AN ALTERNATIVE METHOD FOR ESTIMATING DENSIFICATION POINT VELOCITY BASED ON BACK PROPAGATION ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

The establishment of Turkish National Fundamental GPS Network (TNFGN) was completed in 2001 and Large Scale Map and Map Information Production Regulation (LSMMIPR) came into force in 2005 in parallel with the establishment of TNFGN and the increase in the use of GPS applications. TNFGN has been designed as first order GPS network and it comprises second-, third- and fourth-order GPS densification networks. LSMMIPR has required determining the positions of first-, second- and third-order GPS densification (C1, C2 and C3) points with the reference epoch besides the measurement epoch. Therefore, it is necessary to estimate the velocity vectors of the densification points. In practise, the velocity vectors of C1, C2 and C3 points are estimated from TNFGN points or higher-order densification points velocity vectors by interpolation methods but LSMMIPR did not specify the interpolation method for this procedure. The objective of this study is to use a back propagation artificial neural network (BPANN) that has been more widely applied in engineering among all other neural network models for estimating the velocity of the densification point as an alternative to the interpolation methods. BPANN and selected ten interpolation methods are evaluated over a test area, in terms of root mean square error (RMSE). The results showed that the employment of BPANN estimated the densification point velocity ($V_{X,Y,Z}$) with a better accuracy (±5.0 mm, ±4.0 mm, ±3.9 mm, respectively) than the interpolation methods in the test area and indicated that BPANN can be a useful tool for estimating point velocity in the densification networks as a real alternative to the interpolation methods.

Keywords: site velocity determination, artificial neural network, interpolation, densification network, back propagation, BPANN, TNFGN

1. INTRODUCTION

The Global Positioning System (GPS) provides location, direction, speed and time information to suitably equipped worldwide users continuously, anywhere on the Earth in all meteorological conditions. The GPS measurements are frequently used in geodetic applications for determining three-dimensional (3-D) coordinates that is the base in large-scale mapping, cadastre and geographic information systems. The technological and scientific developments and the increasing use of GPS, during the last decade, have made fundamental changes in Turkey.

The Turkish National Geodetic Network (TNGN) was established with conventional techniques by the General Command of Mapping between 1934 and 1954. The datum of TNGN was European Datum 1950 (ED50) and it was realised by connecting to 8 geodetic control stations of European network from Bulgaria and Greece. The tectonic characteristics of Turkey were ignored while establishing TNGN. Scientific investigations show that positions change almost 2 cm every year because of crustal movements (*Çelik et al., 2004*). Because of the crustal movements and the displacements based on earthquakes since 1954, TNGN was not suitable for modern geodetic applications, especially GPS. A new geodetic network was required to account of the regional deformations based on Anatolia active tectonic structure which interacts with the African, Arabian and Eurasian plates.

Turkish National Fundamental GPS Network (TNFGN) has been established to provide reliable and robust geodetic network infrastructure for current and future geo-based data collection technologies (*Çelik et al., 2004*).

TNFGN has been established in 2001 and some of the stations have been re-surveyed due to the earthquakes that happened in 1999 (M_W = 7.5 İzmit, M_W = 7.2 Düzce), 2000 (M_W = 6.1 Çankırı-Çerkeş), 2002 (M_W = 6.5 Sultandağı) and 2003 (M_W = 6.4 Bingöl). The total number of stations is about 600 and 145 of them were re-surveyed in 2003 and 172 of them in 2004 together with reconnaissance of about 210 points in western Anatolia for the purpose of improvement/maintenance of TNFGN in 2005. For each station, 3-D Coordinates and their associated velocities were computed in ITRF2000. Positional accuracies of the stations are about 1–3 cm whereas the relative accuracies are within the range of 0.1–0.01 ppm. Besides, the network has been connected to the Turkish Horizontal and Vertical Control Networks through overlapping stations and time-dependent coordinates of all stations are being computed in the context of the maintenance of the network with repeated GPS observations (*Çağlar, 2006*).

The Large Scale Map Making Regulation (LSMMR) based on geodetic reference systems was approved in 1988. LSMMR was used only for cadastral mapping and it did not fit the needs of surveying authorities. In order to regularize map production for all purposes, LSMMR was required to be changed. Therefore, the Turkish Chamber of Survey and Cadastre Engineers had prepared the Large Scale Map and Map Information Production Regulation (LSMMIPR) that covered modern and extended technical standards rather than conventional standards. LSMMIPR was approved by the Cabinet and came into force as a lawful regulation in 2005 in parallel to the establishment of TNFGN and the increase in the use of GPS techniques for all kind of geodetic, mapping and surveying applications. LSMMIPR is a suitable regulation for technical developments and contains GPS applications as well.

There has been a need for geodetic network densification since the early days of traditional surveying. The general objective of network densification is to provide a more convenient accurate access to the reference frame (*Ferland et al., 2002*). Nowadays, GPS is undeniably the most convenient densification tool for geodetic networks. Any kind of geodetic applications that will be practiced in Turkey should be based on TNFGN. Densification of the TNFGN is necessary in support of large-scale mapping applications, cadastral measurement and geodetic point construction.

LSMMIPR defines the standard rules of TNFGN densification strategies. TNFGN is defined as first order geodetic network in LSMMIPR and it comprises second order, third order and fourth order GPS densification networks that are generated from TNFGN points and constructed with a baseline length smaller than 20 km within Digital Cadastre Project supervised by the General Directorate of Land Registry and Cadastre. These densification networks are constituted from first order, second order and third order densification (C1, C2 and C3) points where the positional accuracies are ±3 cm, ±5 cm and ±7 cm, respectively. The second order and third order densification networks are established for TNFGN densification and the fourth order densification network is established to allow orientation for conventional instruments to be tied to the GPS networks.

TNFGN is a part of a global network (ITRF96) which means any data collected or map produced on TNFGN has a global meaning and is globally identified and valid. TNFGN has been designed as four-dimensional geodetic network in which the 4th dimension is time (*Çelik et al., 2004*). TNFGN requires taking into account time-dependent coordinate changes caused by the tectonic characteristics of Turkey.

LSMMIPR has required determining the positions of C1, C2 and C3 points with the reference GPS epoch besides the measurement GPS epoch (*Turkish Chamber of Survey and Cadastre Engineers, 2008*).

The velocities of C1, C2 and C3 points are estimated from the velocities of TNFGN points or from higher order densification points. LSMMIPR specifies that the velocities of C1, C2 and C3 points should be estimated with interpolation but did not specify what interpolation method to use.

The velocity field estimation has been considered in several scientific studies (e.g., *Perez et al., 2003*; *Nocquet and Calais, 2003*; *D'Anastasio et al., 2006*; *Deniz and Ozener, 2008*; *Hefty, 2008*; *Wright and Wang, 2010*). The artificial neural network (ANN) has been applied in diverse fields of engineering including velocity field determination and remarkable accomplishments were made with ANN. *Moghtased-Azar and Zaletnyik (2009)* have put a comparison of the ability of artificial neural networks and polynomials for modelling the crustal velocity field and ANN was offered as a suitable tool for modelling the velocity field.

The main objective of this study is to evaluate a back propagation artificial neural network (BPANN) for estimating the velocities of GPS densification points as an alternative method to the traditional interpolation methods. The point velocities that are estimated from BPANN and interpolation methods are compared to the point velocities based on GPS measurements over a test area, in terms of root mean square error (*RMSE*) of the velocity differences.

The theoretical backgrounds of ANN, BPANN and interpolation methods are presented in Section 2. The test area, source velocity data and evaluating methodology are outlined in Section 3. The numerical case study is analyzed in Section 4. The optimisation of BPANN is explained in the context of the application in this section. Section 5 includes the results and conclusions.

2. THEORETICAL BACKGROUND

2.1. Artificial Neural Network

ANN is a distributed parallel processor, consisting of simple units of processing with which knowledge can be stored and used for consecutive assessments (*Haykin, 1999*). ANN is a highly simplified model of decision-making processes of a human brain and is formed by artificial neurons or simply neurons. The input information of the neuron is manipulated by means of synaptic weights that are adjusted during an iterative adjustment process known as training process. After the training procedure an activation function is applied to all neurons for generating the output information (*Leandro and Santos, 2007*). In this study the multilayer perceptron (MLP) model was selected because of its simple implementation among several kinds of ANNs. MLP consists of one input layer with N inputs, one hidden layer with q units and one output layer with n outputs. The output of the model with a single output neuron (output layer represented by only one neuron, i.e. $n = 1$) can be expressed according to *NØrgaard (1997)* by:

$$y = f\left(\sum_{j=1}^{q} W_j f\left(\sum_{l=1}^{N} w_{j,l} x_l + w_{j,0} \right) + W_0 \right), \tag{1}$$

where W_j is the weight between the j-th hidden neuron and the output neuron, $w_{j,l}$ is the weight between the l-th input neuron and the j-th hidden neuron, x_l is the l-th input parameter, $w_{j,0}$ is the weight between a fixed input equal to 1 and j-th hidden neuron and W_0 is the weight between a fixed input equal to 1 and the output neuron (*Valach et al., 2007*). The activation function that is used for hidden layer and output layer is the sigmoid function, represented by:

$$f(z) = \frac{1}{1 + e^{-z}}, \tag{2}$$

where z is the input information of the neuron and $f(z) \in [0,1]$. The input and output values of ANN have to be scaled in this range.

The proposed ANN for estimating the velocities of C1, C2 and C3 points is trained using the classical back propagation algorithm that has well-known ability as function approximators (*Pandya and Macy, 1995*)

Back Propagation Artificial Neural Network

The back propagation artificial neural network (BPANN) has been more widely applied in engineering among all other ANN applications. BPANN is a feed forward and supervised learning network. The architecture of a simple BPANN is shown in Fig. 1.

BPANN is composed of input layer, one hidden layer with sigmoid neurons and output layer. Each layer contains different number of neurons in accordance with the problem in question (*Zhang et al., 1998*). A network with one hidden layer using a sigmoid activation function can approximate any continuous function given a sufficient number of hidden neurons (*Bishop, 1995*).

BPANN training process corresponds to an adjustment that attempts to decrease the residuals of the output of the network (*Leandro and Santos, 2007*), by initializing the weights of the connections between the neurons of each layer. The MATLAB artificial neural network module is used for initializing the weights between 0 and 1 for preventing BPANN from slow learning.

The delta rule based on squared error minimization is used for BPANN training procedure (*Haykin, 1999*). The training process corresponds to an adjustment of the weights between the hidden layer and the output layer to the data set that is composed of the known input and output parameters. This iterative adjustment updates the weights in order to decrease the residuals (difference between the computed output and the actual given output) of the output of the neural network. The training procedure consists of two main steps: feed-forward and back-propagation. These steps continue over the training set for several thousand iterations.

The mean square error (*MSE*) can be used as a neural network performance indicator. For a given set of N inputs, MSE is defined by:

$$MSE = \sum_{i=1}^{N} \left(y_i^{act} - y_i^{pred} \right)^2 \Big/ N^2 \ , \tag{3}$$

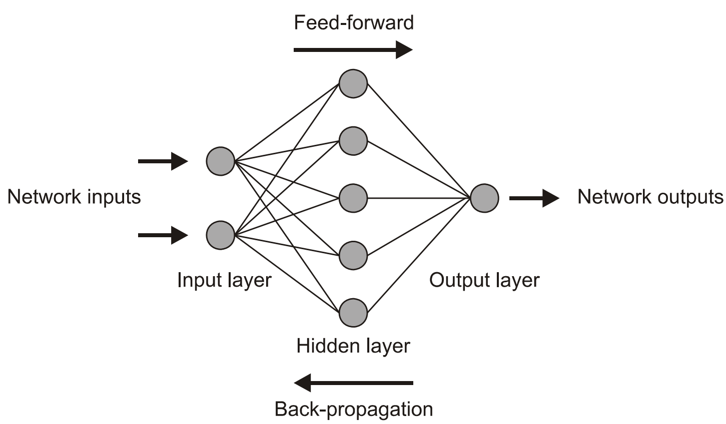

Fig. 1. The BPANN architecture.

where y_i^{act} denotes the given actual output value and y_i^{pred} denotes the neural network (predicted) output. BPANN is trained to minimize the MSE by a gradient method. BPANN can be tested over a check data set that is not used in the training procedure.

The details about the training procedure of BPANN can be found in numerous sourcesincluding *Fausett (1994)*, *Bishop (1995)*, *Ripley (1996)* and *Haykin (1999)*.

BPANN developed in MATLAB artificial neural network module allows to dynamically change the parameters of a learning algorithm, to monitor error values and weight changes, and to generate digital data and graphs that show whether learning is sufficient.

2.2. Interpolation Methods

The interpolation methods used in this study are chosen on the base of existing research studies in respect of data density and distribution that affects the interpolation accuracy (*Yang et al., 2004*; *Nikolova and Vassilev, 2006*; *Yılmaz 2009*).

The Inverse Distance Weighting Method

The Inverse Distance Weighting method (INDW) has technical appropriateness for programming. INDW is particularly used in defining continuously changing data on the same area (*Yılmaz, 2009*). INDW is a weighted average interpolator. With INDW, data are weighted during interpolation, so that the influence of one point, relative to another, declines with distance from the grid node. Weighting is assigned to data through the use of a weighting power, which controls how the weighting factors drop off as distance from the grid node increases (*Yang et al., 2004*).

The Kriging Method

The Kriging method (KRIG) is a geostatistical and flexible gridding method which has been extensively used in many fields such as mining, climatology and agriculture and has proved to be useful and accurate in its fields of use. KRIG uses the distance or navigation between the reference points as a function that helps surface characterisation. Thus, in order to determine the output values for each location, it assigns a mathematical function to a certain number of points or all the points located within a certain area of effect. KRIG uses weighting which allows the closely located points to have a greater influence (*Chaplot et al., 2006*).

The Minimum Curvature Method

The Minimum Curvature method (MCRV) is extensively used in earth sciences. A surface interpolated with MCRV could be compared to a linear, elastic and thin plane which passes through the reference points with a minimum amount of bending. MCRV generates the smoothest possible surface while attempting to fit data as closely as possible (*Nikolova and Vassilev, 2006*).

The Modified Shepard's Method

The Modified Shepard's method (MSHP) uses an inverse distance weighted least squares method. The surface generated with MSHP interpolates each scatter point and is influenced most strongly between scatter points by the points closest to the point being interpolated. MSHP has been used widely because of its simplicity (*Yılmaz, 2009*).

The Natural Neighbour Method

The Natural Neighbour method (NANG) method, which is based on the average mean, is similar to INDW. While investigating the points to be interpolated it uses the distance-dependent weights of reference points to the grid corner. With this method, the data on the reference points with irregular distribution are classified and the interpolation process is completed using the triangular irregular network functions without any need for custom-defined parameters (*Skumar et al,. 2001*).

The Nearest Neighbour Method

The Nearest Neighbour method (NENG) assigns the value of the nearest point to each grid node. NENG is useful when data are already evenly spaced. Alternatively, in cases where the data are close to being on a grid, with only a few missing values, NENG is effective for filling in the holes in the data (*Yang et al., 2004*). NENG predicts the attributes of unsampled points based on those of the nearest reference point and is best for qualitative data, where other interpolation methods are not applicable (*Burrough and McDonnell, 1998*).

The Polynomial Regression Method

The Polynomial Regression method (PRGS) is used to define large-scale trends and patterns in your data. PRGS is not really an interpolator because it does not attempt to predict unknown Z values (*Yang et al., 2004*)

The Radial Basis Function Method

The Radial Basis Function method (RBAF) is the name given to a large family of exact interpolators. In many ways the RBAF methods applied are similar to those used in geostatistical interpolation, but without the benefit of prior analysis of variograms. On the other hand they do not make any assumptions regarding the input data points and provide excellent interpolators for a wide range of data. For terrain modelling and earth sciences generally the so-called multi-quadric function has been found to be particularly effective, as have thin plate splines (*Smith et al., 2007*).

The Triangulation with Linear Interpolation Method

The Triangulation with Linear Interpolation method (TLNI) uses the optimal Delaunay triangulation. TLNI creates triangles by drawing lines between data points. The original points are connected in such a way that no triangle edges are intersected by other triangles. The result is a patchwork of triangular faces over the extent of the grid (*Yang et al., 2004*).

The Moving Average Method

The Moving Average method (MAVR) involves simple averaging using a moving window such as an ellipse or circle. For each interpolated grid point a circle of specified radius is placed with its centre at the grid point. The output grid node value is set equal to the arithmetic average of the identified neighbouring data. If there are fewer than the specified minimum numbers of data within the neighbourhood, the grid node is blanked (*Yang et al., 2004*; *Smith et al., 2007*)

3. TEST AREA, SOURCE DATA AND METHODOLOGY

The test area is located in the internal Aegean region of Turkey within the geographical boundaries: 38.10°N $\le \varphi \le$ 39.45°N; 29.70°E $\le \lambda \le$ 31.15°E defining a total area of 14000 km^2 (140 × 100 km) with an active tectonic structure (Sultandağı earthquake in 2002, $M_w = 6.5$).

The evaluating tests of the densification points' velocity refer to a source data set in the test area (Fig. 2). The source data set comprises 12 control points that belong to TNFGN and it is separated into two groups for training (modelling) process and testing process.

The velocities of TNFGN points used in this study for evaluating BPANN and interpolation based point velocities, were computed in ITRF2000 (reference epoch 2005.00) with repeated GPS observations at sub-millimetre level (up to 4 decimal places) with respect to LSMMIPR.

The evaluation is based on the determination of the differences between the known point velocity and the point velocities estimated by BPANN and interpolation methods, using the equation

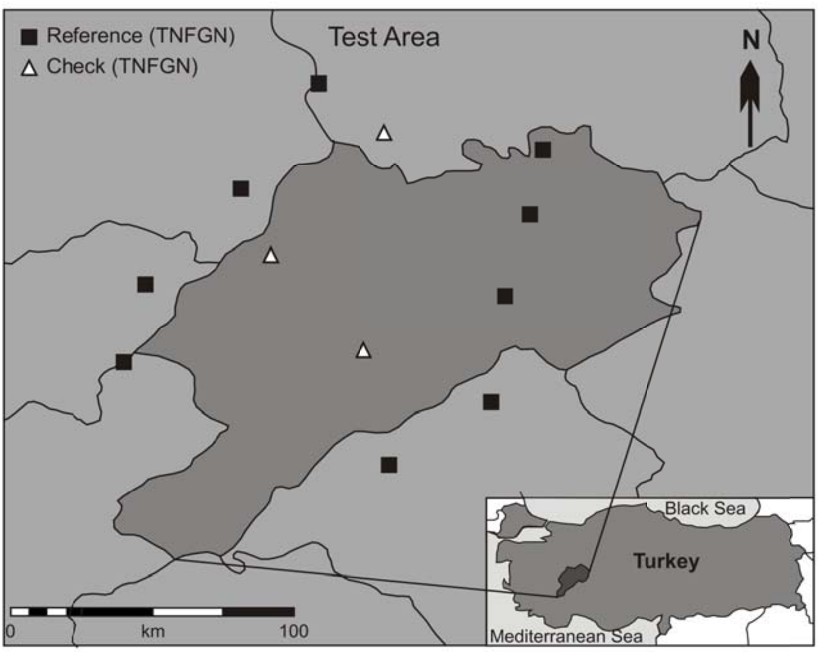

Fig. 2. Geographical point distribution over the test area.

$$\Delta V_{X,Y,Z} = V_{known} - V_{estimated} \, , \tag{4}$$

where $\Delta V_{X,Y,Z}$ is the point velocity residual, V_{known} is the point velocity known through GPS observations and $V_{estimated}$ is the point velocity based on BPANN or interpolation methods.

The point velocity residuals are investigated at sub-millimetre level by root mean square error (*RMSE*) value because *RMSE*s are sensitive to even small errors, which is good for comparing small differences between estimated and known discharges on models. *RMSE* is defined by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\Delta V_i\right)^2} \, . \tag{5}$$

4. CASE STUDY

The source data set (12 TNFGN points) is classified into two groups as reference data set and check data set (Fig. 2). The reference data set consists of 9 TNFGN points that cover the test area from the outside and the check data set consists of 3 TNFGN points that can be considered as densification points in the test area (Fig. 2). In the neural network approach, the reference points are used to train BPANN and check points are used to evaluate the performance of BPANN. In the interpolation method approach, the reference points are used to generate a surface model of the test area and check points are used to test the accuracies of the interpolation methods.

BPANN that developed for this study has two neurons in the input layer and one neuron in the output layer. Easting and northing coordinates of the point are selected as input quantities and the velocity component of the point ($V_{X,Y,Z}$) is used as output quantity for training and testing procedure of BPANN. A trial-and-error strategy was employed in order to determine the optimal number of the neurons in the hidden layer. The training process was carried out with progressively increasing numbers of hidden neurons. After a given number of training cycles, the number of the hidden neurons was selected as 20, which produced the smallest MSE. Thus, the optimum BPANN structure was determined as [2:20:1].

BPANN is trained by using the velocities of the reference points. After the training procedure, the velocities of the check points are estimated via BPANN for testing procedure. Reference data set velocities and check data set velocities based on BPANN are given in Tables 1 and 2.

MSE based on the reference points is used for analyzing the performance of BPANN in the training process. The statistical values of reference data set velocity residuals are summarized in Table 3.

The surface models of the test area are generated from the reference data set by the ten selected interpolation methods mentioned in Section 2.2. Surfer 8.0 surface modeling program is used in the interpolation method approach. From these models, the velocity residuals of the check points are computed. *RMSE* is used for investigating the velocity residuals of the check data set. The statistical values of check data set's velocity residuals are presented in Table 4.

Table 1. Reference data set velocities over the test area (values in m/year).

Point	GPS			BPANN		
	V_x	V_y	V_z	V_x	V_y	V_z
RFR01	0.0110	0.0078	0.0227	0.0064	0.0052	0.0165
RFR02	–0.0017	–0.0018	0.0055	0.0055	0.0046	0.0138
RFR03	–0.0060	–0.0034	0.0043	–0.0132	–0.0082	–0.0021
RFR04	0.0006	0.0009	0.0073	–0.0017	–0.0024	0.0047
RFR05	–0.0162	–0.0086	–0.0066	–0.0113	–0.0056	–0.0007
RFR06	–0.0185	–0.0096	–0.0072	–0.0111	–0.0048	–0.0012
RFR07	–0.0160	–0.0076	–0.0047	–0.0185	–0.0110	–0.0089
RFR08	–0.0032	0.0001	0.0023	–0.0061	0.0002	0.0009
RFR09	–0.0001	0.0001	0.0045	–0.0001	–0.0001	0.0050

Table 2. Check data set velocities over the test area (in m/year).

Point	GPS			BPANN		
	V_x	V_y	V_z	V_x	V_y	V_z
CHK01	–0.0048	–0.0017	0.0068	–0.0088	–0.0080	0.0016
CHK02	–0.0081	–0.0041	0.0025	–0.0020	–0.0015	0.0058
CHK03	–0.0199	–0.0108	–0.0075	–0.0125	–0.0084	–0.0050

The *RMSE* values of the check points velocity residual based on BPANN and the interpolation methods are shown together in Fig. 3.

5. RESULTS AND CONCLUSIONS

The analysis of the *RMSE* values summarized in Tables 3 and 4 shows that the reference data set and the check data set are very similar. The absolute differences between the *RMSE* values based on the reference data set and the check data set are small (0.1, 0.2 and 1.4 mm, respectively). It can be considered that the reference data set represents the test area quite well.

Table 3. Statistics of reference data sets velocity residuals based on BPANN over the test area (in m/year).

Data Set		*Min*	*Max*	*MSE*	*RMSE*
Reference	ΔV_x	–0.0074	0.0072	0.0000	0.0051
	ΔV_y	–0.0064	0.0048	0.0000	0.0038
	ΔV_z	–0.0083	0.0064	0.0000	0.0053

Table 4. Statistics of check data set velocity residuals based on BPANN and interpolation methods over the test area (in m/year).

Method		*Min*	*Max*	*Mean*	*RMSE*
BPANN	ΔV_x	−0.0074	0.0040	−0.0032	0.0050
	ΔV_y	−0.0026	0.0063	0.0005	0.0040
	ΔV_z	−0.0033	0.0052	−0.0002	0.0039
INDW	ΔV_x	−0.0112	−0.0050	−0.0071	0.0077
	ΔV_y	−0.0068	−0.0026	−0.0040	0.0045
	ΔV_z	−0.0075	−0.0025	−0.0045	0.0050
KRIG	ΔV_x	−0.0111	−0.0040	−0.0071	0.0077
	ΔV_y	−0.0067	−0.0017	−0.0039	0.0044
	ΔV_z	−0.0068	−0.0008	−0.0042	0.0050
MCRV	ΔV_x	−0.0158	−0.0055	−0.0113	0.0120
	ΔV_y	−0.0099	−0.0030	−0.0069	0.0075
	ΔV_z	−0.0123	−0.0021	−0.0083	0.0094
MSHP	ΔV_x	−0.0086	0.0033	−0.0029	0.0057
	ΔV_y	−0.0048	0.0054	0.0003	0.0044
	ΔV_z	−0.0017	0.0106	0.0033	0.0063
NANG	ΔV_x	−0.0120	−0.0039	−0.0074	0.0082
	ΔV_y	−0.0073	−0.0017	−0.0041	0.0047
	ΔV_z	−0.0076	−0.0009	−0.0046	0.0053
NENG	ΔV_x	−0.0158	−0.0039	−0.0087	0.0101
	ΔV_y	−0.0095	−0.0023	−0.0050	0.0059
	ΔV_z	−0.0159	−0.0028	−0.0072	0.0095
PRGS	ΔV_x	−0.0118	−0.0028	−0.0072	0.0081
	ΔV_y	−0.0072	−0.0009	−0.0040	0.0047
	ΔV_z	−0.0074	−0.0014	−0.0043	0.0050
RBAF	ΔV_x	−0.0109	−0.0032	−0.0071	0.0077
	ΔV_y	−0.0066	−0.0011	−0.0038	0.0044
	ΔV_z	−0.0065	0.0002	−0.0041	0.0052
TLNI	ΔV_x	−0.0121	−0.0029	−0.0070	0.0080
	ΔV_y	−0.0075	−0.0013	−0.0041	0.0048
	ΔV_z	−0.0077	−0.0004	−0.0044	0.0054
MAVR	ΔV_x	−0.0123	0.0003	−0.0048	0.0072
	ΔV_y	−0.0071	0.0008	−0.0027	0.0042
	ΔV_z	−0.0082	0.0025	−0.0021	0.0049

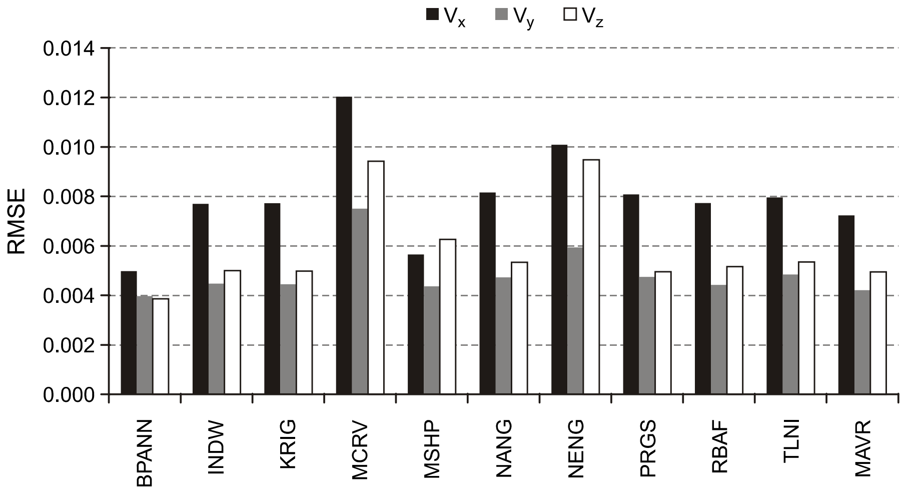

Fig. 3. The check data set's *RMSE* based on BPANN and the interpolation methods (in m/year).

When the results presented in Table 4 are evaluated, it can be seen from Fig. 3 that BPANN estimated point velocities more accurate for the check data set with respect to the interpolation methods in the test area. BPANN provided the smallest *RMSE* value (±5.0, ±4.0 and ±3.9 mm, respectively) of the point velocity residual that relates the sufficient positional accuracy for the check data set (±3 cm for TNFGN points).

The objective of this study was to evaluate the applicability of BPANN for estimating the densification point velocities. From the results of this study, the following conclusions can be made:

1. The employment of BPANN estimated the densification point velocity with a better accuracy when it is compared the interpolation methods, in terms of *RMSE*. The main advantage of BPANN is free-model estimation that interpolation methods can not be applied.
2. The adaptation of an ANN that is properly trained with a back propagation algorithm to the estimating of the densification (C1, C2 and C3) points velocities is an alternative tool to the interpolation methods. The proposed ANN is computationally robust and has ability for learning and decision-making.
3. With more dense GPS networks and with improved geographical coverage, more accurate velocity estimations can be expected from BPANN and also interpolation methods.

Furthermore, the evaluation of BPANN and the other ANN models with diverse architecture (e.g., different training algorithms and activation functions, additional hidden layers and neurons) for determination the strain rate field and the velocity field of geodetic GPS networks, would be an interesting objective in the future research.

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