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Position Adjustment Using the Artificial Neural Network Backpropagation Technique

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ABSTRACT

Nowadays, the usual adjustment methods of the surveying networks are typically addressed through the principle of Least Squares (L.S.) methodologies. One of the most important field data that needs to be adjusted is the observed coordinates of the stations. This kind of adjustment is commonly performed by using the L.S. criterion through solving a set of complex nonlinear functions. Therefore, this research aims to present an approach for implementing position adjustment in surveying networks based on the Artificial Neural Network Backpropagation (ANNB) concept. The proposed method is built on forming one or more geometrical conditions that consider the misclosure error of observations depending on the network's field measurement circumstances. The initial weights of input data are determined based on their variances, which are then trained and updated. The weights updating are obtained according to the used activation function. Thus, the main advantage of the ANNB method lies in its adoption of a set of linear functions that vanish the misclosure error existing in each geometrical condition according to the network's situation. The desired residuals are determined based on the updated weights for departures and latitudes of all formed geometrical conditions. Therefore, all misclosure errors in all geometrical conditions will be eliminated perfectly. The evaluation of the proposed ANNB method is done according to the well-known, Least Squares adjustment. The obtained results of the evaluation reveal a logic convergence with minor differences between the outcomes of the ANNB method and those of the parametric L.S. method.

1. Introduction

The adjustment procedure to the observed positions is one of the crucial post-data collection procedures that provide the adjusted coordinates of the measured stations. The adjusted position usually involves determining the most probable values of the measured Eastings and Northings of the network's stations. Although the approximation methods of adjustment are inadequate in adjusting high-precision survey networks that involve traversing, trilateration & triangulation networks, they are still very attractive to land surveyors who specialize in property boundary establishment, engineering construction, mapping activities in conjunction with satellite imageries (Hart 2021). In field surveying works, after eliminating mistakes and making corrections for systematic errors, the presence of the remaining random errors will be evident in the form of misclosures (Ghilani 2006). The approximation method of adjustment of the traverse network used by geomatics and allied professionals includes but is not limited to the following: the transit method, the Bowditch method, and the Crandall method (Hart 2021). However, the most rigorous and popular method of adjusting these misclosures is the least squares adjustment which produces a mathematical solution based upon some geometric conditions (Alsadik 2019). The term adjustment does not have any proper statistical meaning, a better is "least squares estimation" since nothing, especially observations, are actually adjusted. Rather, coordinates are estimated from the evidence provided by the observations (Scofield 2007). Thus, it is worth mentioning that the Artificial Neural Network (ANN) allows the use of very simple computational operations to solve complex mathematically defined problems or stochastic problems (Graupe 2007). The output function of a neural network itself isn't an error function (Jain 2025). But it can be turned into one easily because the error is the difference between the target training values and the actual output values (Kwestan O. Abdalkarim 2023). Neural networks use a backpropagation algorithm to update the parameters such that the difference between the prediction of the network and the observed data is minimized (Mercorelli. 2021). It Observed that most of the ANN based models use back propagation as the training technique. Some global optimization techniques can be used as ANN training for better prediction of software development efforts (Bisi 2017).

2. ANNB Method

The current research introduces a new application of conducting the position's adjustment that uses the popular Artificial Neural Network (ANN) technique. The proposed ANNB method utilizes the principle of machine learning according to the artificial neural network backpropagation technique. The steps of the proposed method are illustrated in Fig. 1 below, which comprises two main phases. The initial phase includes the weights estimation and initial training of input data. In contrast, the second phase involves the determination of the existing misclosure errors, defining the activation function, updating weights, and data training according to the updated weights through the backpropagation process. Then, these updated weights in turn will lead to the identification of the required residuals for adjustment of the measured Eastings and Northings.

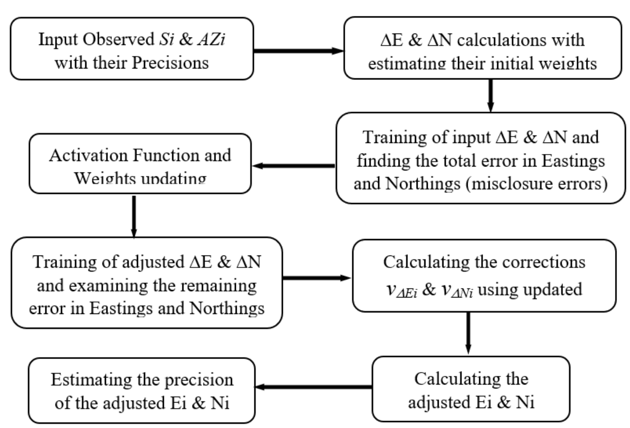


Figure 1: Workflow of the ANNB method of position adjustment

The data training process is done according to a set of functions that describe the relationships between the observations, based on which, the geometrical conditions within the surveying network will be formed (Sahand K. Khidr 2025). The backpropagation technique is a supervised learning algorithm that enables a neural network to learn from field data concerning a set of geometrical relationships. This is achieved by updating its weights and using them to minimize the difference between the predicted value and the target value (adjusted value). The concept of estimating the initial weights of the observations for ANNB adjustment is inspired by understanding the relationship between the weight and the variance. Thus, the value of the desired residuals will be determined with the aid of the ANNB according to the following considerations:

i- The weight of the measured quantity is the inverse of its variance.

ii- The relationship between the observations' variance in a single geometrical condition, which is formed according to the nature, geometry, and size of the observed data (Jassim 2021).

This research proposes an interesting concept of position adjustment, aiming to avoid the complexities in the non-linear models that are often necessary in most L.S. methods, by using an application of the backpropagation technique. The principle of the proposed method involves establishing a set of functions that represent a set of controlled geometrical relationships (geometrical conditions). These conditions are designed to consider the sum of departures (ΣΔEi) and a sum of latitudes (ΣΔNi) based on the predetermined misclosure errors, which exist in observations under the circumstances of size and shape of the surveying network. Fig. 2 below illustrates one of the most used networks in field surveying, which is the traverse consist of three stations between two baselines. A traverse is a series of geodetic control points, each intervisible with its adjacent points, which are chosen to form a system of broken lines called a traverse (Zhiping 2014).

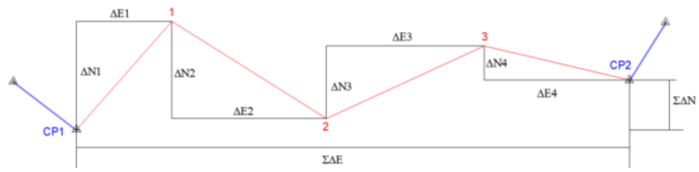


Figure 2: Straight controlled traverse as a kind of survey network.

Thus, ANNB method was applied to adjust the stations 1, 2, & 3 of the travers shown in Fig. 2 according to the following sequence:

- Input layer which is consist of the measured distances and azimuths with their estimated precisions (i.e., standard errors).
- Finding the departures and latitudes for each side as a hidden layer.
- Calculating the weights of departures & latitudes using the variances of the measured distances and azimuths.
- Applying the summation of the departures and latitudes to find the value of misclosure errors in departures and latitudes individually (summation function and bias).
- Activation function (sigmoid function) to calculate the updating of weights.
- Training the updated weights and applying the backpropagation.
- Finding the updated residuals to find the adjusted departures and latitudes and then the adjusted coordinates of the traverse stations 1, 2, & 3.
- Estimation the precisions of the adjusted values.

So, the basic geometrical conditions for data training are created using the principle of the network's geometrical control, as follows:

$$\text{Sum of Departures } (\Sigma \Delta E_i) \text{ should} = (E_{CP2} - E_{CP1}) \quad (1)$$

$$\text{Sum of Latitudes } (\Sigma \Delta N_i) \text{ should} = (N_{CP2} - N_{CP1})$$

Where (ECP, and NCP) are the coordinates of the Ground Control Point (GCP), which are located at the edges of the traverse (i.e., baselines stations).

2.1 Weights of Observations

The weight is assumed to be inversely proportional to the squares of their respective mean square error (Duggal 2013). Furthermore, for the uncorrelated observations, the weights of the observations are inversely proportional to their variances (Ghilani 2016). However, it is worth remembering that departure and latitude are functions of two factors: the side's length (S) and the side's azimuth (AZ). So, referring to the general law of error propagation for uncorrelated observations and the principle of forward computations, the variance of the ith departure and latitude is determined as follows:

$$\sigma_{\Delta Ei}^2 = \left(\frac{\partial f_E}{\partial Si}\right)^2 * \sigma_{Si}^2 + \left(\frac{\partial f_E}{\partial AZi}\right)^2 * \sigma_{AZi}^2 \quad \text{------------- (2)}$$

$$\sigma_{\Delta Ni}^2 = \left(\frac{\partial f_N}{\partial Si}\right)^2 * \sigma_{Si}^2 + \left(\frac{\partial f_N}{\partial AZi}\right)^2 * \sigma_{AZi}^2$$

Where (σ_{Si}^2, σ_{AZi}^2) are the variances of length (S_i) and azimuth (AZ_i), respectively for the ith side. Hence, the initial weight of a single departure and latitude can be estimated as the following (Duggal 2013):

$$w_{\Delta Ei} = \frac{1}{\sigma_{\Delta Ei}^2} \quad \text{----------------- (3)}$$

$$w_{\Delta Ni} = \frac{1}{\sigma_{\Delta Ni}^2}$$

Where $(\sigma_{\Delta Ei}^2, \sigma_{\Delta Ni}^2)$ is the variance of the measured departure and latitude, respectively.

2.2 Training of Input Data

The training of input data starts with passing the input departures and latitudes (ΔE_i & ΔN_i) in the network to find the predicted values SE and SN considering their initial weights (i.e., forward propagation process). Then, the values of the existing misclosures of coordinates in each established condition (ME_E and ME_N) are to be determined as follows:

$$ME_E = \Sigma\Delta E_i - (E_{CP2} - E_{CP1}) \quad \text{------------- (4)}$$

$$ME_N = \Sigma\Delta N_i - (N_{CP2} - N_{CP1})$$

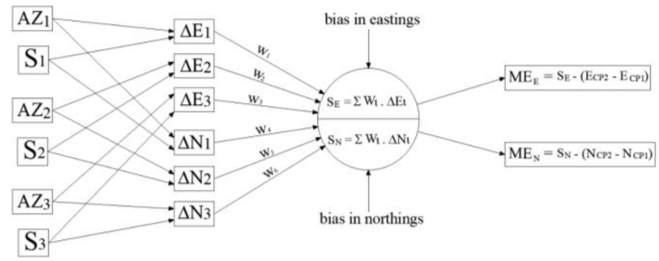


Figure 3: Forward propagation process and calculation of misclosure error.

Fig. 3 clarifies the structure of the forward propagation process, which includes the layer of inputs (field data) and the intermediate layer of measured departures and latitudes with their initial weights. Meanwhile, the output of this process is the predicted values of misclosure errors in eastings and northings ordinates for a single geometrical condition. It is worth mentioning that the required adjustment will be done based on the determination of the required value of residual (v_i) for each departure and latitude separately. Therefore, the possible geometrical conditions for the traverse above can be written as the following:

$$(\Delta E_1 + v_{\Delta E1}) + (\Delta E_2 + v_{\Delta E2}) + (\Delta E_3 + v_{\Delta E3}) + (\Delta E_4 + v_{\Delta E4}) = E_{CP2} - E_{CP1} \quad \text{------------- (5)}$$

$$(\Delta N_1 + v_{\Delta N1}) - (\Delta N_2 + v_{\Delta N2}) + (\Delta N_3 + v_{\Delta N3}) - (\Delta N_4 + v_{\Delta N4}) = N_{CP2} - N_{CP1}$$

Where ($v_{\Delta Ei}$, $v_{\Delta Ni}$) are the residuals required to find the adjusted value of departure and latitude, respectively. Thereby,

$$v_{\Delta E1} + v_{\Delta E2} + v_{\Delta E3} + v_{\Delta E4} = (E_{CP2} - E_{CP1}) - \Sigma\Delta Ei = V_E \quad \text{--------------- (6)}$$

$$v_{\Delta N1} - v_{\Delta N2} + v_{\Delta N3} - v_{\Delta N4} = (N_{CP2} - N_{CP1}) - \Sigma\Delta Ni = V_N$$

Where (V_E, V_N) is the sum of required corrections, which is equivalent to the sum of the required residuals for the departure and latitude ordinates, respectively within a single geometric condition.

The training of the ANN model can be done by several algorithms, one of them being the Gradient Descent (GD) (Alqadi 2023). Gradient descent is often performed in 3 steps, namely, (1) internal variable initialization, (2) evaluating the model based on the internal variable and loss function, and (3) updating internal variables in the direction of finding optimal points (Thuy-Anh 2021). Thus, in the next development, the internal variables will be understood as the required residuals (v_E & v_N) and the gradient descent will be done according to the sigmoid functions $f(S_E)$ and $f(S_N)$ (see 2.2.1).

2.2.1 Activation Function

The commonly used activation function is the simple S-shape sigmoid function since it is the more realistic and logistic function (Sumit Chaudhary 2025). Thus, the activation functions for departures $f(S_E)$ and latitudes $f(S_N)$ inside a single geometrical condition will be found as follows:

$$f(S_E) = \frac{1}{1+e^{-S_E}} \; ; \qquad f(S_N) = \frac{1}{1+e^{-S_N}} \; , \quad \text{and}$$

$$S_E = w_{E1} * \Delta E_1 + w_{E2} * \Delta E_2 + w_{E3} * \Delta E_3 + w_{E4} * \Delta E_4 \quad \text{--------------- (8)}$$

$$S_N = w_{N1} * \Delta N_1 + w_{N2} * \Delta N_2 + w_{N3} * \Delta N_3 + w_{N4} * \Delta N_4$$

Where (w_{Ei}, w_{Ni}) are the initial weights of input data, departure (ΔE_i) and latitude (ΔN_i), respectively.

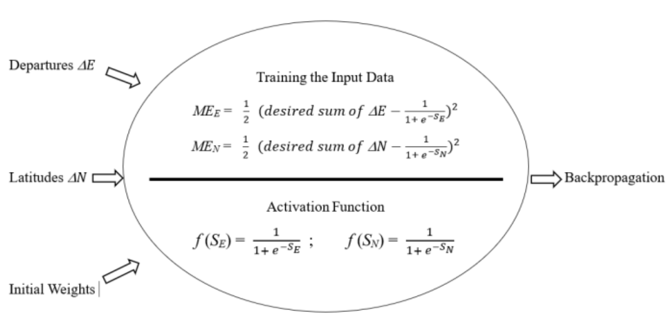


Figure 4: Training of inputs and activation function.

The diagram in Fig. 4 illustrates the concept of training the input data of departures and latitudes within a geometrical condition and the application of the designed threshold for training those data. The prediction of the existing errors (MEE and MEN) will be expressed as the sum of differences between the target value (adjusted) and the predicted value (the actual), i.e.,

$$ME = \frac{1}{2}\,(Target - Predicted)^2$$

So, the equation of error prediction for a set of departures and latitudes within a single geometrical condition will be presented as follows:

$$ME_E = \frac{1}{2}\,\left(desired\ sum\ of\ \Delta E - \frac{1}{1+e^{-S_E}}\right)^2 \quad \text{--- (9)}$$

$$ME_N = \frac{1}{2}\,\left(desired\ sum\ of\ \Delta N - \frac{1}{1+e^{-S_N}}\right)^2$$

2.2.2 Weights Updating

To find the demand changes in the weights of departures and latitudes, Eq. 9 should be expanded based on the predicted outputs. These changes will be determined by taking the partial derivatives of predicted errors (ME_E, ME_N) with respect to the weights of each departure and latitude (w_{Ei} and w_{Ni}) separately as follows:

$$\frac{\partial ME_E}{\partial w_{Ei}} = -\,ME_E * \frac{1}{1+e^{-S_E}} * \left(1 - \frac{1}{1+e^{-S_E}}\right) * \Delta Ei \quad \text{--(10)}$$

$$\frac{\partial ME_N}{\partial w_{Ni}} = -\,ME_N * \frac{1}{1+e^{-S_N}} * \left(1 - \frac{1}{1+e^{-S_N}}\right) * \Delta Ni$$

Where the terms ($\frac{\partial ME_E}{\partial w_{Ei}}$ and $\frac{\partial ME_N}{\partial w_{Ni}}$) are represent the changes in the weights of departures and latitudes, respectively. Hence, the weights of departures and latitudes will be updated as follows (Rashid 2016):

$$\text{New } w_{\Delta Ei} = \text{previous } w_{\Delta Ei} - L * \frac{\partial ME_E}{\partial w_{Ei}} \quad \text{------- (11)}$$

$$\text{New } w_{\Delta Ni} = \text{previous } w_{\Delta Ni} - L * \frac{\partial ME_N}{\partial w_{Ni}}$$

Where (L) is the learning rate, which commonly takes a value between (0.01 – 0.05). Practically, the value of (L) has been considered equal to the number of redundant observations in the network multiplied by 0.01. Notice that one of the most crucial steps in the backpropagation process is the training of the updated weights to evaluate the remaining errors, which consequently will serve to minimize the difference between the target value and the predicted value in order to eliminate the errors in departures and latitudes inside each geometrical condition individually.

2.3 Outputs of ANNB Method

For the determination of the adjusted departures and latitudes, their residuals will be calculated according to the updated weights individually. The values of the required residuals for each departure and latitude are obtained using the updated weights within the corresponding condition, based on the following concept:

$$v_{\Delta Ei} = \frac{w_{\Delta Ei}}{\Sigma w_{\Delta Ei}} * V_E \qquad \text{----------} \ (12)$$

$$v_{\Delta Ni} = \frac{w_{\Delta Ni}}{\Sigma w_{\Delta Ni}} * V_N$$

Where ($\Sigma w_{\Delta Ei}$, $\Sigma w_{\Delta Ni}$) are the sum of weights for departures and latitudes in a certain geometrical condition, respectively. ($v_{\Delta Ei}$, $v_{\Delta Ni}$) are the resulting residuals that are needed to adjust the departures and the latitudes for the ith position in a geometrical condition. Thus, the final results of the adjusted position of station 1 (for instance), in the traverse, can be found as follows:

$$\overline{E_1} = E_{CP1} + \overline{\Delta E_1}\ ; \quad \text{and} \quad \overline{N_1} = N_{CP1} + \overline{\Delta N_1} \qquad \text{----} \ (13)$$

Where ($\overline{\Delta E_1}$, $\overline{\Delta N_1}$) are the adjusted departure and latitude, respectively for the first station in the traverse, and (E_{CP1} and N_{CP1}) are the coordinates of the first control points in the traverse.

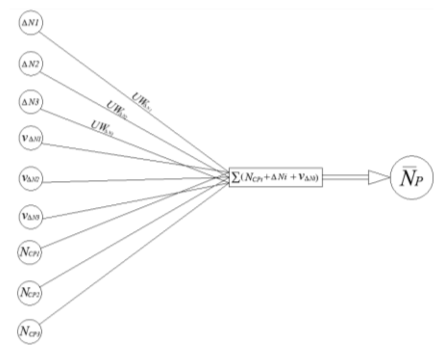
Similarly, to find the position adjustment of ith station, the adjusted coordinates of the previous station will be used to find the required adjustment for the next station as in the following:

$$\overline{E_i} = \overline{E_{i-1}} + \overline{\Delta E_i} \qquad \text{-----------} \ (14)$$

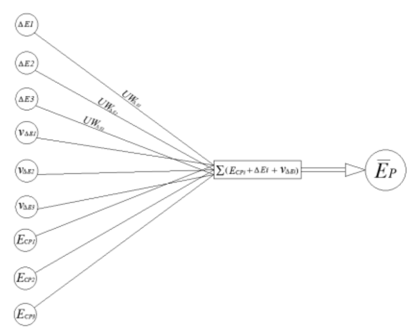
$$\overline{N_i} = \overline{N_{i-1}} + \overline{\Delta N_i}$$

Where ($\overline{E_1}$, $\overline{N_1}$) are the adjusted easting and northing, respectively.

It is worth mentioning that if the adjustment of position shared by more than one geometrical condition (which is, called node point) is required, then the ANNB method will consider all these conditions shared by that node point (see Fig. 5).



(a)



(b)

Figure 5: ANNB output layer for intersection point. **a-** Easting & **b-** Northing

Fig. 5 above shows the ANNB position adjustment for a case of node point, in which ($UW_{\Delta Ei}$ & $UW_{\Delta Ni}$) are the updated weights of departures and latitudes in each shared geometrical condition, and ($v\Delta Ei$ & $v\Delta Ni$) are the values of the obtained residuals.

2.4 Precision of The Adjusted Coordinates

The precision of ANNB outputs has been presented based on the consideration of the standard deviation of the obtained residuals for each adjusted departure and latitude separately. Thus, the standard deviation of the adjusted departures and latitudes will be computed according to their updated weights and the resulting residuals (Ghilani 2016).

$$\sigma_{\Delta Ei} = \pm \sqrt{\frac{\Sigma(W_{\Delta Ei} * v^2{}_{\Delta Ei})}{(n-1) * W_{\Delta Ei}}} \qquad \text{------------- (15)}$$

$$\sigma_{\Delta Ni} = \pm \sqrt{\frac{\Sigma(W_{\Delta Ni} * v^2{}_{\Delta Ni})}{(n-1) * W_{\Delta Ni}}}$$

Where ($v_{\Delta Ei}$, $v_{\Delta Ni}$) is the obtained residual for a certain easting and northing, respectively, ($W_{\Delta Ei}$, $W_{\Delta Ni}$) is the updated weight of departure and latitude, respectively, and (n) is the number of measured sides of the network.

3. Results of Experimental Data

Even though the field surveying operations are varied and have different forms of networks, the ANNB method has been applied to adjust stations of two commonly used kinds of field surveying networks. The first one is the case of a straight controlled traverse (as in Fig. 2 above) and the second one is the case of a resection point (case of node station). The experimental data of the traverse consists of three stations and the field measurements including the azimuths and distances for the four sides of the traverse. While, the data of the resection point contains the measurements of azimuths and distances of three routes, which are started from three ground control points and intersect in one node station. These numerical field data served as a practical experiment illustrating the main steps of ANNB adjustment. Furthermore, the obtained results of ANNB adjustment are evaluated according to the results of the parametric method of Least Squares adjustment. The ANNB adjustment for both cases are done with the aid of dedicated programs written for that purpose on the MATLAB programming platform. The obtained residuals of traverse adjustment by ANNB method are illustrated in the Fig. 6 below.

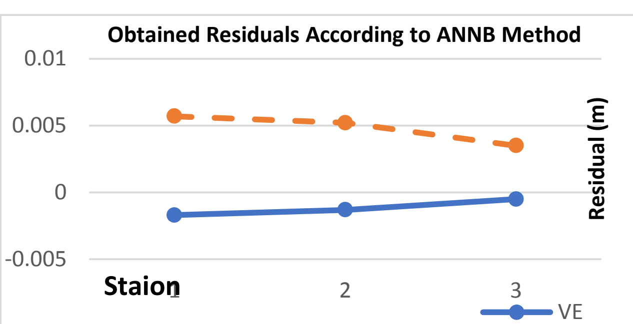


Figure 6: ANNB adjustment – values of obtained residuals (for traverse shown in Fig. 2)

Table 1: Adjusted coordinates using both methods - case of straight control traverse

St.	Coordinates (m)		σ (m)
1	Easting (ANNB)	1378.9042	±0.001
	Northing (ANNB)	461.7794	±0.012
	Easting (L.S.)	1378.9058	±0.001
	Northing (L.S.)	461.7736	±0.0009
2	Easting (ANNB)	1477.6261	±0.002
	Northing (ANNB)	400.8691	±0.012
	Easting (L.S.)	1477.6289	±0.0008
	Northing (L.S.)	400.8583	±0.002
3	Easting (ANNB)	1578.5774	±0.002
	Northing (ANNB)	446.3906	±0.015
	Easting (L.S.)	1578.5806	±0.0002
	Northing (L.S.)	446.3762	±0.001

4. Discussion

The output of the ANNB adjustment method for the traverse stations is presented in Table 1, which includes the results of the parametric method of L.S. adjustment (for the same tested traverse). The obtained standard deviations (σE & σN) in Table 1 indicate that the precision of the adjusted positions is approximately the same as it shown in Fig. 7.

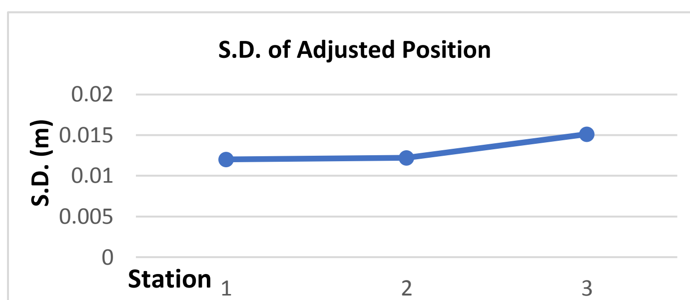


Figure 7: Standard deviations of adjusted traverse stations using ANNB.

Table 2: Experimental results of both methods for the case of node station.

Method of Adjustment	Easting	σ_E (mm)	Northing	σ_N (mm)
ANNB	3595.499	±0.02	2771.000	±0.02
L.S.	3595.503	±0.07	2770.980	± 0.09

The obtained results of the node station are illustrated in Table 2, which indicates the convergence in the obtained results and the degree of compatibility between the ANNB method and the parametric method of L.S. Even though, the obtained results of the ANNB adjustment, for both cases, were evaluated by comparing them with the results of the parametric method of L.S. adjustment. This evaluation was obtained by identifying the discrepancies in the easting and northing, coordinates, for all traverse stations and the node station as well, as shown below:

$$\delta_E = \text{Easting (ANNB)} - \text{Easting (L.S.)} \quad \text{----- (16)}$$

$$\delta_N = \text{Northing (ANNB)} - \text{Northing (L.S.)}$$

Where (δ_E, δ_N) are the discrepancies in easting and northing, respectively.
Thus, the root mean square error of discrepancy in easting and northing can be calculated as follows:

$$\text{RMSE (E)} = \pm\sqrt{\frac{\Sigma(\text{E}_{ANNB} - \text{E}_{LS})_i^2}{n}} = \pm\sqrt{\frac{\Sigma\,\delta_{Ei}^2}{n}} \quad \text{-- (17)}$$

$$\text{RMSE (N)} = \pm\sqrt{\frac{\Sigma(\text{N}_{ANNB} - \text{N}_{LS})_i^2}{n}} = \pm\sqrt{\frac{\Sigma\,\delta_{Ni}^2}{n}}$$

The RMSE in easting (E) is found equal to (± 2.4 mm) whereas, the RMSE in northing (N) is found as (± 10.8) mm. However, the discrepancy of the adjusted position (δP_{adj}) can also be derived by considering the discrepancies in the easting and northing of each station individually, as in below:

$$\delta Pi_{adj} = \pm\sqrt{\delta_{Ei}^2 + \delta_{Ni}^2} \quad \text{------------- (18)}$$

The evaluated positions for the three traverse stations are presented in Table 3, in which the results indicate that the average discrepancy in position in both tested cases is about ± (10 – 16) mm.

Table 3: Position Discrepancy for both cases

Straight Controlled Traverse			
Station No.	δ_E	δ_N	δP_{adj}
Station 1	- 0.002 m	0.006 m	± 0.006 m
Station 2	- 0.002 m	0.011 m	± 0.011 m
Station 3	- 0.003 m	0.014 m	± 0.014 m
Average	- 0.002 m	0.010 m	± 0.01 m
Node Sta.	- 0.004 m	0.015 m	± 0.016 m

It is important to note that the results of the evaluation, in terms of comparison, are deemed acceptable as they closely align with the precision of the adjusted departures and latitudes and adjusted position as well. Additionally, to enhance the evaluation results and as a kind of validation measure, the obtained adjusted departures and latitudes were backward used to verify the vanishing of the network's misclosure error. The results of this verification reveal that the misclosure error in the sum of departures and latitudes does not vanish exactly when using the L.S. adjustment, especially in the case of node station, whereas it vanished when utilizing the ANNB adjustment. This highlights the significance of establishing a rigorous geometrical condition and the importance of determining the misclosure errors in our observations during the process of adjustment. That indicates one of the important advantages of the ANNB method indeed.

5. Conclusions

The presented research presents an application of position adjustment, which is utilizing Artificial Neural Networks and backpropagation technique (ANNB). The research has drawn attention to the following conclusions:

- The proposed ANNB method for position adjustment can be characterized as the easiest adjustment method for adjusting the position of stations within the surveying network. It relies on constructing a straightforward linear mathematical model tailored for adjustment purposes.

- Each condition in the mathematical model is designed to control the existing geometrical relationships between observations within the entire surveying network. Therefore, it considers the calculated misclosure error values in both departures and latitudes for all sides. Moreover, the constructed mathematical model should take into consideration the misclosure error of all possible geometric conditions especially if the case of node stations is under adjustment consideration.
- The initial weights of the input layer are set based on the variances of those inputs. The sigmoid function is employed to activate and train the misclosure errors in each geometric condition individually.
- The new (updated) weights are determined based on their changing values for both departures and latitudes. Subsequently, these updated weights are trained to assess the misclosure errors in departures and latitudes separately.
- The evaluation results of the ANNB adjustment, conducted by comparing its outcomes with those of the parametric method of L.S. adjustment, indicate that the average difference between them did not exceed (± 16 mm) in the obtained adjusted position.

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Conflict of interest

There is no conflict of interest.

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