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## The Use of Neural Networks for Modeling the Movement of Surface Water Masses in Enclosed Sea Areas

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**Abstract:**

**Purpose:** The article presents the use of neural networks to predict the parameters of the movement of surface water masses in enclosed sea areas.

**Design/Methodology/Approach:** The input data were meteorological parameters recorded at the stations Trzebież and Świnoujście. The output data were the parameters of moving drifters, obtained because of an experiment in 2018 in the waters of the Szczecin Lagoon. The model uses Multi-Layer Perceptron networks with different activation functions. As a criterion for selecting the best networks, the highest correlation statistics for the test and validation sample were used.

**Findings:** As a result of the research, predictions of the speed and direction of surface water masses were obtained based on the meteorological conditions recorded on the outskirts of the studied reservoir.

**Originality/value:** The presented research is a new application of artificial neural networks in security in restricted waters. The results obtained in the study may be beneficial for the maritime administration, which is responsible for the safety of navigation in the studied water area. The model can be used to design a survivor's route or a contamination route.

**Keywords:** Safety, surface flow, wind, neural networks, Szczecin Lagoon.

**JEL classification:** C69.

**Paper Type:** Research study.

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## **1. Introduction**

The literature on SAR and existing search procedures for survivors has focused on open waters deeper than 3m. However, in recent years there has been an increase in the popularity of tourist navigation in enclosed sea areas, for which the IAMSAR (International Aeronautical and Maritime Search and Rescue) manual does not describe in detail how to estimate surface current parameters and thus how to calculate the search area for a missing person and the movement of debris.

Several water circulations models have been developed at global and even at selected local scales. Some of them are very complex three-dimensional hybrid flow models, (Haidvogel and Beckmann, 1999; Korotenko *et al.*, 2004), but there is a lack of a universal model that can be easily applied to closed marine areas with similar characteristics. Several forces are causing specific water circulation in marine areas, such as atmospheric pressure fluctuations, tides, winds, rotation of the Earth, tidal currents. Although they are components of the 3D model, the short-term variability of surface currents is mainly due to the influence of winds. This property is particularly pronounced in enclosed marine areas of small size.

The development of dynamic areas of search for survivors and displacement of pollutants as a function of hydrometeorological conditions over a given period in a limited marine area is not an easy task but could be a beneficial achievement. In this case, it would be necessary to obtain a theoretical basis and then implement machine learning algorithms using neural networks to obtain an advanced integrated model combining hydrometeorological data obtainable from meteorological stations located closest to the body of water. The proposed solution can be a tool combining various sources of information into one. The resulting systems should integrate already existing and functioning elements. The input and output data should be understandable for the operators and provide convincing arguments to take specific actions. Integrating several elements into one should translate directly into reduced situation assessment time and thus directly into increased navigational safety and improved search and rescue effectiveness.

In addition to the potential benefits in SAR, the description of the movement of water layers in closed marine areas can - and should - be used to determine the direction and speed of movement of contaminants that may be associated with shipwrecks while navigating in these areas or with other events in the land infrastructure that affects or is associated with the basin area. From an ecological point of view, this is a significant issue. Analysis of the movement of surface drifters depending on the prevailing wind conditions was carried out, e.g., the Gulf of Finland in different seasons of 2011 and 2013. The authors showed that in the Gulf of Finland, in many cases, the drift is influenced by coastal effects in the Gulf of Finland and its complex bathymetry. On the other hand, in another paper (Chang, 2012), the authors obtained a relationship between observed near-surface current vectors and surface wind vectors for the Pacific

Northwest under solid winds (20-50 m/s). However, these were studies for an open water body and only for strong winds.

Despite the theoretically many factors that may influence the movement of the waters of a limited marine area, the short-term variability of surface currents is essentially related to wind parameters. This property is particularly noticeable in small water bodies, such as the Szczecin Lagoon. It is worth emphasizing that these reservoirs are mostly water bodies that do not have any features of an ocean basin. Therefore, adopting the circulation of oceanic waters to the conditions taking place in the waters of closed sea areas is not a proper approach. It is worth noting that no comprehensive studies of current and drift parameters, leading to universal SAR models or procedures, have been carried out to date in similar areas.

In the literature (Breivik and Allen, 2008; Burciu, 2003; 2012; Kasyk *et al.*, 2016; Bugajski and Pleskacz, 2016), search and rescue areas in waters used for navigation are determined using the Monte Carlo method, Bayesian methods, regression models for object drift speed, Fokker-Planck equations, or graphical models. To determine such areas, it is necessary to obtain data on surface currents and wind. The path parameters with their uncertainties are determined based on the wind parameters, e.g., by linear regression or by constructed probability distributions. The survivor's position vector at a given time  $t$  is calculated as the integral of the survivor's velocity vector from the initial moment to time  $t$  plus the velocity vector from the initial moment.

IAMSAR estimates of the surface current and wind parameters can be obtained from direct observations, maps, wind roses, reliable hydrodynamic numerical models, and numerical weather prediction models. The best way to obtain information on current and wind parameters is through direct observations. Such observations can be obtained from in situ measurements, ships passing through the area, aircraft flying over the area, suitably installed buoys or platforms, or satellite measurements.

However, such data are not always available. Other sources of such data are, e.g., charts or diagrams. These can be used to determine long-term seasonal averages of currents and winds. However, these sources are used in remote areas. Nevertheless, estimation of these parameters using these sources should not be used in coastal areas, especially in sea areas less than 25 nautical miles from the coast and with water depths of less than 100 meters. Other sources include reliable high-resolution hydrodynamic numerical models and weather forecasts.

Processes in the atmosphere and hydrosphere have different temporal and spatial scales. Moreover, they are characterized by high complexity and variability. In order to describe them reliably, different contexts of approach and a wide range of scales must be considered. However, a complete mathematical, hardware, and software description is a limitation. Therefore, selected processes are modeled. The models describing the processes under study should have an adequate temporal and spatial resolution. A model may describe large-scale movements well but may significantly

underestimate or overestimate or even omit small-scale movements. However, small-scale processes can be essential and, depending on the issue. Their inclusion should be considered to predict, for example, surface currents and wind parameters as accurately as possible.

Of the existing hydrodynamic models covering enclosed marine areas, the PM3D model, which is a parallel version for the 3D hydrodynamic model M3D, is in operation at the Institute of Oceanography, the University of Gdansk (Kowalewski and Kowalewska-Kalkowska, 2017), and is based on a coastal ocean circulation model known as the Princeton Ocean Model (POM). This one covers the Szczecin Lagoon with a resolution of 1/6 NM (about 300 m), and data from the SatBaltic system, such as current parameters, are updated four times a day.

In turn, the UM weather prediction model is operated at the ICM (Interdisciplinary Centre for Mathematical and Computer Modelling) at the University of Warsaw (Herman-Iżycki *et al.*, 2002), and is based on the Unified Model, developed by the UK Meteorological Service Met Office, and the COAMPS model from the U.S. Naval Research Laboratory. The UM model provides data at 4 km or 1.5 km resolution and is calculated four times a day. Of the other models developed and used, the NEMS (NOAA Environmental Modelling System) example has a resolution of about 4 km, and its data are updated every 12 hours. The ECMWF (European Center for Medium-Range Weather Forecasts) model, with a resolution of about 9 km, is updated every 12 hours. The NEMS model is a local European model. The ECMWF model is a global weather model.

Experience has shown that, despite the relatively small size of enclosed sea areas, the process of searching for a survivor is often complex and not easy, despite apparently favorable factors: limited waters, number of rescue units (sea and air), and short time of reporting an accident and arriving at the scene. Therefore, in addition to modeling studies, experimental studies must be carried out. Information on wind strength is obtained from anemometers, while information on wind direction is obtained from anemoscopes. These devices are often combined into one. Water level measurement is commonly referred to as the rise of the water level above the water table in a river or water region above a conventional reference level. It is not synonymous with the depth of a water body. The zero datum of each water level gauge is determined regarding the state leveling network. With this information, we can determine the water level. Measurements are made with the help of water level gauges, which are placed in the water level profile.

## **2. Research Area**

The study area, in this case, is the Szczecin Lagoon, which is an excellent representation of a body of water described as a closed sea area. Usually, these are small and relatively safe reservoirs for sailing and motorboat sports. The Szczecin

Lagoon is about 28 km long and over 52 km wide. The danger is the shape of the shoreline and the bottom, which, together with changing hydrodynamic conditions, have led to many dangerous incidents. The Szczecin Lagoon is a relatively shallow water reservoir. Its average depth is 3.8 m. The main participants of tourist traffic in closed sea areas are small boats with limited draught. Due to the specifics of water sports and the size of the vessels that can be used, the most critical task of the SAR services is to search for people who have fallen overboard or are drifting in the water after capsizing.

In order to develop a model that could be useful in any enclosed maritime area, hydrometeorological parameters were measured and tested in the Szczecin Lagoon, which is a typical representative of such an area. It covers the waters at the mouth of the Odra River (Figure 1). On the northern side of the Lagoon, the islands Wolin and Uznam separate it from the Baltic Sea. The middle part of the Lagoon is divided into the "Great Lagoon" with an area of 488 km<sup>2</sup> on Polish territory and the "Small Lagoon." (German: Kleines Haff), with an area of 424 km<sup>2</sup>, which almost entirely belongs to Germany. The southern boundary of the Great Lagoon is marked by the mouth of the Jasienica Channel (on the western shore) and the mouth of the Krępa River (on the east) (Baltic Pilot, 2018).

The Pomeranian Bay relates to the Szczecin Lagoon through the straits, Dziwna, Świna and Piana. The Świna is of tremendous significance for the hydrological system of the Szczecin Lagoon. These straits are not branching of the Oder River as their currency is not a river current, but it results from permanent equalization of sea waters and the Szczecin Lagoon.

**Figure 1.** Szczecin Lagoon



**Source:** Own study, based on NAVI-SAILOR 3000 ECDIS-i and [www.online/seterra.com.pl](http://www.online/seterra.com.pl).

### **3. Experiment Description**

The experiment consisted of 10 drifter launches during the summer season (end of June 2018 - beginning of October 2018), the design was developed at the Maritime Academy in Szczecin, and a specialized company commissioned the construction. As the subject of the study was surface currents in the Szczecin Lagoon, the drifter - afloat - had a small height of 18 cm and a balanced buoyancy so that it did not protrude from the water was not directly exposed to the wind. Each drifter was equipped with a Spot Trace locator, which enabled the real-time recording of the drifter's position via a satellite network (Kasyk, Pleskacz, and Kapuscinski, 2021).

Drifters during the ten launches were deployed in pairs or threes. The locations were, for each launch, determined individually depending on the wind parameters and to maximize the drift time of the drifters (due to the cost of the launching operation). The drifters were drifting in the waters of the Szczecin Lagoon until they got stuck in the reeds at the shores of the Lagoon or until the need to recharge the battery was signaled. At the same time, wind direction and strength were recorded at the nearest meteorological stations, Trzebież and Świnoujście. Based on the recorded routes of the drifters, the depth of the body of water at the points where the drifters were located was also assigned.

Performed analyses of drifters' speed showed a significant dependence of this speed on the direction of the blowing wind (Kasyk, Kijewska, and Pleskacz, 2019b). The  $V_d/V_w$  ratio, which is essential for searching for survivors, showed significant differences depending on the wind direction. From about 3% for northern winds, 5% for westerly winds, 9% for south-easterly (Świnoujście) or south-westerly (Trzebież) winds.

The movement of surface water masses in the central part of the Szczecinski Lagoon was primarily caused by the movement of air masses in its area. The variability of drift directions of the designed drifter was highly dependent on wind speed. Drift directions close to straight lines were observed at moderate and more vigorous winds. On the other hand, in weak or very weak winds, the wind direction usually changes, which entails a change in the drift direction of the drifter.

A study (Kasyk, Kijewska, and Pleskacz, 2019a) confirmed the general correspondence of drift directions with the directions of air mass movement recorded at both Trzebież and Świnoujście. This was confirmed by statistical tests verifying the significance of the correlation between buoy drift direction and air mass movement. The influence of individual meteorological parameters on the direction and speed of drifter movement varied greatly. Therefore, an artificial neural network method was used to predict surface water masses' speed and direction of movement.

## 4. Methodology

### 4.1 Description of the Neural Network Method

Artificial neural networks are a variety of nonlinear signal processing systems created based on the nervous system of living organisms. They are a practical implementation of phenomena occurring in nervous systems in the search for new technological solutions (Haukin, 2000; Kecman, 2001; Osowski, 2006; Sholkopf and Smola, 2002). In most applications, the neural network acts as a universal approximator of functions of many variables, implementing a nonlinear mapping of the form:

$$y = f(x) \quad (1)$$

In the case where  $\mathbf{x}$  is an input vector and  $\mathbf{y}$  is an analyzed vector function of many variables (Osowski, 2006). Neural networks are mainly used in regression or classification problems. At the learning stage of this type of network, sets of two vectors are given: the input vector  $\mathbf{x}$  and the associated output data vector  $\mathbf{y}$ . Such a network is called a trained network. Such a network is called a network trained under supervision (with a teacher).

Among the existing network solutions, two basic types of networks can be distinguished, unidirectional multilayer networks, implementing the global type approximation, which is commonly called MLP (Multi-Layer Perceptron) network, and a network using essential functions of a finite medium (most often Gaussian functions) implementing the local type approximation, commonly called RBF (Radial Basis Functions) network. Both types of networks are versatile tools that can serve as both predictors and classifiers.

MLP network is one of the most used neural networks, repeatedly discussed in various scientific publications (Haukin, 2000; Osowski, 2006). A schematic of such a network with one hidden layer is shown in the figure below.

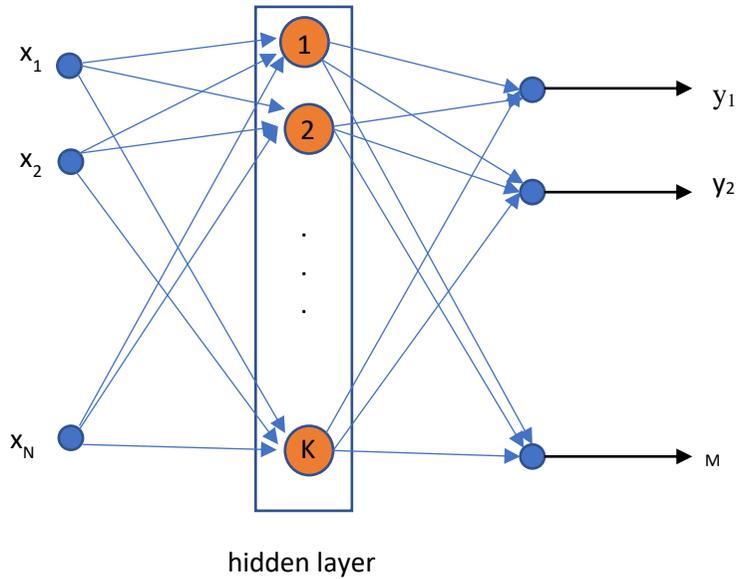
The number of hidden layers can be arbitrary, with two layers being entirely sufficient to map the input signals forming the vector  $\mathbf{x}$  arbitrarily accurately ( $\mathbf{x}$  is contained in  $\mathbb{R}^n$ ) into the output signals described by the vector  $\mathbf{y}$  ( $\mathbf{y}$  is contained in  $\mathbb{R}^m$ ) according to the given mapping function  $y=f(x)$ . Moreover, in many regression problems, one hidden layer is enough. At the learning stage, the values of vector  $\mathbf{y}$  are known and equal to vector  $\mathbf{y}_0$ . Individual neurons of the network realize a nonlinear mapping of the form:

$$y_i^{(k)} = f(u_i^{(k)}) = f\left(\sum_j w_{ij} y_j^{(k-1)}\right) \quad (2)$$

where all weights of the network  $w_{ij}$  form a vector of weights  $\mathbf{w}$ .

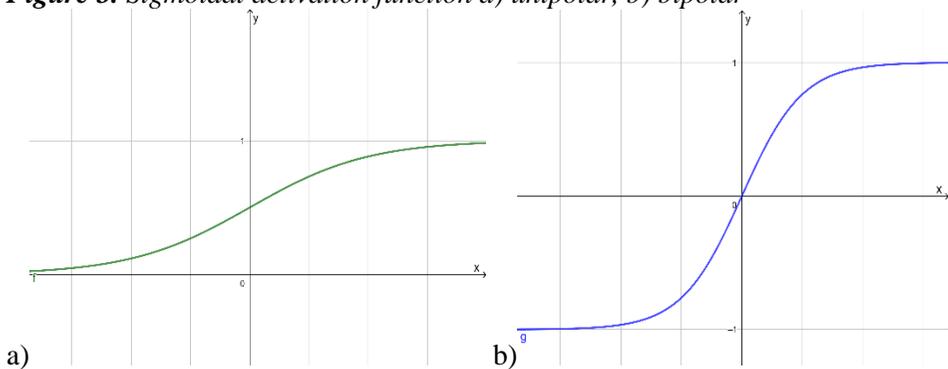
An essential element of a neural network is the activation functions responsible for the signal transmission from the earlier neurons, which is determined by a specific pattern. The choice of the activation function has a significant impact on the performance of the network. The perceptron network's activation function  $f(u)$  is sigmoidal, unipolar or bipolar type (Figure 3).

**Figure 2.** Single-layer neural network diagram



Source: Own study.

**Figure 3.** Sigmoidal activation function a) unipolar, b) bipolar



Source: Own study.

The sigmoidal flow of the activation function is a characteristic element of MLP networks (Osowski, 2006). The flow of signals in these networks takes place in only one direction, from input to output.

The methods of teaching these networks are convenient to use in practical issues. The learning of a multilayer perceptron is usually performed under supervision, and the basis of learning is a set of related learning pairs  $(x, y_0)$ , in which  $x$  is a vector of input data, and  $y_0$  is the corresponding vector of output data.

The objective of the learning process is to determine the values of weights of all network layers in such a way that for a given input vector  $x$ , the output values of the signals in the vector  $y$  correspond with sufficient accuracy to the set values represented by the vector  $y_0$ .

Learning of the network consists of such a selection of weights that the minimum value of the error on the analyzed learning set is obtained, i.e., in a general form, it will be the minimum of the error function:

$$E = \sum_{i=1}^N (d_i - y_i)^2 \quad (3)$$

where:

$d_i$  – values calculated using networks

$y_i$  – values of the output vector

There are many different methods for minimizing the error function. In the case of MLP networks, the most used are:

- backpropagation of error (fastest gradient) method
- coupled gradient method
- variable metric method (BFGS)

In the case of phenomena in which we do not know the nature of correlations of co-existing variables, artificial neural networks can give measurable benefits in predicting the value of the phenomenon under study. Necessary, in this case, are the input and output vectors of the data. The experiment considered in this paper provides this type of data, which made it possible to apply SSN to model the direction and velocity of surface movement of water masses in the Szczecin Lagoon.

## 4.2 Procedures Used in the Article

STATISTICA Automatic Neural Networks (SANN) is a module of the STATISTICA statistical package which assists researchers in the most critical stages of network design, applying state-of-the-art network architectures and learning methods. It also has innovative solutions for designing the network structure using appropriately selected error functions to facilitate the interpretation of output data.

The input data set included four meteorological parameters (wind direction and strength at Trzebież and Świnoujście stations) at time points corresponding to the recorded positions of drifters. The output variables were the direction and speed of the

drifter determined from the recorded positions. All input and output variables were quantitative variables: wind strength and drifter speed were expressed in m/s, and wind direction and drifter direction in degrees. Spherical trigonometry formulas were used to determine the distance between the recorded positions and the drifter's direction of travel:

$$\cos D = \sin \varphi_A \sin \varphi_B + \cos \varphi_A \cos \varphi_B \cos |\Delta\lambda| \quad (4)$$

and

$$\operatorname{tg} \alpha = \frac{\sin |\Delta\lambda|}{\operatorname{tg} \varphi_B \cdot \cos \varphi_A - \sin \varphi_A \cdot \cos |\Delta\lambda|} \quad (5)$$

Where:

$\varphi_A, \lambda_A, \varphi_B, \lambda_B$  – the geographical coordinates of points A and B of the recorded positions,

$D$  – the spherical distance between points A and B,

$\alpha$  - initial angle of the great circle.

Networks were learned on sets of varying sizes, depending on the length of the drift. Longer drifts with variable directions were divided into several parts. 75% of all data was the learning set, 15% the testing set, and 15% the validation set. The points were selected randomly. With these settings configured, the automatic SANN network wizard checked 100 networks of both MLP and RBF types, from which the best five were selected. As a criterion for selecting the best networks, the highest correlation statistics for the test and validation sample were used. The selected nets were recorded and then used to predict the drifter's speed and direction based on the wind direction and strength recorded at the Trzebież and Świnoujście stations. Based on the generated velocities and directions, the drifter's displacement was determined.

## 5. Results

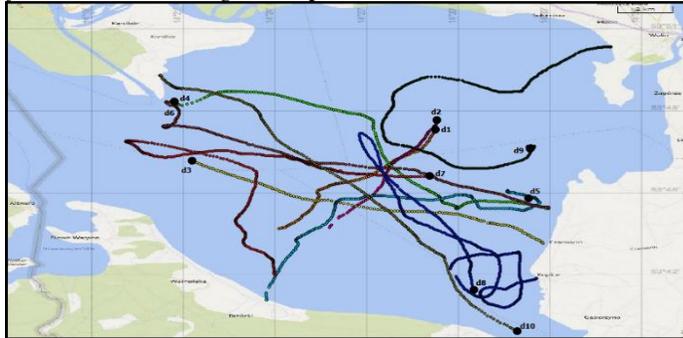
Drifts with different structures were selected for analysis. In some, the direction of movement was not strongly differentiated, while in others, there were significant direction changes. The movement of drifters in different parts of the Szczecin Lagoon was also modeled.

### *Drift 1:*

The first drift analyzed started on 29.06.2018 at 16.00 (53.78855 N, 14.48773 E) and ended at position (53.72776 N, 14.40228 E). It lasted 24 hours, and the distance traveled was 9330 m. The direction of drift was not enormously varied, so all recorded points were used to learn and test the network - there were 138 in total. Out of 100 networks learned and analyzed, the best five were selected, which turned out to be 4-n-2 MLP networks with one hidden layer and number of neurons n from 5 to 10. Four networks had a tan activation function for the hidden layer, and one had an exponential

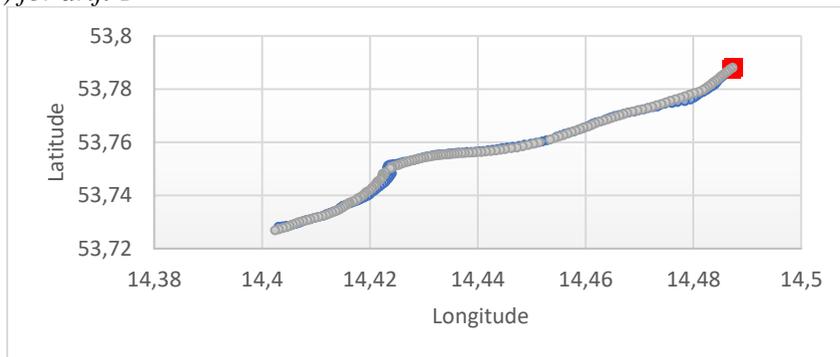
function. One network had a linear activation function, one exponential, one tanh, and two logistics for the output layer. The learning quality ranged from 0.78 to 0.86 for the test set. The variable metric (BFGS) method was used to minimize the error function. The drifter speeds and directions, generated from the learned network, reproduced the drifter route No. 1 very well (Figure 5).

**Figure 4.** Drifters' routes during the experiment



*Source: Own study.*

**Figure 5.** Real route (blue points) and route based on learned MLP network (grey points) for drift 1



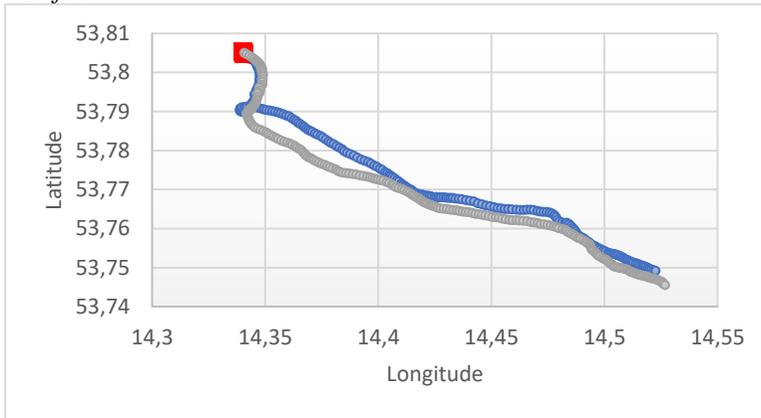
*Source: Own study.*

### **Drift 6:**

Drift 6 started on 13/07/2018 at 14.00 (53. 80556 N, 14.34505 E) and ended at position (53.74090 N, 14.54948 E). It lasted 43 hours, and the distance traveled was 28042 m. The drift was characterized by one significant change of direction of the drifter. As shown in Figure 6, the network model reproduced this change well. Of the 100 networks learned and analyzed, the best five were selected, which turned out to be 4-n-2 MLP networks with one hidden layer with the number of neurons n ranging from 4 to 6. Two networks had a tanh activation function for the hidden layer, two had an exponential function, and one had a logistic function. In contrast, one network had an exponential activation function for the output layer, one a tanh, and three a logistic function. The learning quality ranged from 0.65 to 0.73 for the test set. The variable

metric (BFGS) method was used to minimize the error function. All recorded points were used for learning and testing the network - there were 198 points in total.

**Figure 6.** Real route (blue points) and route based on learned MLP network (grey points) for drift 6



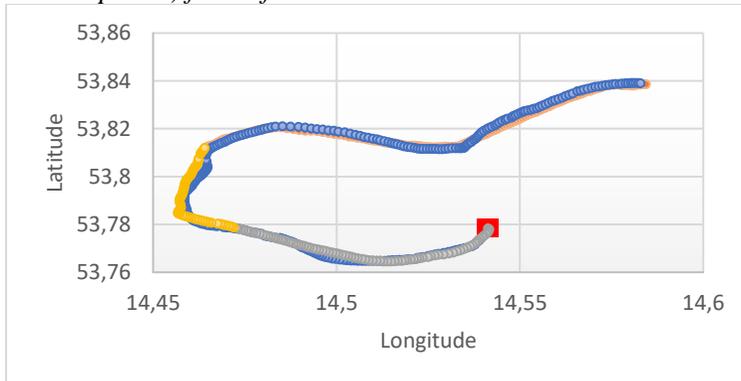
**Source:** Own study.

**Drift 9:**

Drift No. 9 started on 06.09.2018 at 15.00 (53.77719N,14. 53882 E) and ended at position (53.83897 N, 14.58360 E). It lasted 50 hours, and the distance traveled was 28685 m. The drift direction was highly variable, so the whole drift was divided into three parts (Figure 7). The first part included 87 points, the second 67, and the third 136.

As in previous cases, out of 100 networks learned and analyzed, the best five were selected, which turned out to be MLP networks. The types of activation functions and the methods for minimizing the error function were like the earlier examples. The speeds and directions of the drifter's movement generated based on the learned networks very well represented individual parts of the drifter's route no. 9

**Figure 7.** Real route (blue points) and route based on learned MLP network (grey, yellow and brown points) for drift 9

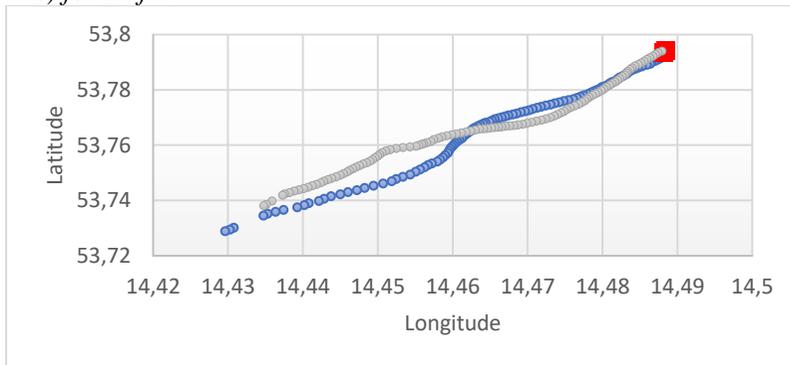


**Source:** Own study.

### 5.1 Network-Based Route Modeling for Other Drifts

The learned networks were used to predict the drifter's route under different but similar meteorological conditions. For example, for drift 2, networks learned from drift 1 data were used, where the compatibility of prevailing wind directions (northeast winds) was critical. The results of the drift two route prediction are presented in Figure 8. The distance between the actual drift termination points and the point determined from the learned MLP network for drift 1 was about 1km.

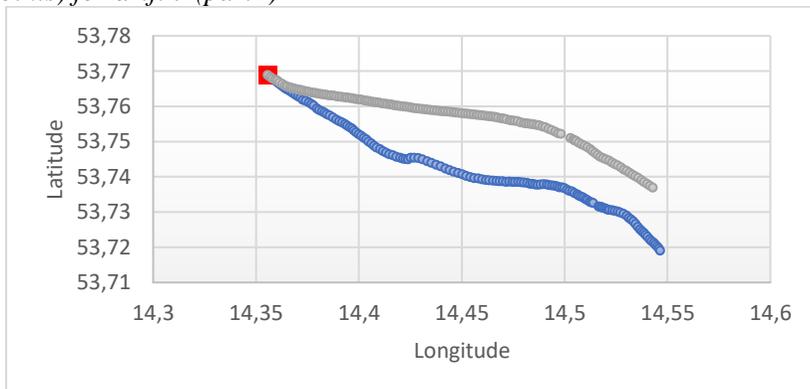
**Figure 8.** Real route drift 2 (blue points) and route based on learned MLP network (grey points) for drift 1



*Source: Own study.*

Another example is the use of networks learned on the part of the data of drift 7, corresponding to north-westerly winds, to predict the route of drift 3. The general direction of movement of the drifter was maintained, but the distance between the actual drift termination points and the point determined from the learned MLP network for drift 7 was about 2 km.

**Figure 9.** Real route drift 3 (blue points) and route based on learned MLP network (grey points) for drift 7 (part2)



*Source: Own study.*

## **6. Conclusion**

Artificial neural networks proved to be a good tool for modeling the route of a moving drifter. Prediction of drift direction and speed was based on meteorological data recorded in Trzebież and Świnoujście. The mapping of the route of individual drifters based on data from these drifters was very good. On the other hand, the use of the network for modeling the course of drifter movement based on other meteorological conditions was not as accurate. The obtained differences between the prediction results and the actual routes, in the order of 1 km to 2 km, during 24 hours of drift, are a good starting point for improving the model.

It seems that the drifter prediction could be further improved if it was possible to obtain wind parameters from the central part of the Szczecin Lagoon, which is not possible at present. However, this would require the installation of appropriate wind gauges, e.g., at the gates of the Szczecin-Świnoujście fairway. Nevertheless, it is worth adding that proper prediction of drift in the waters of the central part of the Szczecin Lagoon may make it possible to estimate the area of search for survivors or estimate the location of contaminant transfer.

## **References:**

- Baltic Pilot, Volume 2, NP 19, 17th Edition, United Kingdom Hydrographic Office, 2018.
- Breivik, Ø., Allen. A.A. 2008. An operational search and rescue model for the Norwegian Sea and the North Sea, *Journal of Marine Systems*, 69(1-2), 99-113.
- Bugajski, G., Pleskacz, K. 2016. Modyfikacja metody wyznaczania obszaru poszukiwań podczas akcji ratowniczych na akwenie otwartym, *Autobusy, Technika, Eksploatacja. Systemy Transportowe*, 12, 861-864.
- Burciu, Z. 2003. Modelowanie obszarów poszukiwania w aspekcie bezpieczeństwa transportu i ludzi na morzu, *Prace Naukowe Politechniki Warszawskiej. Transport, Zeszyt*, 5, 3-126.
- Burciu, Z. 2012. Niezawodność akcji ratowniczej w transporcie morskim. *Oficyna Wydawnicza Politechniki Warszawskiej*, Warszaw.
- Chang, Y.C., Chen, G.Y., Tseng, R.S., Centurioni, L.R., Peter, R. Chu, C. 2012. Observed near-surface currents under high wind speeds. *JGR*, 117(C11).
- Haidvogel, D.B., Beckmann, A. 1999. *Numerical ocean circulation modeling*. Imperial College Press, London, 344 p., ISBN: 1-86094-114-1.
- Herman-Iżycki, L., Jakubiak, B., Nowiński, K., Niezgódka, B. 2002. UMPL – the numerical weather prediction system for the operational application. In: *Research works based on the ICM's UMPL numerical weather prediction system results*. Wydawnictwo ICM, Warsaw, 14-27.
- Kasyk, L., Kijewska, M., Kowalewski, M., Leyk, M., Pyrchla, J. 2016. Modeling of surface currents impact in the harbor using graph theory. *Scientific Journals of the Marine University of Szczecin*, 46(118), Szczecin, 189-196.
- Kasyk, L., Kijewska, M., Pleskacz, K. 2019a. *Statistical Analysis of the Real Surface Currents and Wind Parameters for the Szczecin Lagoon*, *Advances in Marine Navigation and Safety of Sea Transportation*, Edited by Adam Weintrit, Tomasz Neumann. Taylor & Francis Group, London.

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- Kasyk, L., Kijewska, M., Pleskacz, K. 2019b. The influence of the wind direction on the speed of drift in the Szczecin Lagoon. Conference proceedings of MTE-ISIS, Maritime University of Szczecin Press, Szczecin.
- Kasyk, L., Pleskacz, K., Kapuściński, T. 2021. Analysis of Wind and Drifter Movement Parameters in Terms of Navigation Safety: The Example of Szczecin Lagoon. *European Research Studies Journal*, 24(3), 541-559.
- Kecman, V. 2001. Support vector machines, neural networks, and fuzzy logic models. MA: MIT Press, Cambridge.
- Korotenko, K.A., Mamedov, R.M., Kontar, A.E., Korotenko, L.A. 2004. Particle tracking method in the approach for prediction of slick oil transport in the sea: modeling oil pollution resulting from river input. *Journal of Marine Systems*, 48(1-4), 159-170.
- Kowalewski, M., Kowalewska-Kalkowska, H. 2017. Sensitivity of the Baltic Sea level prediction to spatial model resolution. *Journal of Marine Systems*, 173, 101-113.
- Haukin, S. 2000. Neural networks, a comprehensive foundation. Macmillan College Publishing Company, New York.
- Osowski, S. 2006. Sieci neuronowe do przetwarzania informacji. Oficyna Wydawnicza PW.
- Sholkopf, B., Smola, A. 2002. Learning with kernels. MIT Press, Cambridge.