Application of Artificial Neural Network for Height Modelling

Omer Hassan
Surveying Engineering Department
Collage of Engineering
Sudan University of Science and Technology (Sustech)
Khartoum, Sudan
remo7red@gmail.com

Elhadi Elnazeer
Surveying Engineering Department
Collage of Engineering
Sudan University of Science and Technology (Sustech)
Khartoum, Sudan
hadeena2013@gmail.com

Nagi Zomrawi
Surveying Engineering Department
Collage of Engineering
Sudan University of Science and Technology (Sustech)
Khartoum, Sudan
nagizomrawi@yahoo.com

***Abstract*—** Levelling in surveying is the term stand for height difference determination between ground points. If a datum surface is defined for the observed points, the heights of these points (reduced levels) can be computed. In ordinary orthometric levelling Geoid surface is usually used as a datum. Levelling process can be carried out using different survey equipments and techniques. It may be precise; when precise optical or digital levels are used, or it may be ordinary; when using ordinary optical, automatic or digital levels. Moreover it can be carried out trigonometrically or barometrically. Now a day Global Positioning System (GPS) provides a quick modern technology to determine heights of points [4].

Leveling procedure can be considered as one of the most costly procedures. However; some mathematical models are used for condensing spot heights with a relatively low cost.

Artificial neural networks appeared as one of the prediction methods used in many disciplines. Although it is widely applied in different fields, but it is not widely used in surveying applications.

The objective of this research is to test the possibility of using artificial neural networks method for height modelling in different topographic areas, and assessing its resultant precision in comparison with currently used algorithms, taking into account two factors; number of iterations and random seed number (a value that used to stabilize the weight selection).

Results showed that artificial neural networks can successfully be used in height modelling. It produced height precisions of 97%, 97.39, and 93.63% for flat, gently rolling and mountainous areas respectively. These precisions are sufficiently enough for many survey applications. Moreover, an artificial neural networks technique can produce better results compared with kriging method.

Keywords- *Artificial neural networks(ANN); Digital Elevation Model (DEM); Kriging method; Levelling; Triangulated Irregular Network (TIN).*

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I. INTRODUCTION

Surveying may be defined as the science of determining the position, in three dimensions, of natural and man-made features on or beneath the surface of the Earth. These features may be represented in analogue form as a contoured map, plan or chart, or in digital form such as a Digital Ground Model (DGM).

In engineering surveying, either or both of the above formats may be used for planning, design and construction of works, both on the surface and underground. At a later stage, surveying techniques are used for dimensional control or setting out of designed constructional elements and also for monitoring deformation movements [5].

Levelling is the name given to the process of measuring the difference in elevation between two or more points. The heights of points relative to a chosen surface are known as reduced levels of these points. Reference surface is usually known as a datum.

In engineering surveying, levelling has many applications and is used in all stages in construction projects from the initial site survey through to the final setting out. Contour maps, profiles and cross sections can be produced in all the stages of the project [10]. Both conventional and modern methods can be used for height determinations. However it is difficult and cost effective to measure the elevation of all points on the terrain surface. Therefore, point densification may be better executed using mathematical models. These models are particular forms of mathematical surface that deals with numerical representation of the surface of the earth. Digital Elevation Models (DEM). Digital Height Model (DHM), Digital Ground Model (DGM), and Digital Terrain Elevation Model (DTEM) are all common terms.

A digital elevation model can be in a regular grid form, or in a form of Triangulated Irregular Network (TIN). The accuracy of the (DEM) depend on three factors; the precision and the distribution of the known points, surface topography and the implemented interpolation technique used (mathematical model). The precision of the measurements itself depends on the type of instrument used, the observer's experience and the distribution of the points. However the distribution of the points maybe regular, random, or selective. On the other hand interpolation technique used may be kriging, nearest neighbour, or inverse distance to a power.

II. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANN) are mathematical models based on the structure and the performance of Biological Neural Networks (BNN) used to perform pattern recognition tasks. Just like the biological neural networks, the artificial neural networks models consist of unites called the neurons. It can also display some of the features of the biological network.

Generally, neural networks can be categorized into two main types; namely supervised networks and unsupervised networks. The way the network architecture is designed depends on the ability of its training algorithm. In most newly proposed network topologies, the design of the corresponding training algorithm are deemed essential. Apparently, a successful network architecture must be supported by an effective and simple enough training algorithm.

Supervised neural networks are the mainstream of neural network development. The differentiable characteristic of the supervised neural network lies in the inclusion of a teacher on their learning process. The basic block diagram of the supervised learning for all neural network models can be described through figure (1) below.

For learning process, the network needs training data examples consisting of a number of input-output pairs. The desired output vector in the training data set serves as a teacher for the network learning. In the training process error signals are constructed from the difference between the desired output and the system output. Through an iterative training procedure the networks weights are adjusted by the error signal in a way that the neural network output tries to follow the desired output as close as possible. The training procedure is repeated until the error signal close to zero or below a predefined value. The sum of the errors over all the training samples can be considered as a network performance measure, which is a function of the free parameters of the system. Such function can be visualized a multidimensional error surface where network free parameters serve as coordinates. During the course of learning the system gradually moves to a minimum point along an error surface. The error surface is determined by the network architecture and the cost function.

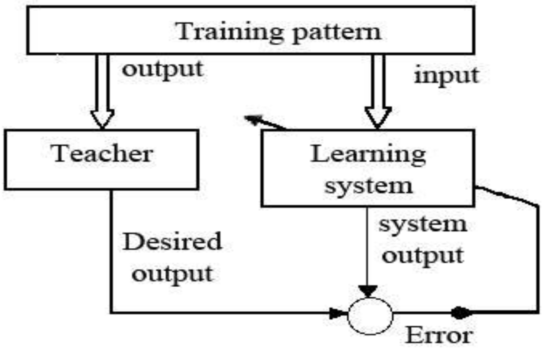

Figure 1. Supervised learning Algorithm

Unlike the supervised networks, unsupervised networks do not have a teacher in the training data set. The learning process of unsupervised neural network is carried out from the self-organizing behaviour. In the course of training, no extra factor is used to affect the weights adjustment of the network. The correct outputs are not available during the course of training. For instance, a typical unsupervised network consists of an input layer and a competitive layer. Through competitive learning the network output automatically reflects some statistical characteristics of input data such as cluster, topological ordering etc.

One of the most widely used unsupervised neural network is Self-Organizing Map (SOM) represented by Figure (2). All neurones arranged on a fixed grid of output layer, containing a weight vector similar to the input dimension. After training, each neuron becomes representative of different data sets. One of the most important characteristics of SOM lies in its topological ordering which means that the neurones that have similar weights (in the input dimension) are also close to each other in the SOM output map. This type of sum map is useful in many applications including visualization, quantization, and retrieval clustering [1].

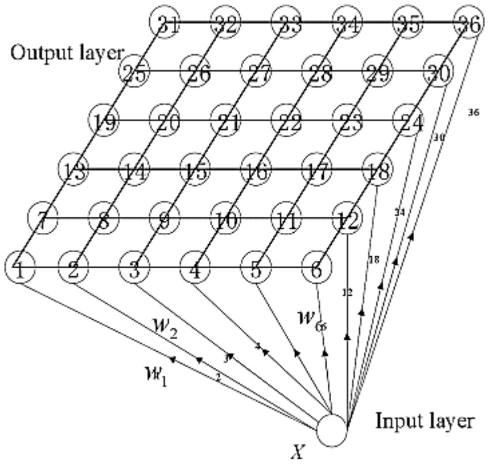

Figure 2. SOM network architecture.

III. TESTS AND RESULTS

This research work concentrated on examining an artificial neural network as a new alternative technique of height estimation and modelling i.e. Digital Elevation Modelling. Also, the study access the technique considering three parameters; the topography of the area, number of iterations adopted and random seed values used.

This study considers three different types of terrains; these are flat, gently rolling, and mountainous terrain.

An area of 500×450 m, with 0.06 maximum difference in height was selected to represents a flat area. While, a gently rolling area was selected to cover an area of 1000×2000 m, with 5.13 m maximum difference in height. The third typed of the terrain considered, was a mountainous area of 1000×800 m, with maximum difference in height of 9 m.

The conjugate gradient algorithm was selected as a training algorithm, and logistic and hyperbolic function as activation functions for hidden layer and output layer respectively. The tests were carried out by Alyuda neurointellgance software package. It focused on two factors, namely, weights randomization, and number of iteration.

Weight randomization methods were used to initialize network weight before training. The main purpose of using a certain value is to allow the same initial condition of the network to be reproduced for different training settings while, the number of iterations determine the amount of generalization for the network.

Three random seed values were specified in the random seed number generator (100, 250, and 500), while number of iterations were selected to be (500, 1000, and 2000).

Twenty seven tests were carried out. Nine tests for each one of the terrain types. The main idea of the tests were to fix the seed number while allowing the number of iterations to be changed and vice versa. Also the 15% of the total number of points were selected as testing points (unknown points), with the same percentage for the validation points. The networks' architecture option was used to find the network with the best fitness .i.e. the network that gives prediction with least absolute residuals. The inverse test error was chosen as fitness criteria. The number of neurones in the hidden layer was limited to a maximum of 20 neurons.

From the results obtained, the standard errors of the mean on each terrain type compared with the relationship between number of iterations and random seed value are tabulated as shown in table (1) below.

TABLE 1. STANDARD ERROR OF THE MEAN VIA AREA TYPE

Area Type	**Random Seed Value**	**Iterations**			**Mean** (m)
		500	1000	2000	
		Standard Error			
Flat	100	0.02	0.02	0.02	0.02
	250	0.02	0.02	0.02	
	500	0.02	0.02	0.02	
Gently Rolling	100	0.14	0.14	0.13	0.11
	250	0.13	0.14	0.07	
	500	0.120	0.11	0.11	
Mountainous	100	0.413	0.413	0.413	0.41
	250	0.574	0.574	0.574	
	500	0.460	0.460	0.460	

From the table it can easily be noted that in flat terrain, increasing number of iteration does not improve the accuracy. This is true for all seed values adopted.

A non-significant improvements can be noted in a gently rolling area by increasing the number of iteration. While increasing the number of iteration - for a fixed seed value - did not improved the accuracy in mountainous terrain.

Therefore, in general it can be said that, increasing the number of iteration does not improves the accuracy in all area types.

Now, concentrating on changing the seed value for a particular iteration, no change appeared in flat terrain while, a slight improvement can be noted in gently rolling area. But, unfortunately this improvement disappeared in mountainous area.

Again, generally, it can be said that, changing the random seed value does not regularly affect the end result.

An important result that can be remarked, is that better accuracy of applying an artificial neural network technique in height estimation and modelling, can be obtained in flat areas. While this accuracy decreases with increment in variation in topography i.e. flat to mountainous areas.

Figure (3) below illustrates the relationship between number of iterations and random seed value based on the standard error of the mean on each terrain type.

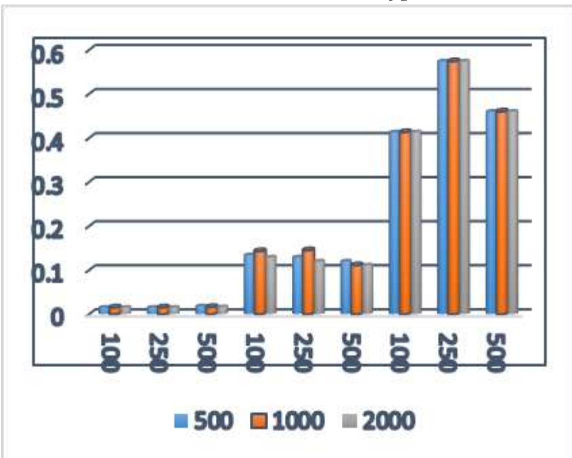

Figure 3. Relationship between number of iterations and random seed value for different topographic areas.

To assess the results of artificial neural networks technique in height modelling, compared with the running techniques, it was compared with results of Kriging method as one of most reliable method used in surveying. The same data of the three types of areas was recomputed with kriging method. Results of artificial neural networks technique compared with kriging method are tabulated in as shown in table (2) below.

TABLE 2. ARTIFICIAL NEURAL NETWORKS TECHNIQUE VS. KRIGING METHOD.

Area	**Standard Error of the Mean**	
	ANN	**Kriging**
Flat	0.02	0.02
Gently rolling	0.11	0.09
Mountainous	0.41	0.59
Mean	**0.18**	**0.23**

By referring to table (2) above it can be noted that both artificial neural networks technique and kriging method produced equal results in flat area. Accuracy decreased in gently rolling area for both methods but kriging method seem to be better in gently rolling area. Although, accuracy decreased in both for mountainous area but artificial neural networks technique produced better result. The mean standard error of the three types of areas was computed for both areas and it was found to be 0.18m for artificial neural networks technique and 0.23m for kriging method. This result shows that artificial neural networks technique is more accurate than kriging method.

A graphical representation of the results of both artificial neural networks technique and kriging method demonstrated by figure (4) below.

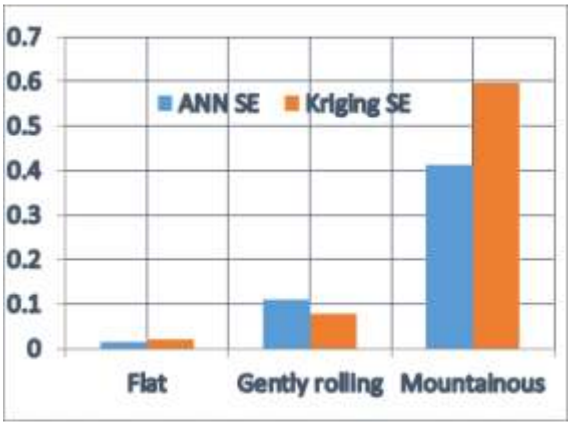

Figure 4. ANN Standard error of the mean vs. Kriging SE

IV. CONCLUSIONS

Based on the tests carried out and analysis of results obtained, it can be concluded with the following:

i. Artificial neural networks can successfully be used as an alternative technique for height modelling.

ii. In flat areas, neither the random seed number nor the numbers of iteration affecting the end result. Moreover, artificial neural networks technique is expected to produce the same accuracy as kriging method.

iii. Increasing the number of iteration does not improves the accuracy in all area types.

iv. Changing the random seed value does not regularly affect the end result.

v. Better accuracy of applying an artificial neural network technique in height estimation and modelling, can be obtained in flat areas. While this accuracy will decrease with increment in variation in topography i.e. flat to mountainous areas.

vi. Artificial neural networks technique and kriging method produce equal results in flat areas but, in general, an artificial neural networks technique is more accurate than kriging method.

vii. Artificial neural networks can produce accuracy of 97, 97.39, and 93.63% for flat, gently sloping and mountainous terrains respectively.

RECOMMENDATIONS

This research work does not totally cover the application of artificial neural networks in height modelling. Therefore, extended works can be oriented to:

- Investigate the effect of the distribution of validation points.
- Use different training algorithms and compare their results with the conjugate gradients.
- Test the possibility of using Self Organized Map (SOM) and genetic artificial neural networks in this field.

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