International Journal of Earth Sciences Knowledge and Applications (2024) 6 (3) 323-333

International Journal of Earth Sciences Knowledge and Applications
journal homepage: http://www.ijeska.com/index.php/ijeska

Research Article
e-ISSN: 2687-5993

Adjustment of Real-time Kinematic-Global Positioning System (RTK-GPS) Survey Data: A Comparative Performance Analysis of the Back Propagation Artificial Neural Network (BPANN) and the Total Least Squares (TLS) Techniques

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INFORMATION

Article history
Received 08 September 2024
Revised 08 December 2024
Accepted 09 December 2024

Keywords
Back Propagation Artificial Neural Network
Real Time Kinematic Global Positioning System
Global Navigational Satellite System
Horizontal Displacement
Total Least Square

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ABSTRACT

This study seeks to conduct an empirical evaluation of the performances of two soft computing methodologies comprising the Levenberg-Marquardt Back Propagation Artificial Neural Network (LMBPANN) and the Bayesian Regularisation Backpropagation Artificial Neural Network (BRBPANN). The study also assesses the performance of the soft computing techniques with the conventional Total Least Square (TLS) approach to calibrating Real-Time Kinematics Global Positioning System (RTK-GPS) survey data. The horizontal displacements (*HD*), arithmetic mean error (*AME*), arithmetic mean square error (*AMSE*), and arithmetic standard deviation (*ASD*) are the model evaluation and validation criteria used for the performance assessment. The analysis of results from the statistics viewpoint demonstrated that LMBPANN, BRBPANN, and TLS precisely adjusted RTK-GPS survey data with good precision in the study area. However, TLS better adjusts RTK-GPS survey data compared to LMBPANN and BRBPANN. Corresponding to the mean horizontal displacement measurement, the *AME*, *AMSE*, and *ASD* for TLS reached 1.41459E-09 m, 2.00428E-18 m, and 9.760E-14 m, and for the LMBPANN and BRBPANN, they reached 0.005595 m, 4.99277E-05 m, 0.000137 m, and 0.001287 m, 0.3.30633E-06 m, 4.06585E-05 m, correspondingly. The study concludes that although TLS is the most precise, BRBPANN offers a good alternative for adjusting RTK-GPS data in Ghana, thereby establishing a precise realistic technique for national and local applications.

1. Introduction

Traditional survey measurements of point estimation are usually riddled with errors (Ghilani and Wolf, 2012; Peprah and Mensah, 2017; Yakubu et al., 2018a). This has thus put the demand to understand the underlying structures of the set of data, hence the effective study of accuracy improvement for point estimates (Devi and Karthikeyan, 2015; Booij et al., 2011; Okwuashi, 2014). These investigations typically examine the characteristics of datasets that exhibit deviations from a normal distribution (Kriegel et al., 2010). These diversities and discrepancies in the Global Positioning System (GPS) readings can be a result of several factors that involve human errors, instrument errors, natural variation in the population, malicious acts, changes in system behavior, or system failure (Devi and Karthikeyan, 2015; Kizza et al., 2011).

Conversely, it could be due to tectonic movement within the Earth's crust (Agnew, 2007), and the ionospheric propagation delay of the signal (Rao et al., 2016; Otsuka et al., 2001). On the other hand, poor choice of processing software compromises the accuracy of the outputs in the final result (Mohammed and Eldin, 2011; Bala et al., 2018). The classical least square technique is one of the most used in handling adjustment field data of ground truth points (Peprah and Mensah, 2017). In the past several decades, the least squares regression model developed by Gauss (1823) has addressed several challenges within the geosciences (Qin et al., 2020). This model finds extensive applications across various areas of earth science research (Jarmolowski and Bakula, 2013). Notably among some of its applications in Ghana are adjustment of survey field data (Yakubu et al. 2018a; Peprah and Mensah, 2017; Annan et al., 2016a; Ansah, 2016), and determination of datum transformation parameters (Okwuashi and Eyoh, 2012a; Annan et al., 2016b; Kumi-Boateng and Ziggah, 2016a; Kumi-Boateng and Ziggah, 2016b; Okwuashi and Eyoh, 2012b; Laari et al., 2016; Ziggah et al., 2013; Ziggah et al., 2016a). These classical techniques have found successful applications, but they suffer from some practical disadvantages discussed in detail by several authors (Acar et al., 2006; Annan et al., 2016a; Qin et al., 2020).

In traditional ordinary least squares methodologies, the alteration of the observation matrix is implemented with the understanding that only the observations are treated as stochastic, aiming to minimize the total of the residuals (Acar et al., 2006; Annan et al., 2016a). However, there are cases where the elements of the design matrix include errors that are often overlooked in classical ordinary least squares approaches, thereby contributing to uncertainties in the resulting solutions (Peprah and Mensah, 2017). Thus, it is clear that errors due to the source of data acquisition are not involved with the coefficient matrix of the least squares model (Qin et al., 2020). The efficiency of the least square collocation (LSC) in data modeling is developed based on manipulating the cross-variance function (Ophaug and Gerlach, 2017; Darbehesti, 2009). Poor choice of the covariance parameter results in inaccurate and imprecise values (Jarmolowski and Bakula, 2013).

In the context of the Total Least Square (TLS) estimator, large sample characteristics such as strong and weak consistency, and asymptotic distribution are observed (Yakubu et al., 2018a). The singular value decomposition (SVD) on an augmented data matrix has been considered the standard approach to the least squares problem (Lemmerling et al., 1996). However, SVD does not preserve the structural feature of the augmented data matrix. This implies that the least square approach will not yield the statistically optimal parameter vector in the frequently occurring case where the extended data matrix is structured (Golub and Van Loan, 1980). Hence, there is a need to investigate more sophisticated and advanced models for data pruning, denoising, and eliminating uncertainties in large datasets (Yakubu and Dadzie, 2019). Against this background, several researchers have developed various improvements to surmount some major challenges confronting the geoscientific world. Of these, Artificial Neural Network (ANN) stands out as one of the most commonly used soft computing methods (Veronez et al., 2011; Kaloop et al., 2017; Akyilmaz et al., 2009; Suliman and Omarov, 2018).

ANN has been successfully used to develop a correction model to rectify field survey data obtained in Ghana (Yakubu et al., 2018a; Yakubu and Dadzie, 2019). This new approach can resolve complex issues (Kaloop et al., 2019). The ANN method, which is largely used in the geoscience area, can identify a linear relationship between nonlinear variables (Cakir and Konakoglu 2019; Konakoglu and Cakir 2018; Ziggah et al., 2016b). Over the last decades, ANN has been successfully used in solving different mathematical and satellite geodesy problems in Ghana. The suitability for practicing the method with other methods of geodetic problem solution has also been studied (Yakubu and Dadzie, 2019; Yakubu et al. 2018a).

Among its many applications in Ghana, some include the adjustment of post-processing data from DGPS (Yakubu et al., 2018a), modeling uncertainties in DGPS data (Yakubu and Dadzie, 2019), the prediction of orthometric height in a mining environment (Peprah and Kumi, 2017), air overpressure prediction (Temeng et al., 2020), the estimation of vertical total electron content in the ionosphere for GPS observation (Yakubu et al., 2017), tide prediction at different parts of the country of Ghana (Yakubu and Kumi-Boateng, 2020; Yakubu et al., 2018b), datum transformation (Kumi-Boateng and Ziggah, 2020a; Ziggah et al., 2019a; Ziggah et al., 2019b; Ziggah et al., 2017), the prediction of ground vibrations due to blast-induced vibration (Arthur et al., 2019), and the normal gravity evaluation (Kumi-Boateng and Ziggah, 2020b). Therefore, in general, the results obtained using ANN model techniques are encouraging and have very good scope for utilization in the future in finding the solution to some geodetic problems. It can also be observed from the related reviews that, the application of ANN techniques is restricted to a few numbers of applications so far and hence, remains adequately investigated for appropriateness regarding the adjustment of RTK-GPS survey data.

This study compares two machine learning algorithms of the Back Propagation Artificial Neural Network (BPANN) learning methodology, namely the Levenberg-Marquardt approach and Bayesian Regularisation methods, by considering the Total Least Squares Technique in conjunction with RTK-GPS survey data. These latter models will describe the statistical results obtained from the models' work efficiently and their functionalities within the modification of the RTK-GPS survey data. Data used for this study was acquired from the Greater Kumasi Local Geodetic Reference Network situated in Ghana. In this regard, since all the performance criteria indicators of the modeling techniques were done about horizontal displacement, mean arithmetic error, arithmetic mean square error and minimum and maximum residual values, arithmetic standard deviation analysis is made. Therefore, this research will help the researchers to understand how well the country's various geodetic problems can be solved by soft computing techniques.

2. Study Area

The Kumasi Metropolitan Area consists of the core municipality of Kumasi and other surrounding municipalities and districts: Kwabre East, Afigya Kwabre Districts, Atwima Kwanwoma, and Atwima Nwabiagya Districts and Asokore Mampong Municipal, Ejisu-Juaben Municipal, and Bosomtwe District. This is geographically located between the latitude of 6º 35`N to 6º 40`S and longitudes 1º 30`W and 1º 35`E with an elevation of approximately 250 to 350 meters above sea level (Acheamfour and Tetteh, 2014). The total land area covers 2,60 3km² with a total population of 3,190,473 Fields (Oduro et al., 2014). The topography is undulating, traversed by a major river (Owabi) and streams like Subin, Wiwi, Sisai, Aboabo, and Nsuben (Acheamfour and Tetteh, 2014; Atayi et al., 2018). The horizontal geodetic datum of the study area is the War Office 1926 ellipsoid, and the vertical datum is the Mean Sea Level (MSL) which approximates the geoid (Peprah and Mensah, 2017; Peprah and Kumi, 2017; Peprah et al., 2017). The type of coordinate system utilized in the study area is Ghana projected grid derived from the Transverse Mercator with 1° W Central Meridian and the World Geodetic System 1984, WGS84 (UTM Zone 30N) (Yakubu et al. 2018a). The Metropolis is in the wet sub-equatorial type. The average minimum temperature is about 21.5 ºC, and the maximum average temperature is about 30.7 ºC; the average humidity was about 84.16% at sunrise and 60% at sunset (Atayi et al., 2018). The area has been receiving a double maxima rainfall regime of about 214.3 mm in June and 165.2 mm in September (Acheamfour and Tetteh, 2014).

This puts the area within the transition forest zone, mainly within the moist semi-deciduous Southeast ecological zone of Ghana (Acheamfour and Tetteh, 2014). The middle Precambrian rock dominates the study area comprising two main lithostratigraphic/litho tectonic complexes, namely: the Paleoproterozoic supracrustal and intrusive rocks and the Neoproterozoic to early Cambrian lithological diverse platform sediments, exist in the study area. The unique geological structure has led to the development of the construction industry in the Metropolis with few small-scale mining activities and the proliferation of stone quarrying and sand winning Industries (Osei-Nuamah and Appiah-Adjei, 2017). Fig. 1 shows the map of the study area.

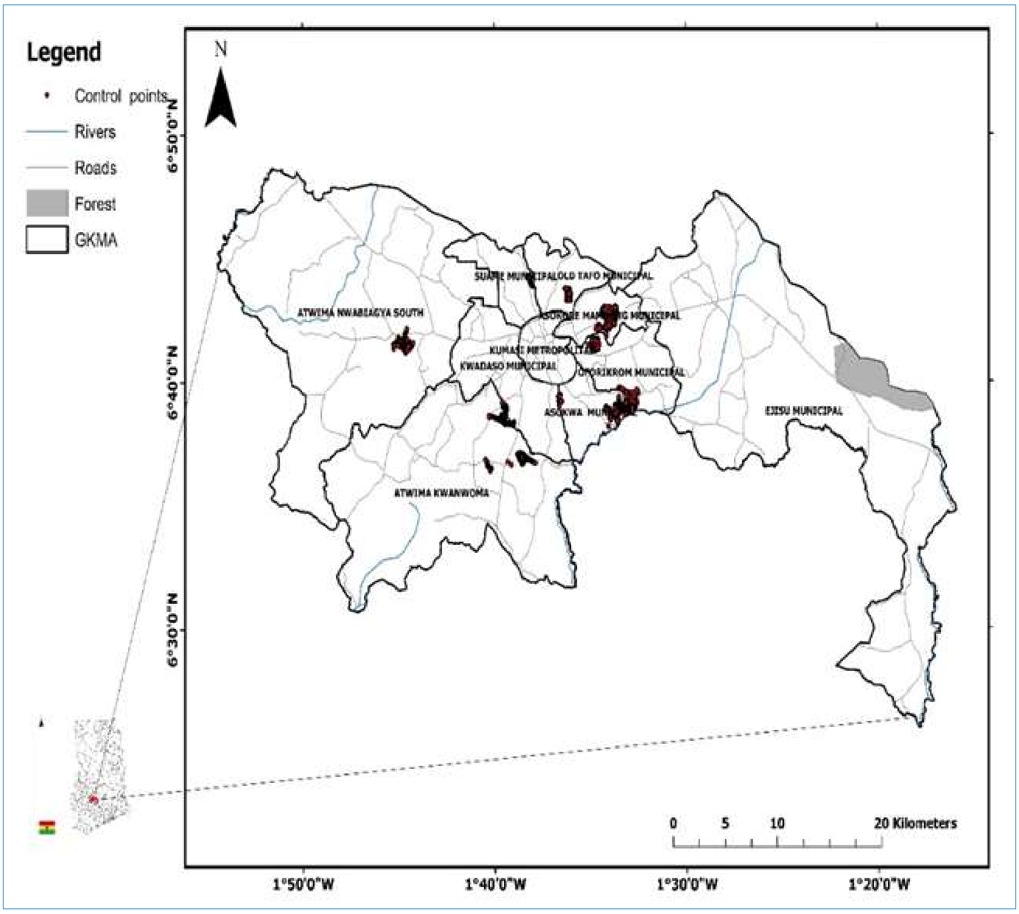

Fig. 1. Map of the study area

3. Resources and Methods Used

3.1. Resources Used

Primary data for the study comprise topographic data from a survey of the Ghana urban water supply project in the Greater Kumasi Metropolitan Area (GKMA). Sample data consists of 1000 control points collected with Real Time Kinematics (RTK) GPS instruments. The RTK-GPS recorded data on three-dimensional coordinates of eastings, northings, and ellipsoidal heights represented as (E, N, h). A sample of the dataset collected from the field is tabulated in Table 1. However, it is worth admitting that one of the contributory factors to the estimation accuracy of models relates to the quality of the datasets used during model building (Devi and Karthikiyan, 2015; Dreiseitl and Ohno-Machado, 2002; Ismail et al., 2012).

Therefore, to ensure that the obtained field data from the GPS receivers are reliable, several factors, such as checking of overhead obstruction, observation period, observation principles and techniques, as suggested by many researchers (Yakubu et al., 2018a; Yakubu and Dadzie, 2019; Ziggah et al., 2016c) were performed on the field. In addition, all potential issues relating to RTK-GPS survey work were also considered.

Table 1. Sample of data used for the study (units in meters)

ID	Easting	Northing	Elevations (*h*)
Pt1	658143.7	741095.1	311.380
Pt2	658340.9	741791.2	308.365
Pt3	658340.8	741792.4	308.387
Pt4	658339.8	741792.3	308.382
Pt5	658339.9	741791.2	308.386
Pt6	658342.0	741790.2	308.516
Pt7	658342.8	741789.6	308.505
Pt8	658343.1	741787.1	308.585
Pt9	658340.8	741789.3	308.474
Pt10	658339.1	741788.8	308.32
Pt11	658338.4	741788.6	308.302
Pt12	658338.7	741788.4	307.710
Pt13	658338.2	741788.4	308.341
Pt14	658345.1	741772.4	309.595
Pt15	658346.5	741761.9	310.349
Pt16	658344.6	741761.7	309.961
Pt17	658342.3	741761.3	309.439

3.2. Methods Used

3.2.1. Backpropagation Artificial Neural Network (BPANN)

The most widely used supervised learning technique is BPANN. It is preferred compared to other models for its relative simplicity in understanding and execution (Dilruba et al.,2006), and it can handle linear and nonlinear relationships (Cakir and Konakoglu, 2019). BPANN consists of one input layer with M inputs, one or more hidden layers with q units, and one output layer with n outputs. In this study, the M inputs were the 2D horizontal coordinates, the q units obtained by trial-and-error training by changing the number of hidden neurons, and the n outputs were the estimated outputs obtained by the BPANN model, respectively. The single output neuron model production (y_i) is given by *Equation 1* (Mihalache, 2012).

$$y(i) = f\left(\sum_{j=1}^{q} W_j f\left(\sum_{i=1}^{M} w_{j,i} x_i\right)\right) \quad (1)$$

where; W_j represents the weight between the hidden and output layers, w_j is the weight between the input and hidden layers, and x_i represents the input layer.

Learning of a multi-layer feed-forward neural network is carried out by the backpropagation algorithm. The data set should be preprocessed using transfer functions so that the dataset is rendered free from systematic and gross errors. Transfer functions normally used in this network are a log-sigmoid that generates output between 0 to 1, a tan-sigmoid that generates output from negative to positive infinity, and a linear whose output can take any value. For this analysis, the chosen input and output variables were normalized between the range -1 to 1 using *Equation 2* given as (Mueller and Hemond, 2013).

$$Z(i) = \frac{y_{\min} + (y_{\max} - y_{\min}) \times (x_i - x_{\min})}{(x_{\max} - x_{\min})} \quad (2)$$

where; z_i is normalized data, x_i is the value of the measured coordinates, and x_{min} and x_{max} are the minimum and maximum values, respectively, of the measured coordinates. y_{max} and y_{min} are set to values of 1 and -1.

Before training a feedforward network, initial values of the weights and network biases are provided (Buscema, 2009). In training, the weights and network biases are iteratively adjusted to minimize network performance. The optimal model is obtained from the arithmetic mean error, arithmetic mean square error, minimum residual error, maximum residual error, and arithmetic standard deviation. Their mathematical representations are given in the model performance evaluation section. Like in most literature, Hornik et al. (1989), one hidden layer has been considered in the BPANN of this research. Also, to infuse nonlinear capability in the network, a hyperbolic tangent activation function has been selected for the hidden units, while a linear function has been used for the output units. Tan-h, the hyperbolic tangent function defined by *Equation 3* according to Yonaba et al. (2010) as:

$$Z(x) = \tanh(x) = \frac{2}{1 + e^{-2x}} - 1 \quad (3)$$

where; x is the sum of the weighted inputs.

Fig. 2 depicts the flowchart of the structured methodology adopted in this work using the two ANN training methods. A Bayesian Regularisation training algorithm, trainbr, and the Levenberg-Marquardt algorithm, trainlm are used to train the dataset independently. The models are checked with untrained data. The resultant data generated from the various algorithms were further compared with the Total Least Square model (TLS).

3.2.1.1. Levenberg-Marquardt Algorithm (trainlm)

The Levenberg-Marquardt model, sometimes called (trainlm), is an example of an iterative technique used to determine the minimum of a multivariable error function; Z as described by *Equation 4*. This function is defined as the sum of the squares of the difference in the actual output, y_i, and target output, t_i given by *Equation 4* (Adeoti and Osanaiye, 2013):

$$Z_{i,j} = \frac{1}{2}\sum(y_i - t_i) \quad (4)$$

The main formula for the trainlm algorithm is specifically implemented to obtain the efficiency of second-order training without requiring the computation of the Hessian matrix (Baghirli, 2015). The Hessian matrix (H) and the gradient (g) can be obtained from *Equations 5* and *Equations 6*, respectively, by assuming that the performance function is defined by a sum of squares (Kisi and Uncougli, 2005):

$$H = J^T J \quad (5)$$

$$g = J^T e \quad (6)$$

where; J is the Jacobian matrix composed of the first derivatives of the network errors concerning the biases and weights and e is the vector of network errors.

After that, the Jacobian matrix is obtainable by a standard backpropagation technique, which is much less complex as compared to the computation of the Hessian matrix itself, as mentioned by Baghirli (2015). This approximation of the Hessian matrix is used for the next Newton-like update as in *Equation 7*.

$$w_{i+1} = w_i - \left| J^T J + \delta I \right|^{-1} J^T e \quad (7)$$

where, w is the connection weights, δ is the damping term and I is the identity matrix.

The trainlm uses the combination of the Gauss-Newton method and gradient descent in its iterative process (Arthur et al., 2020). When the δ is zero, it becomes a Gauss-Newton method, using the approximate Hessian matrix. When the parameter δ is considerably large, the approach transitions into a gradient descent algorithm characterized by a reduced step size (Arthur et al., 2020). Newton's method exhibits greater speed and accuracy in proximity to a minimum error point; thus, the objective is to transition to Newton's method as expeditiously as possible (Baghirli, 2015). Therefore, δ decreases after every successful step, that is, after a reduction in the performance function, and increases only when a presented step would increase the performance function. In this way, the performance function will decrease at each step of the algorithm (Peprah and Larbi, 2021). However, this 'trainlm' is an efficient training method compared to other traditional gradient descent training methods (Wilamowski, 2009).

3.2.1.2. Bayesian Regularization (traimbr)

Change to Bayesian Regularization, referred to as (trainbr), updates the weights and bias parameters step by step based on Levenberg-Marquardt optimization (Foresee and Hagan, 1997). The method minimizes a linear combination of squares errors and weights, thus finding their optimal combination in building a network with the best generalization performance (Kaur and Salaria, 2013). Regularization is the process used to enhance generalization (Arthur et al., 2020). The ultimate goal of the training is to minimize the total squared error, ε_D. In other words, the goal of the training objective function may be expressed as $F_w = \varepsilon_D$. However, the addition of regularization brings an additional term, ε_W. Thus, the objective function is defined as presented in *Equation 8* (Foresee and Hagan, 1997):

$$F_w = \tau \varepsilon_D + \vartheta_{\varepsilon w} \quad (8)$$

where; ε_W is the sum of squares of the network weights, ε_D is the sum of the network errors, and τ and ϑ are the parameters of the objective function.

In the trainlm, the weights given to the network are considered as random variables, and also the distribution of the network weights and the training set are assumed to be Gaussian distribution (Baghirli, 2015). From the work done by Foresee and Hagan (1997), the relative size of the objective function parameters prescribes the emphasis on training. If τ ≪ ϑ then the training algorithm will drive the errors smaller and if τ ≫ ϑ, training will emphasize weight size reduction at the expense of network errors. Thus, producing a smoother network problem.

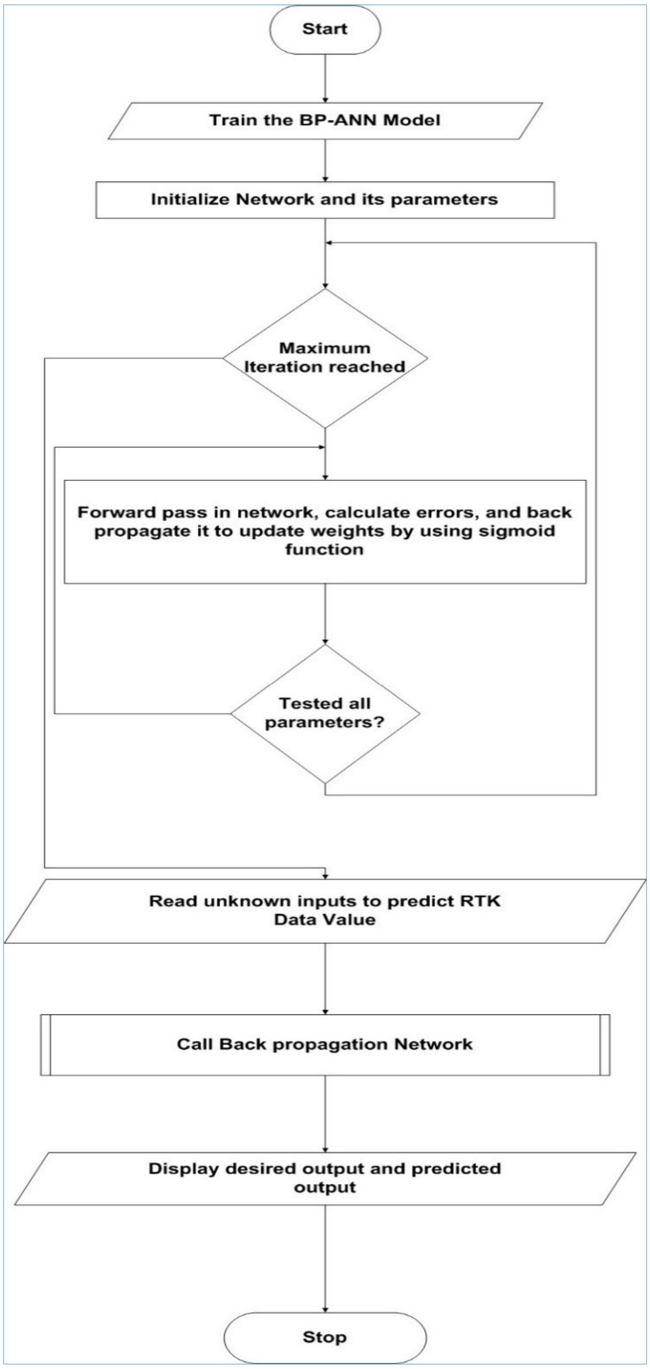

Fig. 2. Flowchart of the BPANN algorithm methodology

Another big problem associated with the use of regularization is how to find appropriate values of the parameters of the objective function. The factors τ and ϑ are determined using Bayes' theorem. A detailed approach to obtaining the exact values of τ and ϑ is given in the work by Foresee and Hagan (1997). Bayes' theorem relates two random variables α and β through their prior or marginal probabilities with the posterior or conditional probabilities defined in *Equation 9* (Li and Shi, 2012).

$$P\left(\alpha/\beta\right) = \frac{P\left(\beta/\alpha\right)P(\alpha)}{P(\beta)} \quad (9)$$

where, $P\left(\alpha/\beta\right)$ is called the posterior probability of α given β and $P\left(\alpha/\beta\right)$ is called the prior probability of β conditioned on α. P(β) is a non-zero prior probability of an event β and normalizing constant. To find the optimum weight space, this is the objective function to be minimized as shown in *Equation 8*. It is equivalent to maximizing the posterior as given in *Equation 10*:

$$P\left(\alpha,\beta/D,M\right) = \frac{P\left(D/\alpha,\beta,M\right)P\left(\alpha,\beta/M\right)}{P\left(D/M\right)} \quad (10)$$

where; α and β are the factors needed to be optimized, D is the weight distribution, M is the particular neural network architecture, $P(D/M)$ is the normalization factor, $p\left(\alpha,\beta/M\right)$ is the uniform prior density for the regularization parameters and $p(D/\alpha,\beta,M)$ is the likelihood function of D given by α,β,m. Maximizing the posterior function $P\left(\alpha,\beta/D,M\right)$ is equivalent to maximizing the likelihood function $P\left(D/\alpha,\beta,M\right)$.

This process would compute the most appropriate parameters α and β in the given space. Then, this model goes to the trainlm stage that, because of the Hessian matrix, will allow computation; therefore, the weight space will be updated to minimize the objective function by Baghirli (2015). In case of no convergence, the algorithm undergoes a recalculation for a new estimate of α and β. This is done iteratively until convergence is reached (Peprah and Larbi, 2021).

In this process, optimum values for α *and* β for a given space are found. Hence, trainbr model moves into trainlm phase, where Hessian matrix computations take place and updates the weight space in order to minimize the objective function (Baghirli, 2015). If the convergence is not met, algorithm estimates new values for α *and* β and the entire procedure repeats itself until convergence is reached (Peprah and Larbi, 2021).

3.2.1.3. Total Least Square (TLS)

TLS stands for a method of solving an overdetermined system of linear equations by finding the unknown parameters, $\hat{X}$ according to *Equation 11* (Golub and Van Loan, 1980) using the following formulation:

$$L + V_L = (A + V_A)\hat{X}, rank(A) = m < n \quad (11)$$

where; V_L *and* V_A are the vector of discrepancies in observation and the data matrix, respectively.

They become zero V_L and V_A mean (Felus and Schaffin 2005). This TLS is normally an iterative algorithm that minimizes an error at a given minimizing matrix $[\hat{A},\hat{L}]$. Iterations continue to run until every $\hat{X}$ that satisfies $\hat{A}\hat{X} = \hat{L}$ become the TLS solution (Yanmin et al., 2011). For the solution of the TLS problem, singular value decomposition of the matrix $[A, L]$ was used. Through SVD, the $[A, L]$ can be represented as given in *Equation 12*, expressed by:

$$[A, L] = USV^T \quad (12)$$

where; $U = [U_1, U_2], U_1 = [U_1, \dots, U_m], U_2 = [U_{m+1}, \dots, U_n], U^TU = In$ *and* $U_i \in R^n, V = [V_1, \dots, V_m, V_{m+1}], V^TV = I_{m+1}$ and $V_1 \in R^{m+1}$. $S = diag(\delta_1, \dots, \delta_m, \delta_{m+1}), S \in R^{n(m+1)}$.

Through the SVD, the solution for the TLS problem is finally given by *Equation 13*.

$$\left[\hat{X}^T, -1\right] = \frac{-1}{V_{m+1,m+1}} \times V_{m+1} \quad (13)$$

If $V_{m+1}, m+1 \neq 0$, then $\hat{L} = \hat{A}\hat{X} = {}^{-1}/_{(V_{m+1}, m+1)}\hat{A}[V_1, m+1, \dots, V_m, m+1]^T$ which belongs to the column space of $\hat{A}$, so $\hat{X}$ solve the basic TLS problem.

The corresponding TLS correction is expressed by *Equation 14*.

$$\left[\Delta\hat{A}, \Delta\hat{L}\right] = [A, L] - \left[\hat{A} - \hat{L}\right] \quad (14)$$

3.3. Model Performance Assessment

A statistical error analysis was carried out to check the precision of the models used. The statistical tools involved horizontal displacement, arithmetic mean error, arithmetic mean square error, maximum and minimum residuals, and arithmetic standard deviation. The mathematical relations for the mentioned indicators could be expressed by *Equation 15* to *Equation 20*, respectively:

$$HE = \sqrt{(E_2 - E_1)^2 + (N_2 - N_1)^2} \quad (15)$$

$$AME = \frac{1}{n}\sum_{i=1}^{n}(\alpha_i - \beta_i) \quad (16)$$

$$AMSE = \frac{1}{n}\sum_{i=1}^{m}(\alpha_i - \beta_i)^2 \quad (17)$$

$$r_{max} = \alpha_i - \beta_i \quad (18)$$

$$r_{min} = \alpha_i - \beta_i \quad (19)$$

$$ASD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(\mu - \bar{\mu})^2} \quad (20)$$

where; n is the total number of observations, α_i and β_i are the measured and adjusted 2D horizontal coordinated from the various techniques, μ denotes the residual between the measured and adjusted field data, $\bar{\mu}$ is the mean of the residual and i is an integer varying from 1 to n.

4. Results and Discussions

4.1. Developing ANN Models

The single-layer BPANN model was first trained using the Bayesian Regularisation and Levenberg-Marquardt algorithms. The Tansig-Purelin functions for training the BPANN model were used in the order of trainbr and trainlm, respectively. The best model structure was achieved when the number of hidden neurons was set according to a sequential hit-and-trial approach for which minimum values of AME, $AMSE$, r_{max}, r_{min}, and ASD were acquired. For the model developed in the current study, the number of hidden neurons varied between 1 and 20 for training. Each training in iteration was allowed to train the network up to 5000 epochs, with a learning rate of 0.03, minimum performance gradient of 0.0000001, goal of 0, maximum validation failures of 6, and momentum coefficient of 0.9. It stops at the minimum gradient and the maximum epoch during the training of a neural network in the process of validation. This ANN models trainbr and trainlm training have been implemented and coded using MATLAB software, R2018a. After several trial-and-error methods, the best model achieved by the trainbr model after successive iterative training in adjusting the 2D horizontal coordinates northings and eastings were [2 12 1] and [2 3 1] respectively, whiles trainlm achieved [2 1 1] and [2 4 1], respectively.

Table 2. Model results for soft computing techniques (units in meters)

BPANN (Northings)					
PCI	**AME**	**AMSE**	$\mathbf{r_{min}}$	$\mathbf{r_{max}}$	**ASD**
Training	-9.07439E-06	4.65074E-07	-0.00177	0.005338	0.000682
Testing	0.002507	7.49642E-06	0.000399	0.004135	6.37836E-05
BPANN (Eastings)					
PCI	**AME**	**AMSE**	$\mathbf{r_{min}}$	$\mathbf{r_{max}}$	**ASD**
Training	-7.17116E-06	2.24938E-07	-0.00573	0.002522	1.79496E-05
Testing	0.001179	1.91465E-06	-0.00011	0.002147	4.19356E-05
LMBPANN (Northings)					
PCI	**AME**	**AMSE**	$\mathbf{r_{min}}$	$\mathbf{r_{max}}$	**ASD**
Training	0.000132	4.27018E-06	-0.01871	0.004464	7.80555E-05
Testing	-0.00117	2.35367E-06	-0.00367	0.000826	5.76025E-05
LMBPANN (Eastings)					
PCI	**AME**	**AMSE**	$\mathbf{r_{min}}$	$\mathbf{r_{max}}$	**ASD**
Training	-0.00013	1.61582E-05	-0.01347	0.023235	0.000152
Testing	0.009242	0.000116	-0.00323	0.019362	0.000322

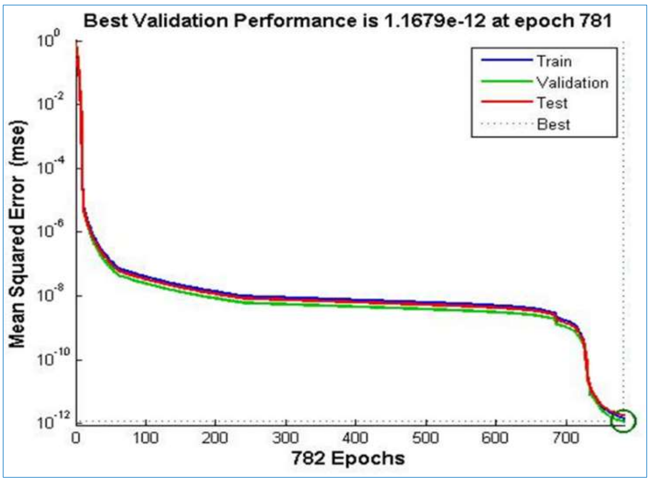

Fig. 3. Plot of trainbr in adjusting the northing data

These optimum BRBPANN and LMBPANN model structures gave the least minimum value in their statistical analysis (AME, $AMSE$, r_{max}, r_{min}, and ASD). Each one of these training has done this by changing the number of hidden neurons from 0 to a maximum of 20 to reach the best outcome. That means the best model obtained from the BRBPANN model for modeling the northings is [2 12 1]. This represents 2 input features with a maximum of 12 hidden neurons and 1 output feature. The best BRBPANN model developed to predict the changes in eastings was [2 3 1]. In other words, 2 inputs, 1 layer of a hidden layer with a maximum 3 number of hidden neurons, and 1 output. The results of the consolidated training and testing done using soft computing techniques are given in Table 2.

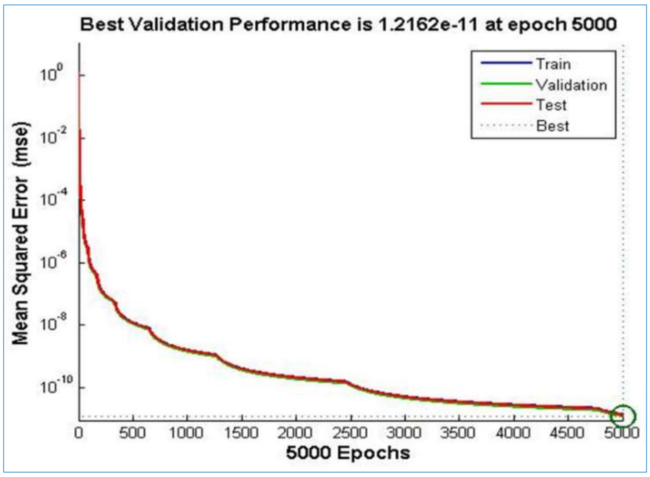

Fig. 4. Plot of trainlm in adjusting the northing data

Remarks based on the statistical results in Table 2 attest to the fact that these soft computing techniques give acceptable results by adjusting the survey field data of the study area with substantially improved accuracy. The minimum and maximum residuals obtained are quite promising. The obtained *AME*, *AMSE*, and *ASD* for the training and testing data sets present good and similar results. However, the *ANN* has already proved to be an extremely efficient practical option in the enhancement of the real-time kinematic GPS data for the studied area, presenting substantial improvement for better accuracy.

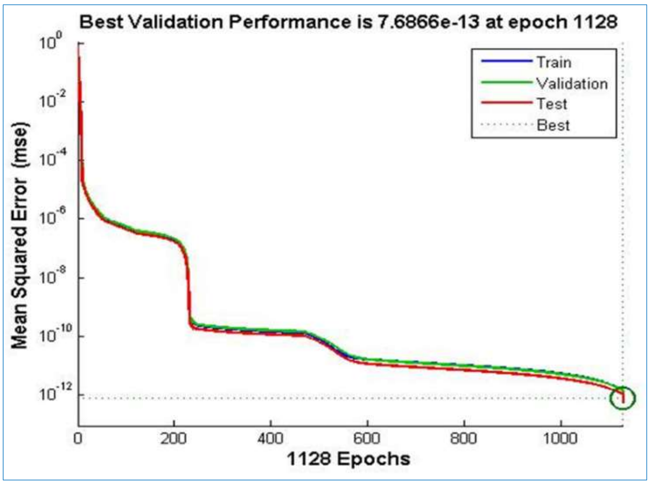

Fig. 5. Plot of trainbr in adjusting the easting data

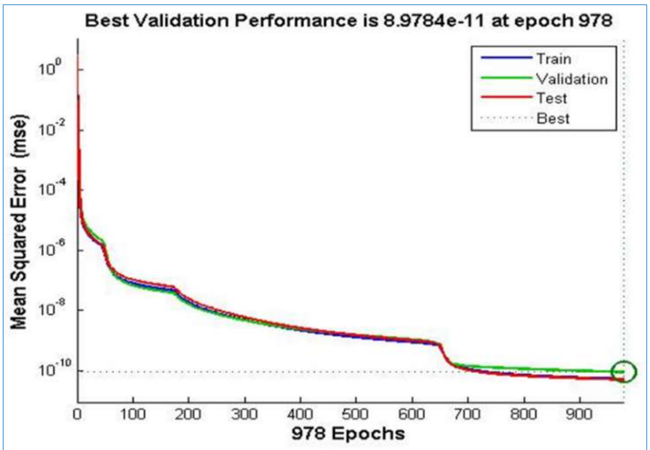

Fig. 6. Plot of trainlm in adjusting the easting data

Fig. 3 to Fig. 6 depicts the plot of the *AMSE* over the Epoch utilizing the two models in adjusting the Northings and Eastings of the RTK survey data. Table 3 tabulates the number of epochs and times achieved by each model.

In Table 4, it is observed that the ANN techniques performed adequately, as there was no notable difference from the classical TLS technique. The explanation is linked to the statistical evidence provided. The summary of statistical analysis shown in Table 4 strongly indicates that the developed supervised ANN models were highly endorsed by the TLS technique in terms of prediction with great precision.

Table 3. Training epoch and time results

NORTHINGS		
Algorithm	**Epoch**	**Time (Sec)**
BRBPANN	782	11
LMBPANN	5000	49
EASTINGS		
Algorithm	**Epoch**	**Time (Sec)**
BRBPANN	1128	13
LMBPANN	978	12

4.2. Comparing the Predictive Performance Results of the ANN Models with the TLS Model

The most optimal model BRBPANN which could adjust the northings and eastings with better statistics was established at a structure comprising of 2 inputs, a hidden layer of 12 and 3 neurons, and 1 output. Likewise, the optimal structure of LMBPANN which performed the best in RTK-GPS data adjustments was 2 inputs, a maximum of 1 hidden layer with 4 neurons, and 1 output. The ANN models (BRBPANN and LMBPANN) used in this work have been compared to the classical TLS techniques using all the data points. Their statistical analysis has been provided in Table 4. Table 4 shows the maximum residuals of BRBPANN and LMBPANN supervised techniques, which were found to be satisfactory and measured 0.007828 m, and 0.023526 m respectively for BRBPANN and LMBPANN. Seeing their statistical results, it becomes clear that the classical model has a minimum residual (r_{max}) of 1.48173E-09 m and *ASD* of 9.76E-14 m respectively for the TLS model. The adjustment of the study area RTK-GPS data is done better using the BRBPANN-based supervised techniques than the LMBPANN-based supervised techniques. This means that the former may also be applied as an alternative approach to the classical TLS technique.

Table 4. Statistical Analysis of all the models (Units in meters)

PCI	r_{max}	r_{min}	AME	AMSE	ASD
BRPANN	0.007828	4.97E-05	0.001287	3.30633E-06	4.06585E-05
LMBPANN	0.023526	0.000147	0.005595	4.99277E-05	0.000137
TLS	1.48173E-09	1.31709E-09	1.41459E-09	2.00428E-18	9.76E-14

5. Conclusions and Recommendations

In the past, conventional ways of establishing ground truth stationery and non-stationary points were insufficient, however, the development of science and technology have improved the traditional ways of coordinating stationary positions. It is a common practice to use a GPS (Global Positioning System) also known as GLONASS, for the densification of points in developing countries like Ghana especially in cadastral, topographical and higher engineering surveys. This method of point positioning still requires post-processing of raw data utilizing specified recommended software to be effective. It is also necessary to modify the statement, which attests that post-processed RTK-GPS survey data and results are precise, accurate, and applicable for any engineering works due to minimal human input, as indeed manufactured post-processed field data has errors and needs adjustments. This involves the adjustment and computation of field data, which has become one of the major research disciplines to determine the magnitude of errors and examine error normal distributions and whether they are within acceptable tolerances. Survey field data have been adjusted in many studies throughout the years using classical least squares techniques and more advanced methods. Yet, the current literature mostly refers to traditional methods of survey data adjustment. In RTK-GPS survey data collection, few studies have only reported using artificial intelligence to correct post-processed field data using supervised methods for Data Adjustment of RTK-GPS Survey by ANN. Hence, the main purpose of this study was to investigate two learning algorithms from soft computing methods and classical TLS technique concerning each method's performance in adjusting RTK-GPS survey data, as well as to propose the best learning training for the study area using the available datasets. In terms of automatic adjustment of the survey field data for the study area, the statistical analysis gave a better result to the classical TLS compared with those two supervised techniques. Nevertheless, BRPANN outperformed LMBPANN methods in fitting field data with remarkable accuracy and exactness. Therefore, the use of soft computing approaches as alternative methods for the adjustment of RTK-GPS survey data in the same problem area has provided a realistic and feasible alternative to traditional least squares techniques. In assessing the effectiveness of applying soft computing techniques for estimating an accurate mobile point, these methods can be beneficial to the geospatial professionals within Ghana. Nevertheless, engaging other training learning soft computing techniques like Variable learning rate algorithm, Resilient algorithm, Quasi-Newton algorithm, Broyden-Fletcher-Goldfard-Shanno, Scaled Conjugate Gradient and more needs to be done in Ghana. The implications of this research are in the interest of geospatial professionals in Ghana and also provide added value to scientific knowledge considering the application of soft computing in solving evolutionary problems during the conductance of space geodetic operations.

Acknowledgment

Acknowledgments are to anonymous referees for valuable comments, time, and efforts to improve the quality of this paper. We appreciate the Geo-Informatics Division, Building and Road Research Institute (CSIR-BRRI), Kumasi, Ghana for giving us their instruments to collect data for our research work.

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