60
Review paper
Doi 10.61892/stp202401070DJ
ISSN 2566-4484

Tanja Đukanović, University of Banja Luka, tanja.djukanovic@aggf.unibl.org
Slavko Vasiljević, University of Banja Luka, slavko.vasiljevic@aggf.unibl.org
Dragana Marković, University of Belgrade, dragana.markoviceva@gmail.com
Slavica Ilijević, University of Belgrade, slavicailijevic7@gmail.com

POSSIBILITIES OF TRANSFORMING RECTANGULAR 3D GEODETIC INTO ELLIPSOIDAL COORDINATES USING NEURONAL NETWORKS

Abstract

The transition from ellipsoidal geodetic coordinates to rectangular 3D coordinates is quite simple, while the reverse procedure is somehow more complex due to the mathematical relationship between the ellipsoidal width and 3D coordinates. Until now, several methods for solving this problem have been defined and described in geodetic literature. In this paper, the possibility of applying a backpropagation algorithm based on a multilayer perceptron (Multilayer Perceptron – MLP) neural network for the transformation of rectangular 3D geodetic into ellipsoidal coordinates is analyzed. The applied MLP model is based on Bayesian regularization (BR). The adequacy of the model was verified by a robustness test and a cross-validation test. Based on the obtained results, it was concluded that the MLP neural network can be used for the transformation from rectangular 3D to ellipsoidal coordinates. Future research should analyze the possibility of applying this procedure to solve the problem of data transformation.

Keywords: Coordinate Transformation, Multilayer Perceptron (MLP) Neural Network, Bayesian Regularization.

МОГУЋНОСТИ ТРАНСФОРМАЦИЈЕ ПРАВОУГЛИХ 3Д ГЕОДЕТСКИХ КООРДИНАТА У ЕЛИПСОИДНЕ КООРДИНАТЕ ПРИМЈЕНОМ НЕУРОНСКИХ МРЕЖА

Сажетак

Прелазак из елипсоидних геодетских координата у правоугле 3Д координате је прилично једноставан, док је обрнути поступак нешто сложенији због математичке везе између елипсоидне ширине и 3Д координата. До сада је у геодетској литератури дефинисано и описано неколико метода за рјешавање овог проблема. У овом раду анализирана је могућност примјене алгоритма повратног ширења заснованог на вишеслојној перцептронској (Multilayer Perceptron – MLP) неуронској мрежи за трансформацију правоуглих 3Д геодетских у елипсоидне координате. Примијењени MLP модел заснован је на Бајесовој регуларизацији (Bayesian regularization - BR). Адекватност модела провјерена је тестом робусности и тестом унакрсне валидације. На основу добијених резултата, закључено је да се MLP неуронска мрежа може користити за трансформацију из правоуглих 3Д у елипсоидне координате. Будућим истраживањима треба анализирати могућност примјене овог поступка за рјешавање проблема датумске трансформације..

Кључне ријечи: трансформација координата, вишеслојна перцептронска (MLP) неуронска мрежа, Бајесова регуларизација.

1. INTRODUCTION

To achieve modern geodetic standards and create a basis for the application of new measurement technologies, networks of permanently operational reference GNSS (Global Navigation Satellite Systems) stations are used in many countries. These networks most often represent the realization of a new spatial reference system. The systems are rectangular, rectilinear, three-dimensional and geocentric. In principle, the positions of points, in these new systems are expressed by rectangular three-dimensional coordinates (X, Y, Z), while the ellipsoid GRS80 (Global Reference System 1980) is used for ellipsoidal coordinates (B, L, h). In light of the modern definition of geodetic reference systems, to describe the position of points in the horizontal plane, it is suggested to use the UTM (Universal Transverse Mercator) projection of the corresponding zone and the associated coordinate system.

The transition from spatial rectangles to curvilinear ellipsoidal coordinates is not carried out directly, due to the characteristics of their mathematical connection. There are several approaches to carry out this calculation, which is often called coordinate conversion or inverse transformation, and the iterative and closed-form methods are the most commonly used.

Machine learning, as a branch of artificial intelligence, deals with the development of algorithms and models, which enable computers to "learn and draw conclusions" from data. Machine learning techniques are a key part of this discipline. They enable computers to discover dependencies and connections in data, draw conclusions based on these findings, and then apply them to unknown data. The two basic categories of machine learning techniques are supervised learning and unsupervised learning. In supervised learning, a model is trained on a dataset containing input attributes and corresponding target values. The ultimate goal is to teach the network how to associate input data with appropriate target values. On the other hand, in unsupervised learning, the model is trained on a data set without target values, i.e. internal stratification and grouping of data is performed.

One of the classifiers for supervised learning is algorithms based on artificial neural networks (ANN). These networks, learning from data relationships, can define models, apply linear and non-linear functions, and apply them to unknown situations. Typically, neural networks are adapted, or trained, so that a particular input leads to a particular target output. Several ANN models can be formed with different architectures, depending on:

- number of additional layers and neurons,
- training algorithms and activation functions and
- neuron connection geometries.

Artificial neural networks are applied in various fields of geodesy and geoinformatics [1]–[4], including coordinate transformation. Barci [5] performed a 3D coordinate transformation using ANN, Zaletnyik [6] performed a coordinate transformation between geographic and plane coordinates, and Lin and Wang [7] transformed projection plane coordinates between two different coordinate systems. Tierra et al. [8] performed a comparison of the results of the transformation of ellipsoidal coordinates using artificial neural networks and standard parameters of data transformation, where it was concluded that ANN can be used as a technique for this type of transformation. Kutoglu [9] introduced ANN to the transformation problem as one of the alternative methods to improve the consistency of transformation between geocentric and non-geocentric (local) coordinate systems.

MLP is a powerful modelling tool, which applies a supervised learning procedure using data with known results [10]. The procedure involves the generation of a non-linear functional model that enables the prediction of the output from the given input data. MLP neural networks consist of units arranged in layers. Each layer consists of nodes and in fully connected networks each node is connected to each node in subsequent layers. Each MLP consists of at least three layers consisting of an input layer, one or more hidden layers and an output layer (Figure 1). The input layer distributes the input data to the following layers. The input nodes have a linear activation function and have no thresholds. Each hidden unit node and each output node have an associated threshold in addition to the weight. The nodes of the hidden units have a nonlinear activation function, and the outputs have a linear activation function.

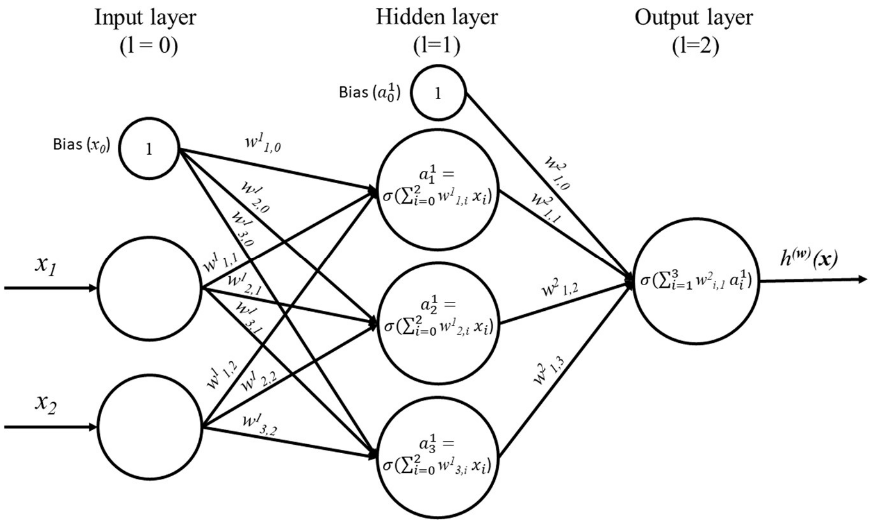

Figure 1. Schematic representation of a three-layer perceptron network [11].

In this paper, the possibility of transforming rectangular 3D into ellipsoidal coordinates was investigated using the MLP neural network. The model was used over a set of points with X, Y, and Z coordinates and their B, L and h coordinates were obtained based on a known mathematical procedure for the transition from one form to another. The results of this research, based on such a set of data, aim at a general verification of the possibility of coordinate transformation using ANN. Also, the results and conclusions of this research can be used as a starting point for researching the possibility of implementing a date transformation from a new to an existing coordinate system, and vice versa, in the research area.

2. MATERIALS AND METHODS

2.1. THE STUDY AREA

The old national reference system of the Republic of Srpska, which has been in use for more than 80 years, is based on the non-geocentric Bessel ellipsoid and the Gauss-Kriger projection of the meridian zones. The system was practically implemented with trigonometric points of various orders within the entire former SFRY. Their coordinates were determined over a long period, and with the use of different measuring technology and methodology. To achieve modern geodetic standards and create a basis for the application of new measurement technologies, since 2011, a network of permanently operational reference GNSS stations of the Republic of Srpska (SRPOS) has been used in the RS. This network represents the implementation of a new spatial reference system, ETRS89 (European Terrestrial Reference System 1989). The system is a rectangular, rectilinear, three-dimensional geocentric system tightly bound to the European lithospheric plate. In principle, the positions of points in this system are expressed by rectangular three-dimensional coordinates (X, Y, Z), while the GRS80 ellipsoid is used for ellipsoidal coordinates (B, L, h). The UTM projection of the corresponding zone is used to reduce the data to the projection plane.

2.2. INPUT DATA

To enable the application of GNSS positioning in various areas, including the state survey and real estate cadastre, the optimal coordinate transformation model between ETRS89 and the existing state reference system of the Republic of Srpska and the residual distribution method was investigated [12]. In this way, the connection between the two reference systems was established on the entire territory of the Republic of Srpska. The data from this research were used in this paper, to investigate the possibility of applying neural networks for the implementation of data transformation between these two systems in the future.

The basic data set for determining the transformation parameters and residuals' grid consisted of 1,758 points with coordinates in both systems (Figure 2). These are trigonometric points of all orders. Their ETRS89 coordinates were determined using the SRPOS grid. Considering the procedure and technology of point coordinates in the ETRS89 system, the accuracy of the horizontal position of the points ranges from 1 cm to 2 cm. Given that the coordinates were determined for each point individually, it can be considered that they are mutually uncorrelated. It can be seen that the basic set of points relatively homogeneously covers the entire territory of Republika Srpska, so it could be used to evaluate the transformation parameters.

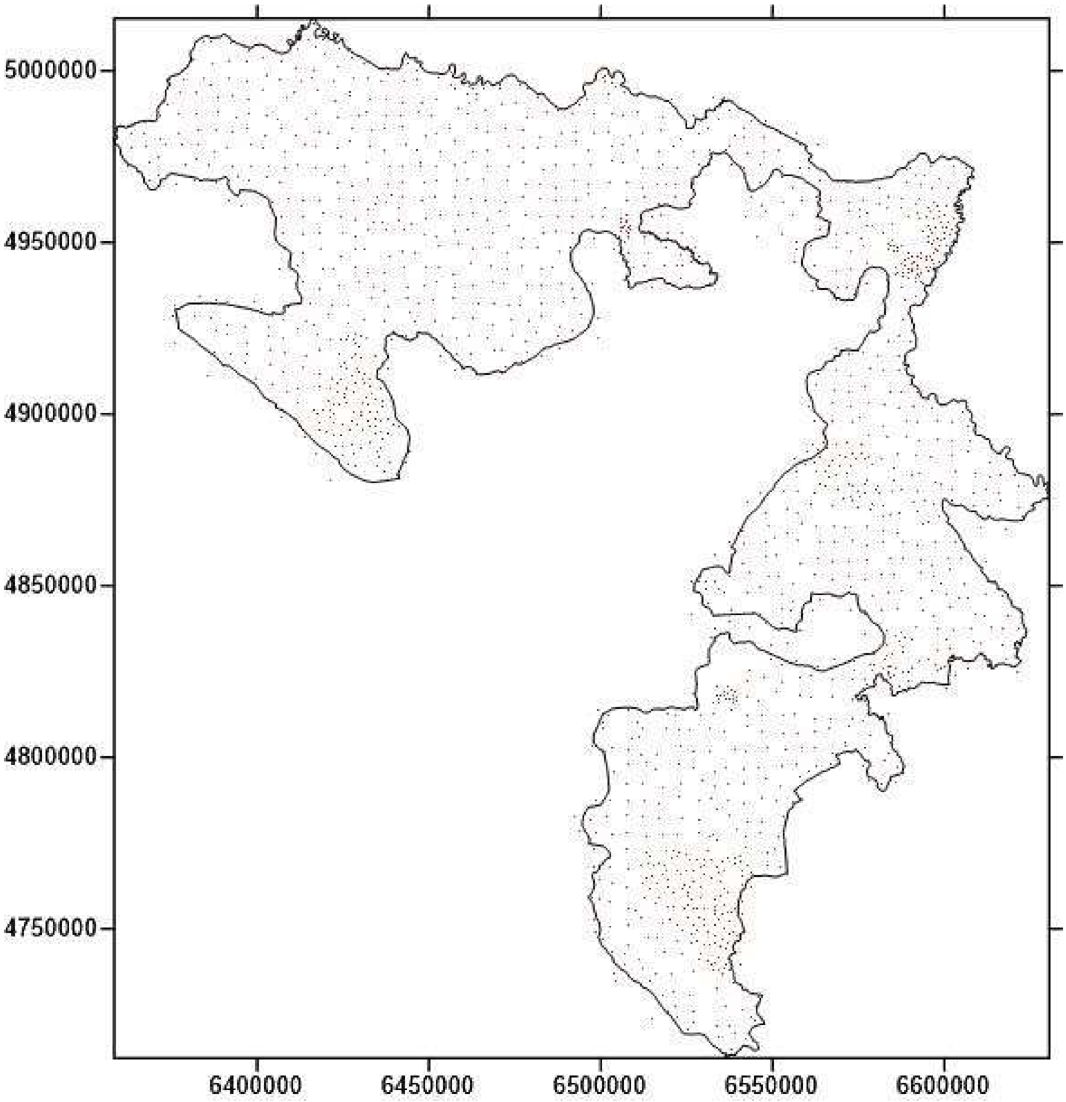

Figure 2. Points used to determine date transformation parameters in the territory of the Republic of Srpska [12]

2.3. CLASSIC TRANSFORMATION OF RECTANGULAR 3D GEODETIC INTO ELLIPSOIDAL COORDINATES

The transformation from rectangular 3D geodetic to ellipsoidal coordinates is not direct, and there are two basic approaches for its implementation: the iterative method and the closed-form method [13], [14]. Both of these approaches use the distance p from the shorter axis of the ellipsoid which is calculated for each point as:

$$p = (N + h)\cos B\,, \tag{1}$$

where N is the radius of curvature:

$$N_i = \frac{a^2}{\sqrt{a^2\cos^2 B_i + a^2\sin^2 B_i}}\,. \tag{2}$$

It is also necessary to give the connection between the geodetic latitude B and the rectangular 3D coordinates obtained when calculating the length of the meridian arc, which reads:

$$\tan B_i = \left(\frac{a}{b}\right)^2 \frac{z_i}{p_i}. \tag{3}$$

It can be written as:

$$z = \left(N + h - e^2 N\right)\sin B\ , \tag{4}$$

where e is the eccentricity of the ellipse:

$$e^2 = \frac{a^2 + b^2}{a^2}\ , \tag{5}$$

and where a is the semi-major axis, b is the semi-minor axis. In the end, we get:

$$\frac{z}{p} = \tan B\left(1 - \frac{e^2 N}{N + h}\right), \tag{6}$$

which is the basis for both approaches.
The closed-form method starts from the formula:

$$p \cdot \tan B - z = e^2 \cdot N \cdot \sin B\ . \tag{7}$$

The only unknown in this equation is B since N is also a function of B. By replacing N, dividing the numerator and denominator of the right side by cos B and squaring the entire equation, we get:

$$p^2 \tan^4 B - 2pz\tan^3 B + \left(\mathrm{Z}^2 + \frac{p^2 - a^2 e^4}{1 - e^2}\right)\tan^2 B - \frac{2pz}{1 - e^2}\tan B + \frac{z^2}{1 - e^2} = 0\ . \tag{8}$$

This is a biquadratic equation by tan B in which all the coefficients are known. When B is obtained from this equation, N, h and L are further calculated. This solution is about 25% faster than the iteration method.
Apart from the described closed-form method, there are several other approaches for this transformation, such as the non-iterative method [15], the iterative method [16] and the vector method [17].

2.4. TRANSFORMATION OF RECTANGULAR 3D GEODETIC INTO ELLIPSOIDAL COORDINATES USING MLP NEURONAL NETWORKS

The author of the paper [18] states that the best results for converting rectangular 3D coordinates into ellipsoidal coordinates were given by models based on MLP, where

X, Y, and Z coordinates are used to obtain one output parameter: B, L or h. A neural network structure with two hidden layers was used, and Bayesian regularization was used for training.

The Bayesian method was first explained in detail by a geophysicist from Cambridge, Sir Harold Jeffreys [19]. The logical basis of this method, based on the use of probabilities as a measure of credibility, was subsequently established by Cox [20], who proved that consistent inference in a closed hypothesis space can be mapped onto probabilities.

BR artificial neural networks (Bayesian regularized artificial neural network - BRANN) are more robust than standard feedback regularization networks and can reduce or eliminate the need for long-term cross-validation. BR is a mathematical process that turns nonlinear regression into a "well-posed" statistical problem. These networks provide solutions to numerous problems such as model selection, model robustness, validation set selection, and network architecture optimization [21]. It is difficult to overload them, because BRANN calculates and trains several network parameters or weights, effectively excluding those that are not relevant. This effective number is usually much smaller than the number of weight coefficients in a standard, fully connected, back-propagation neural network.

Considering that the practical research in the work of Konakoglu [18] was performed in the commercial software environment Matlab, the mentioned neural network, for this research, was reconstructed in a free environment. To solve this task, the Google Colab platform was used, that is, the Python programming language with the sklearn, keras, and tensorflow libraries.

The architecture of the applied model is MLP type (Figure 2). It consists of three input neurons (corresponding to the number of input attributes) and two hidden layers with 15 neurons in each layer. Given that there is no rule for selecting the activation function, it was chosen following the context of the research, that is, according to the task being performed. The Tanh activation function [22] was used, because it has gradients that are not constrained to vary in a certain direction. The output layer contains one neuron, which represents the prediction for B, L and h. A separate prediction was made for each element.

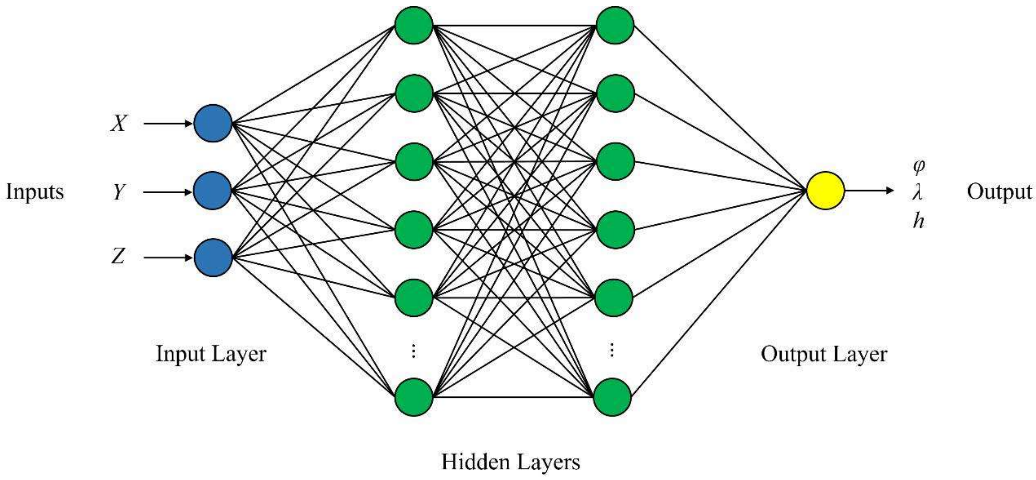

Figure 3. Structure of MLP neural network with one output parameter [18]

Model training was performed on a set of 1,500 points (Figure 2), while the rest was used for validation. The model was trained over 500 epochs, with a batch size of 10, which is an update of the weights every 10 samples.

2.5. STATISTICAL INDICATORS OF ADEQUACY OF TRANSFORMATION USING MLP NEURAL NETWORKS

The quality of the transformation of rectangular 3D geodetics into ellipsoidal coordinates using MLP neural networks was checked by calculating standard statistical measures of quality: root-mean-squared error (RMSE), mean bias error (MBE), mean absolute error (MAE) and Nash-Sutcliffe efficiency coefficient (NSE).

RMSE is the square root of the average of the squared deviations between observed and predicted coordinates. The mean squared error is a type of dimensioned statistical estimate that is always positive and includes the concept of bias and standard deviation. It is used to quantify the degree of dispersion of model predictions on observed data. Ideally, optimal models should have RMSE values of zero. However, in practice, the RMSE could vary from zero to infinity and is calculated as:

$$RMSE = \left(\frac{1}{n} \sum_{i=1}^{n} (O_i - P_i)^2 \right)^{1/2}, \tag{9}$$

where O_i represents the observed coordinates, P_i the predicted coordinates, and n the number of observations.

MBE is an indicator of the average deviation of the predicted values from the corresponding observed data. A positive MBE value indicates that the predicted values of the coordinates are less than their observed values, and vice versa:

$$MBE = \frac{1}{n} \sum_{i=1}^{n} (O_i - P_i). \tag{10}$$

MAE is the average of absolute differences between observed and predicted coordinates and is calculated as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|O_i - P_i\right|. \tag{11}$$

NSE is used to evaluate the predictability of the model. An efficiency of “1”, i.e. NSE = 1, corresponds to a perfect match between the observed and predicted coordinates and is calculated as [23]:

$$NSE = 1 - \left(\sum_{i=1}^{n}\left(O_i - P_i\right)^2 \Big/ \sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2 \right), \tag{12}$$

where $\bar{O}$ represents the mean value of the observed coordinate.

3. RESULTS AND DISCUSSION

In previous research, which considered the possibility of using ANN for coordinate transformation, it was pointed out that the form of a neural network with one hidden layer is not sufficient for precise predictions. Therefore, a neural network with two hidden layers was applied to the data used in this research, which is the approach that was also used in the research described in the work of Konakoglu [18]. Also, based on the conclusion highlighted in the mentioned paper, the MLP neural network model with one output was chosen and applied in this research.

After the transformation of the coordinates using the mentioned model, the minimum deviation in B and L coordinates is 0.000001", while the maximum deviations in B are 0.00009", and in L 0.00005". The minimum height deviation is 0.00002 m, and the maximum deviation is 0.00003 m.

Statistical indicators of the quality of the neural network model, obtained by training on a set of training points, were evaluated on a set of validation points and are shown in Table 1. Based on the RMSE value, it can be said that MLP neural networks gave good results and showed the potential of these networks for transforming rectangular 3D into ellipsoidal geodetic coordinates. MBE and MAE were also used to evaluate the quality of the neural network (Table 1). The low values of MAE and MBE additionally indicate the possibility of applying the generated neural network for predicting the values of unknown quantities. Finally, an NSE value greater than 0.99 confirms the general performance quality of the network obtained by training on the input data set.

Table 1. Results obtained from testing

	RMSE	MBE	MAE	NSE
X, Y, Z →B	0.0000356 ["]	0.0000037 ["]	0.0000237 ["]	0.99998
X, Y, Z →L	0.0000359 ["]	0.0000020 ["]	0.0000246 ["]	0.99998
X, Y, Z →h	0.0000232 [m]	0.0000014 [m]	0.0000201 [m]	0.99999

4. CONCLUSION

In this research, the possibility of applying MLP neural networks trained using the BR algorithm for the transformation of rectangular 3D (X, Y, Z) into ellipsoidal geodetic coordinates (B, L, h) was examined. Compared to previous researches, this model was applied to data belonging to the territory of an irregular shape. The results showed that MLP neural networks, based on Bayesian regularization with one output, can be used to predict the values of unknown ellipsoidal coordinates. The coordinates are estimated with certain error values, which are not statistically significantly higher than the error values of the coordinates of the points on which the network was "trained". Generally speaking, it can be concluded that the estimated values of the ellipsoidal coordinates maintained a good general agreement and relative relationship, defined by the corresponding values of the rectangular 3D coordinates. Also, previous practical research was performed in the commercial software environment MatLAB, while the mentioned neural network, for the purposes of this research, was reconstructed in a free environment, using the Google Colab platform, that is, the Python programming language.

Research has shown that ANN neural networks, based on BR algorithms, can transform rectangular 3D coordinates into ellipsoidal geodetic coordinates. Future research, which will be based on the results of this research, should analyze the possibility of applying neural networks for data transformation between the mentioned geodetic reference systems that are used and coexist in the research area.

LITERATURE

[1] J. B. Miima, W. Niemeier, and B. Kraus, “A neural network approach to modelling geodetic deformations,” in *First International Symposium on Robust Statistics and Fuzzy Techniques in Geodesy and GIS, ETH Zurich, March*, 2001, pp. 12–16.

[2] T. Kavzoglu and M. H. Saka, “Modelling local GPS/levelling geoid undulations using artificial neural networks,” *J. Geod.*, vol. 78, pp. 520–527, 2005.

[3] B. Riedel and M. Heinert, “An adapted support vector machine for velocity field interpolation at the Baota landslide,” *Appl. Artif. Intell. Eng. Geod. (AIEG 2008), S*, pp. 101–116, 2008.

[4] M. Gullu and I. Yilmaz, “Outlier detection for geodetic nets using ADALINE learning algorithm,” *Sci. Res. Essays*, vol. 5, no. 5, pp. 440–447, 2010.

[5] A. Barsi, “Performing coordinate transformation by artificial neural network,” *Allg. Vermessungs-Nachrichten*, vol. 108, no. 4, 2001.

[6] P. Zaletnyik, “Coordinate transformation with neural networks and with polynomials in Hungary,” in International symposium on modern technologies, education and professional practice in geodesy and related fields, Sofia, Bulgaria, 2004, pp. 471–479.

[7] L.-S. Lin and Y.-J. Wang, “A study on cadastral coordinate transformation using artificial neural network,” in *Proceedings of the 27th Asian conference on remote sensing, Ulaanbaatar, Mongolia*, 2006, pp. 1–6.

[8] A. Tierra, R. Dalazoana, and S. De Freitas, “Using an artificial neural network to improve the transformation of coordinates between classical geodetic reference frames,” *Comput. \& Geosci.*, vol. 34, no. 3, pp. 181–189, 2008.

[9] H. S. Kutoglu, “Alternative methods for improving transformation consistency between geocentric and non-geocentric (local) coordinate systems,” *Surv. Rev.*, vol. 41, no. 314, pp. 408–418, 2009.

[10] C. M. Bishop, *Neural networks for pattern recognition*. Oxford university press, 1995.

[11] “Deep Learning Glossary – 70 + terms you should know - inforly.io.” https://www.inforly.io/deep-learning-glossary/ (accessed May 15, 2024).

[12] S. Vasiljević, D. D. Vasić, O. Odalović, D. Blagojević, and B. Milovanović, “Horizontal coordinates transformation and residuals modelling on the territory of the Republic of Srpska,” *Surv. Rev.*, vol. 53, no. 380, pp. 390–401, 2021.

[13] C. Jekeli, “Geometric reference systems in geodesy.” 2006.

[14] C. Jekeli and O. Montenbruck, “Time and reference systems,” *Springer Handb. Glob. Navig. Satell. Syst.*, pp. 25–58, 2017.

[15] B. R. Bowring, “Transformation from spatial to geographical coordinates,” *Surv. Rev.*, vol. 23, no. 181, pp. 323–327, 1976.

[16] K. M. Borkowski, “Accurate algorithms to transform geocentric to geodetic coordinates,” *Bull. géodésique*, vol. 63, no. 1, pp. 50–56, 1989.

[17] J. Pollard, “Iterative vector methods for computing geodetic latitude and height from rectangular coordinates,” *J. Geod.*, vol. 76, no. 1, pp. 36–40, 2002.

[18] B. Konakoglu, “TRANSFORMATION OF 3D CARTESIAN (X, Y, Z) COORDINATES TO GEODETIC (φ, λ, h) COORDINATES USING A MULTILAYER PERCEPTRON (MLP) NEURAL NETWORK,” in *Euro Asia 9th. International congress on applied sciences*, 2021, pp. 347–367.

[19] H. Jeffreys, “Theory of probability: Oxford Univ. Press.” Inc, 1939.

[20] R. T. Cox, “Probability, frequency and reasonable expectation,” *Am. J. Phys.*, vol. 14, no. 1, pp. 1–13, 1946.

[21] F. Burden and D. Winkler, “Bayesian regularization of neural networks,” *Artif. neural networks methods Appl.*, pp. 23–42, 2009.

[22] S. Sharma, S. Sharma, and A. Athaiya, “Activation functions in neural networks,” *Towar. Data Sci*, vol. 6, no. 12, pp. 310–316, 2017.

[23] J. E. Nash and J. V Sutcliffe, “River flow forecasting through conceptual models part I—A discussion of principles,” *J. Hydrol.*, vol. 10, no. 3, pp. 282–290, 1970.