i^2 - \lambda_0 K \sum_{j=1}^{n} \sum_{i=1}^{n} \omega_{ij}^2 + \sum_{i=1}^{n} p_i(t)(-y_i x_i +$$
$$+ g_i(x_i(t) + \bar{u}_i) = \max(-\lambda_0 \sum_{i=1}^{n} M_i[\max(0; x_i - B_i)]^2 - \lambda_0 \sum_{i=1}^{n} L u_i^2 -$$
$$- \lambda_0 K \sum_{j=1}^{n} \sum_{i=1}^{n} \omega_{ij}^2 + \sum_{i=1}^{n} p_i(t)(-y_i x_i + g_i(x_i(t) + \bar{u}_i) + v_i) =$$
$$= -\lambda_0 \sum_{i=1}^{n} M_i[\max(0; x_i - A_i)]^2 - \sum_{i=1}^{n} p_i(t) y_i x_i +$$
$$+ \sum_{i=1}^{n} \max_{w_{ij}}(p_i(t) g_i(x_i w_{ij})(\bar{v}_i) - \lambda_0 K \sum_{j=1}^{n} w_{ij}^2) + \sum_{i=1}^{n} \max_{v_i}(p_i(t) v_i - \lambda_0 L u_i^2)$$  \hspace{1cm} (7)

Conjugate vector functions are calculated using the formulas:

$$\tilde{p}_k(t) = -\frac{\partial H}{\partial x_k}(t) - \frac{\partial H}{\partial y_k}(t + h), \text{where} \ y_k = x_k(t + h)$$
$$\tilde{p}_k(t) = 2\lambda_0 M_k \max(0; x_k - A_k) + p_k(t) y_k - \lambda \sum_{i=1}^{n} p_i(t + h) \omega_{ik}(t +$$
$$+ h) \exp(-\lambda \sum_{j=1}^{n} \omega_{ij}(t) x_j(t + h)) (1 + \exp(-\lambda \sum_{j=1}^{n} \omega_{ij}(t) x_j(t + h))^2;$$  \hspace{1cm} (8)
and satisfy the transversality conditions:
\[ p_k(T) = -\lambda_0 \frac{\partial \Phi}{\partial x_k} = -2\lambda_0 (x_k(T) - A_k). \] (9)

The maximum principle reduces the optimal control problem of a process to the solution of the boundary value problem:
\[ p_k(t) = 2\lambda_0 M_k \max(0; x_k - A_k) + p_k(t)\gamma_k - \lambda \sum_{i=1}^{n} p_i(t + h)\bar{\omega} \exp \left( -\lambda \sum_{j=1}^{n} \omega_{ij} (t)x_j(t - h) \right) \] 
\[ - \left( 1 + \exp \left( -\lambda \sum_{j=1}^{n} \omega_{ij} (t)x_j(t - h) \right) \right)^2; \]
\[ x_i(t) = -\gamma_i x_i(t) + \sum_{j=1}^{n} \bar{\omega}_{ij} \Phi \left( x_j(t) \right) + \bar{u}_i(t); \quad i, j = 1 \ldots n; \]
\[ \dot{x}_i(t) = -\gamma_i x_i(t) + g_i(x_i(t)) + u_i(t); \quad i, j = 1 \ldots n; \]
\[ x_i(0) = a_i, \quad \gamma_i \bar{\omega}_{ij}, \bar{u}_i - \text{optimal controls} \] (10)

However, unlike the Near-Sea Situation Assessment methodology, in order to speed up the system, this step is only conducted in a dimensional change mode and does not have a final human control phase. Additionally, the resolution of the graphical component should be lowered, as it is not important at this stage, but its processing may take a significant part of resources and entail an increase in the data processing time [8].

The result is fed to the input of the second neural network. According to the experiments conducted, the neural network has the architecture of a multilayer feedback perceptron, i.e. a recurrent neural network. This neural network is the second part of the neural network cascade underlying this methodology. The results of the first neural network, i.e., an anamorphic mapping of the near-sea environment assessment, are fed to the network's input [2, 9].

The second neural network is also trained using an error back propagation algorithm, but the structure of the training set is significantly changed. In this situation, not each area separately, but all areas are evaluated as a whole. That is, the training set consists of a matrix, the rows of which are the regions into which the mapping is divided, while the columns are input values: distance from the shortest route and evaluation of the situation in the region, and the output value, taking values 0 and 1, respectively - the route does not pass or passes through the region in question.

3. Conclusion
Because the whole map must be evaluated, more training sets (20 000 for this task) will be needed to train the neural network. Based on the results, the neural network constructs a broken line running from the starting point of the route to the destination. The finer is the regional partitioning, the more accurate the route will be. However, smaller partitioning brings about greater complexity in terms of data processing and machine resources.

Taking into account the previously defined coordinate grid, the detopologisation process is carried out, i.e. transition from a graphical mapoid to a geographic map. It is worth noting that such a transition is not possible using classical shapefile-based models. However, it is an important step in the methodology, allowing to build a route in real map conditions. The output of the neural network is a map with the source and destination points highlighted and the route constructed between them.

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