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Accuracy Improvement of the Absolute Positioning Using Artificial Neural Networks

تحسين دقة تحديد الموقع المطلق بإستخدام الشبكات العصبية الاصطناعية

Thesis submitted in a partial fulfillment of the degree

Of M .Sc in Geodesy and GIS

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بسم الله الرحمن الرحيم

قال تعالى :

﴿وَاللَّهُ جَعَلَ لَكُمُ الْأَرْضَ بِسَاطًا﴾ {19}

صدق الله العظيم

سورة نوح(الاية 19)

ABSTRACT

The low cost navigator can be used to observe coordinates with a low accuracy and in a flexable way.

This Research is directed towards the investigation of possibility of improvement of low cost Navigator observations using Artificial neural networks the main conclusions are:

- It is possible to enhance navigator coordinates by Artificial neural networks
- A large number of data points is required with this method .
- The method is useful for large area rather than small area.

المستخلص

جهاز الموقع العالمي الملاحي قليل التكلفة يمكن إستخدامه في رصد إحداثيات النقاط بدقة بسيطةوطريقة مرنة.

هذا البحث يهدف إلى دراسة إمكانية تحسين أرصاد جهاز الموقع العالمي الملاحي بإستخدام الشبكات العصبية الإصطناعية.

اهم النقاط التي تم التوصل اليها:

جُود أنه من الممكن تحسين الإحداثيات المرصودة بال الموقع العالمي الملاحي باستخدام الشبكات العصبية

الإصطناعية، ولكي تتم عملية التحسين يجب أن يتوفر عدد كبير من النقاط .

هذه الطريقة مفيدة في المساحات الواسعة وليس الصغيرة .

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CHAPTER ONE

INTRODUCTION

The determinations of position is not new in our life, since the ancients, people used several various techniques for surveying positioning e.g. the use of field astronomy.

However due the limitation of accuracy and practical difficulties of using such techniques especially in surveying made it necessary to establish new technique.

Such a technique was developed by the us navy in the $60^{th}$of past century and it was called *Transite*, which was based on the use of satellite system and by using principles of intersection between the satellites and the location on the earth the position will be computed depending on the accuracy there , are two types of ground receivers are used, the geodetic*)*with accuracy of sub-millimetres and the navigator with has an accuracy up to meters .

Anew technique suggested for prediction is the artificial neural network (ANN) .it based on the structure and the performance of our biological neural network.ANN consists of units called neurons . These units are subdivided into three connected layers with an activation functions (initial functions) .The produce an output (predicted values) referring to its input value(known values).

The main objective of the research focuses on the possibility of using artificial neural net work for enhancing the accuracy of the navigator observations.

This research consist of five chapters ,chapter one is an introduction ,chapter two Isabout the global positioning system, chapter three isthe artificial neural network,thefourth chapter is the tests and results, and chapter five is the conclusion and recommendations.

CHAPTER TWO

Global Positioning System

2.1 Introduction

The use of satellites in surveying is not new, the so- called TRANSIT system has been available for civilian purposes since 1967.The system's accuracy has been in the decimetre range and this method has there, been used mainly for navigation, and in prospecting for natural resources and establishing the basic documentation for use by national topographic department.

2.2 Global Positioning System

The Global Positioning System (GPS) changes this situation, since it is capable of achieving a relative accuracy in centimetre range. It consists of twenty-five satellites that place in six different orbits with 60˚ interval, eachorbit with four satellites. The orbital plane is at an angle of 55˚ relative to the equatorial plane. In addition to the twenty one active satellites, three spare satellites are placed in orbit about the earth and are intended to replace any active satellite that becomes unserviceable, by being immediately brought into service in its stand ,all the satellites are at a height about 20200 km above the earth with an orbiting time of 11h 58 min, i.e. Each satellite is again over the same position at the end of a sidereal day, three further space satellites are kept in readiness on Earth.

2.3 Satellite Signals

The satellites transmit continuously on two carriers frequencies. These are L1 at 1575.42 MHzand L2 at 1227.60 MHZ (with wave length of 19 cm and 24 cm respectively).The use of second frequency allows the elimination of the effects of the ionosphere signal propagation. The carrier frequencies are modulated with the navigation signals which contains privies time information .The navigation signal is a binary code generated by a mathematical algorithm. And transmittedto the user who is ignorant of this code it is reminiscent of random noise . And is therefore known as pseudo – random noise .The phase modulation of the a carrier with a high frequency code is known as pseudo – spectrum modulation .

There are two codes, the C/A (Coarse Acquisition) and the P (Precise) codes. The C/A code is accessible to all users and is modulated on the carrier at frequency 1.023 MHZ (a wavelength of about 300m). It has a period of One millisecond,

In the ultimate stage, access to the P code is restricted to certain military users only . This code is modulated on the carrier with a frequency of 10.23MHZ (wavelength of about 30m) . The P code has a period of 261 day.

In addition to the codes, the satellite transmits at a speed of 50 bites per second (BPS), containing all the parameters necessary for computing the satellite's position which is known as the navigation message.

2.4 GPS Measurements Biases

These biases can be categorized into the following

2.4.1 Satellite Biases

Satellite biases has two components

2.4.1.1 Orbit Biases

The ephemeris information used to calculate the GPS satellite positions is generated from the tracking data collected by the five monitor stations of the Control Segment, data is processed at the Master Control Station and the satellite navigation message information is uploadedto every satellite, and are available to GPS users at the time of observation. The satellite orbit bias istherefore the discrepancy between the "true" position (and velocity) of a satellite and its broadcast ephemeris.

One option for overcoming satellite bias error is to use a precise ephemeris as generated by the International GPS Service (the IGS -- Section 3.1.5). These ephemerides are accurate to the sub metre level and are computed after global tracking data is collected from the IGS stations. Hence they are only available "post-mission" (unlike the broadcast ephemerides which are predicted into the futurefrom the computed orbit and which can be used in real-timeapplications).

2.4.1.2Clock Biases

Although GPS satellites uses high quality cesium or rubidium atomic clocks for time-keeping and signal synchronization, there are unavoidable clock error which changes with time. These satellite clock errors can't be ignored, hence they are significant bias which are monitored by control segments during tracking data analysis. The only way they can be accounted in signal receiver positioning is by using broadcast clock error model defined by polynomial coefficients. These coefficients are known well enough to match the basic pseudo-range accuracy to few meters.

As all the observations made at an instant to particular satellite, by all GPS receivers are contaminated by the same satellite clock error, then the possibility exist for eliminating this bias through the principles of differential positioning.

2.4.2Receiver Biases

Satellite signal receivers are equipped with relatively inexpensive quartz oscillators. Although the time defined by individual receiver clocks has essentially arbitrary origins, they can be tied to a well established time scale, such as GPS Time (GPST). The offset between the receiver clock time and GPST time is the receiver clock error that contaminates all satellite-receiver ranges made at the instant by the receiver, and leads to these quantities being referred to as pseudo-ranges, typically, the solution to this problem is to treat the clock bias as an additional parameter in the pseudo-range navigation estimation procedure, requiring that four or more pseudo-range measurements are available. An alternative strategy is to take the differences between data collected to the different satellite so that the common bias is eliminated.

2.4.3 Signal Propagation Biases

2.4.3.1 Ionospheric propagation delay

The ionosphere is the band of the atmosphere from around 50 to 1000 km above the surface of the earth where free electrons are released. When the electromagnetic GPS signals propagate through this medium dispersion occurs, changing the velocity of the propagated signal which causes the measured range to be longer than the true range. Ionospheric delay can in a range of 50m for signals at the zenith to as much as 150m for observations made at the receiver's horizon. To reduce the ionospheric effect, coefficients of a correction formula are transmitted within the satellite navigation message. The correction can be applied to the measured data. However, the accuracy of the correction is very much dependent on the reliability of the estimate of Total Electron Content (TEC) along the signal path, which varies as a function of: the latitude of the receiver, the season, the time of day the observation of a satellite's signal is being made, and the Level of solar activity at the time of observation.

As the TEC is difficult to accurately determine, applying the correction formulae cannot effectively remove this effect. It is generally conceded that the broadcast correction model can be used to remove up to about 50% of the ionospheric delay at mid-latitude regions. For single frequency receivers the use of the correction model parameters is often the only option for point positioning. However, the ionospheric bias is spatially correlated (it is approximately the same for receivers up to a few tens of kilometres apart), and can be effectively eliminated using differential positioning.

The ionospheric delay on a signal is a function of the signal frequency, hence if dual-frequency receivers are available this factor can be used to remove almost all of the ionospheric effect by making measurements on L1 and L2 signals and combining them in a special linear combination.

2.4.3.2 Tropospheric Refraction Delay

The troposphere extends from the surface of the earth to about 8 km. GPS signals travelling through this medium will experience a tropospheric refraction delay that is a function of elevation and the altitude of the receiver, and is dependent on the atmospheric pressure, temperature, and water vapour pressure. The bias ranges from approximately 2m for signals at the zenith to about 20m for signals at an elevation angle of 10^{o}.The propagation of GPS signals in this medium is frequency independent, therefore this effect cannot be removed by combining observations made on two frequencies. There are several options to minimize the effect of the tropospheric medium which can be summarized in:

a. Using existing tropospheric models e.g. Hopfield model, the Black model, and the Saastamoinen model.
b. For high precision applications the residual tropospheric bias has to be parameterised in the final position solution.
c. Avoid tracking low elevation satellites. Generally satellites below 20^{o}have much greater problems with the tropospheric delay than high elevation satellites,
d. As with the ionospheric bias, the fact that the bias is spatially correlated over distances up to several tens of kilometres means that differential positioning is an effective strategy for mitigating the effect of the tropospheric bias on positioning results.

2.4.4 GPS Measurements Errors

These errors occur during measurement session, they could be modulated. However they could be avoided using some special proportions, and they are discussed in the following.

2.4.4.1Multipath Effect

Multipath effects are propagation errors arising from the interference of the direct signal by reflected signals from water and metallic surfaces and nearby buildings. The combined direct and reflected signals will give rise to incorrect pseudo-range or phase measurements. The maximum multipath error that can occur in the case of pseudo-range data is one half the chip length (or resolution) of the code that is, about 300m to 30m for code measurements. To reduce this effect it is recommended to use special designed antennas and careful antenna mounting. Also new techniques are being developed to effectively filter out multipath effects using advanced signal processing.

2.4.4.2Loss of Track (Cycle Slip)

This error effect only carrier phase observations. It occur when the satellite signal is obstructed by object, or interfered by another signal. On the resumption of lock to the satellite(s), the accurate fractional part of the phase observable can

again be measured, however the integer part will be re-initialised and the initial integer ambiguity will no longer be a valid connection between the ambiguous fractional cycle measurement and the satellite receiver range. For this reason there is a "jump" in the measurement data just before and immediately after the epoch at which the loss of lock occurred, and all measurements beyond this epoch are shifted by the same integer number of cycles. This "jump" is known as a cycle slip, and can occur independently on L1 and L2. The detection and repair of cycle slips is therefore an important carrier phase data pre-processing step.

2.5 Observations Techniques

The GPS observation technique used in a given project depends on

a. Accuracy requirements
b. Urgency of the project
c. Local terrain conditions

d. Available equipment, etc.

Following are the techniques that are commonly used now

a. Static
b. Fast Static (Rapid Static)
c. Kinematic
d. Pseudo-kinematic(Pseudo-static)
e. Real Time Kinematic

2.5.1 Static Mode of GPS Surveying

Also known asstatic surveying. Itis usedin surveying projects that require high accuracy. In this method, each receiver at each point logs data continuously for a pre-planned length of time. where the duration of data collection depend on the required precision , number of visible satellites, satellite geometry(DOP) whether the receivers are single frequency or dual frequency,anddistance between receivers.

However, the duration of data collection should be long enough for the post processing software to resolve the integer ambiguity e.g. the longer duration is the more accuracy obtained.

The slope line between any two antennas is called a *baseline vector* or simply *baseline.* Most GPS survey projects consist of multiple baselines or *networks*, and the baselines can be measured individually using only two receivers or several at a time using multiple receivers. Unlike in conventional surveys, the accuracy obtainable from networks is independent of the network geometry

Fast static mode of GPS surveys

Fast Static or Rapid Static was a method developed for dual frequency receivers .A new algorithm was developed to reduce the amount of data needed to resolve integer ambiguity

Lately, because of modifications in processing algorithms and because a larger number of satellites are available, the amount of data needed can be reduced even with single frequency receivers

Field requirements and procedure for fast static are same as those for static except for the short session lengths.However, fast static is only suitable for low order control surveys, e.g. ground control for photogrammetric mapping

2.5.2 Kinematic Mode of GPS Surveying

This is the mode of positioning from a moving platform. i.e. when the antenna is in motion .This is the mode used in navigation where usually only a single receiver is used. But, unlike in navigation, the kinematic method used in surveying is a relative positioning method where one antenna receiver is stationary and one antenna receiver is moving. When the moving receiver is in constant motion as in navigation it is called 'continuous' kinematic.In most surveying applications, a method called 'stop-and-go' kinematic is used.

The stationary receiver, called the base receiver, is placed at a known point while a second receiver called "rover' will visit all unknown points

Rover will occupy each unknown point for a very short time (less than two minutes); Hence the term "Stop-and-Go" surveying .It is possible to combine both 'continuous' and 'stop and go' methods in the same survey

It also is possible to operate more than one 'rover' with the same base station. The accuracy obtained is not as good as that obtained from static surveying but is better than that obtained in most surveys .The single most advantage of 'stop and go' surveying is its speed.

This method also has certain limitations

a. An initialization process to determine the integer biases of at least 4 satellites is needed at the beginning.

b. The lock on the same four or more satellites must be maintained during the entire survey.

For this reason, kinematic GPS surveying is suitable for an area where there are no large over-hanging trees, over-passes or such structures in rover's route

If for any reason a cycle slip occurs, the rover must return to any previous point which had been determined without cycle slip The Initial integer bias term can be determined in one of 3 ways

a. Using a known baseline less than 20 km in length and having an accuracy of less than 5 cm.
b. Antenna swap
c. Perform a static mode survey first for one of the base lines

When using a known baseline, it is necessary to use one end of the baseline as the base station , the rover will occupy the other end to collect 3 or 4 epochs of data (less than 2 minutes).

Antenna swap is done by first occupying the known point with the base receiver and another point 15-30 feet away with the rover. After collecting data for 3-4 epochs two receivers + antennas are swapped while maintaining lock .Collect data for another 3-4 epochs, return the base receiver + antenna to the base and continue the survey with the rover as usual.

In the third method, a baseline is measured by static method with the base receiver at the known base. This now becomes a known baseline and the rest is similar to the first method

For highest accuracy more than 6 satellites, well distributed over the sky is preferable .Kinematic post processing software is needed to obtain the point coordinates.

2.5.2 Real Time kinematic GPS Surveys

Real Time kinematic (RTK) refers to a stop-and-go method where the coordinates of points are available in real time. In this method, a radio communication link is maintained between the base receiver and the rover, and the base receiver supplies the pseudo-range and carrier phase measurements to the rover which in turn computes its position and display the coordinates.The rover keeps updating coordinates as it moves as long as the lock on satellites is maintained.Kinematic GPS surveying is generally suitable for any type of surveying or mapping.

Some RTK receivers have the capability of resolving the integer ambiguity On The Fly (OTF), and this technique can only be used with dual frequency receivers,this means that there is no need to maintain the lock on satellites while the rover is in motion.

New observables are generated by taking linear combinations of observations made on these codes and carriers (wide laning).The integer ambiguity can be resolved very quickly by this technique while the receiver is still in motion . Wide laning techniques are used in some high-end receivers even if OTF is not being used.

2.5.4Pseudo-kinematic (or Pseudo-static)

This is a combination of both static and kinematic methods. It has the speed of kinematic method but there is no need to maintain lock on 4 satellites. However newer receivers and algorithms can resolve the integer ambiguity much faster and the need for pseudo-kinematic surveys is somewhat diminished. There is a reference (or base) receiver and a roving receiver, and the reference receiver remains at the reference point during the entire survey while the roving receiver visits the unknown points. There is no initialization as in ‘stop and go’ method. Each point is occupied for 5-10 minutes for baselines of 10 km or less.

Each point must be revisited multiple times (at least once more) and these visits must be separated by at least 1 hour and preferably not more than 4 hours .Multiple observations at the same site at different times capture different epochs along the satellite's orbit, and allow the satellite configuration to change and to resolve the integer ambiguity This technique is suitable for areas where there are obstructions to signal and crew movement or if the receivers are not equipped with kinematic software .Pseudo-kinematic is the least precise of all methods but is more productive than static.

Stop-and-Go kinematic method is suitable for details surveys as topographic mapping or boundary survey work whereas pseudo- kinematic is suitable for lower order control such as photogrammetric control etc. A combination of these methods can be used in some projects.

CHAPTER THREE

ARTIFICIAL NEURAL NETWORKS

3.1 Introduction

Artificial Neural Networks (ANN) are mathematical models based on the structure and the performance of our 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. However these models are not expected to reach the performance of the BNN for two reasons:

a. We are not fully understand the operation of the BNN and their interaction,
b. Their operation in the neutral asynchronous is not known.

3.2 Historical Background

The first model was proposed by Warren McClloch and Walter Pittes in 1943. They called it McCulloch Pittesneurons, the proposed model uses the weighted sum of the input followed by a threshold logic operation. The main drawback of this model of computation is that the weight are fixed and hence the model could not learn by itself.

Six years later (in 1949) Donald Hebb proposed a learning law for adjusting a connection weight based on pre and post synaptic values of the variables. Hebb's law become fundamental learning rule of the neural networks.

In 1958 Rosenblatt proposed a perceptron network and a perceptron learning law. The network itself is a supervised network (based on prior knowledge). The learning law was chosen in a way that it covers the problem of patterns classification problem which are linearly separable in the feature space. It was shown that a multilayer perceptron could be used to perform any pattern classification task. However, there was no systematic learning algorithm to adjust the weights realizing the classification task. Ten years later the limitation of the perceptron models was demonstrated by Minsky and Papert through several illustrative examples.

In the 1960sWidrow and his group proposed an Adaline model, which is an adaptive threshold logic element. It uses a Least Mean Square learning algorithm (LMS) to adjust the weights of an Adaline model. The algorithm was successfully used for an adaptive single processing situation. Lack in suitable learning law for multilayer perceptron network had put brakes on the development of the neural networks models for pattern recognition tasks for nearly 15 years till 1984

Actually the increase of the interest in artificial neural network is due to two key development in early 1980s. The first one is the energy analysis of feedback neural networks by John Hopfield. The analysis has shown the existence of a stable equilibrium state in feedback network, provided that the network has symmetric weights and that the state update is made asynchronously. Also, in 1986 Rumelhart, and others, have shown that it is possible to adjust the weight of a multilayer feed forward neural network in a systematic way to learn the implicit mapping in a set of input-output pattern,. The learning law has been called the generalization delta rule or error back propagation learning low (Rumelhart et al 1986).

At the same time Ackley Hinton and Sejnowski proposed the Boltzmann machine, which had included the hidden unites. These unites were used to make a given pattern problem representable in feedback networks. Several learning laws were also developed; the prominent among them being the reinforcement learning or learning with critic

3.3 Network Architecture

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.

3.3.1 Supervised neural networks

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 3. 1. 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 network's 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 is 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. In the coming sections, some example of supervised neural network models are presented.

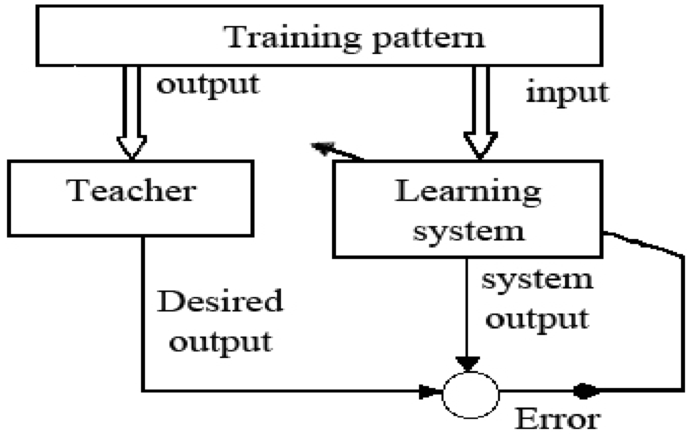

Figure (3.1) overview of the supervised learning

3.3.1.1 McCulloch-Pitts (MP) model

In McCulloch-Pitts model (Figure (3.2)) the activation (x) is given by a weighted sum of its $\boldsymbol{M}$ inputs values $(as)$and a bias term (θ). The output signal *(s)* is typically a nonlinear function, $f(x)$,of an activation function value(x).

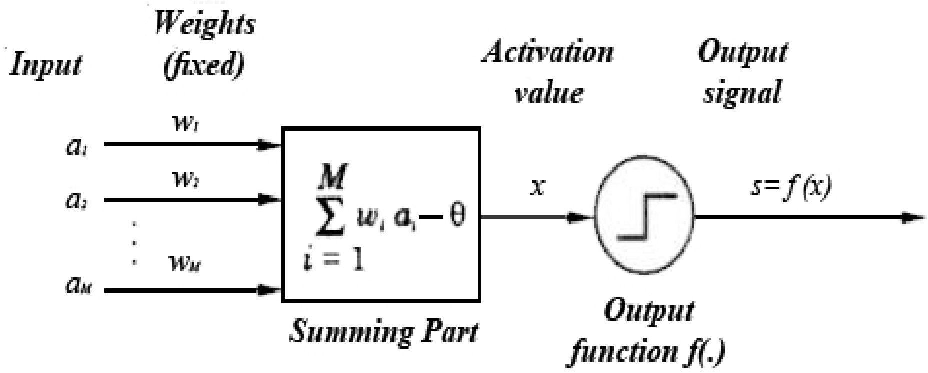

Figure (3.2) McCulloch-Pitts model

The following equations describe the operation of the MP model:

Activation: $x = \sum_{i=1}^{M} w_i a_i - \theta$ **(3.1)**

Output signal: $s=f(x)$ **(3.2)**

There are three commonly non-linear functions used. These are binary, ramp, and sigmoid are shown in Figure (3.2). However only binary function was use in the original multi-preceptron (MP) model.

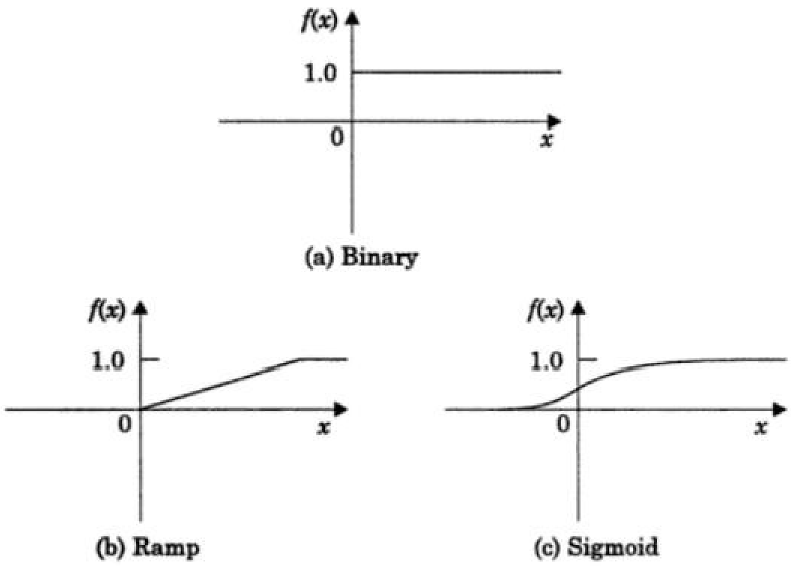

Figure (3.3) some non-linear functions

In MP model the weights are fixed. But a network using this mode doesn't have the capability of learning. Moreover the original model allows only binary output states operating at descried time steps.

3.3.1.2 Rosenblatt Perceptron model

The Rosenblatt perceptron model figure (3.4) is an artificial neural network consisting of outputs from sensory units to a fixed set of association unites, which are fed to a MP neuron.

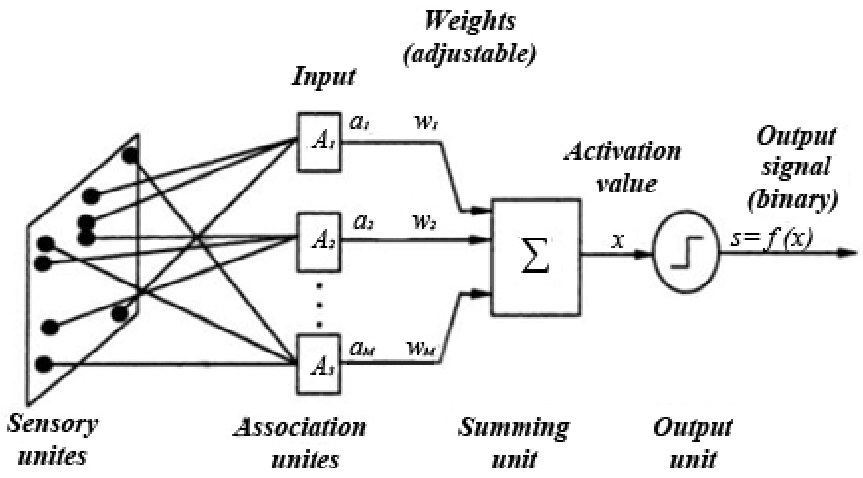

Figure (3.4) Rosenblatt perceptron model of neurons

The association unites preform predetermined manipulation on their units. The main deviation from the MP model is that learning (i.e. adjustment of weights) is incorporated in the operation of the units. The desired, or target output, (b) is compared with the actual binary output (s) and the error (δ) is used to adjust the weight. The following equations describe the operation of the perceptron model of a neuron:

Activation $x = \sum_{i=1}^{M} w_i a_i - \theta$ **(3.3)**

`

Output signal $s = f(x)$ **(3.4)**

Error $\delta = \boldsymbol{b} - \boldsymbol{s}$ **(3.5)**

Weight change $\Delta\omega_i = \eta\ \delta a_i$ **(3.6)**

where η is the learning rate

There are perceptron learning laws that give a step-by-step procedure for adjusting the weight. The converges or noncoverganse of the adjustment depend on the nature of input-output pairs to be represented by the model. The perceptron convergence theorem enables us to determine whether the given pattern pairs are representable or not. If the weight values converge, the corresponding problem is said to be representable by perceptron network.

3.3.1.3 Adeline

ADAptiveLInear Element (ADALINE) is another computing model proposed by Widrow in. In the Adaline model the activation value (x) is compared with the target output (b). In other words the output is a linear function of the activation value (x). The equations that describes the operation of an Adaline are as follows:

$$x = \sum_{i=1}^{M} w_i a_i - \theta \qquad \textbf{(3.7)}$$

$$s = f(x) = x \qquad \textbf{(3.8)}$$

$$\delta = b - s = b - x \qquad \textbf{(3.9)}$$

$$\Delta\omega_i = \eta\, \delta a_i \qquad \textbf{(3.10)}$$

All the variables as defined as before. This weight role minimises the mean squared error (δ^2) averaged over all inputs. Hence it is called least mean squired (LMS) error learning law. This law is derived using the negative gradient of the error surface in the weighted space. Hence it is also known as a gradient descent algorithm.

3.3.1.4 Multilayer feedforward neural networks

In a simple, form a feedforward network consists of an input layer and a single layer of neurons. Such a single layer feedforward network is not capable of classifying nonlinear separable pattern. Multilayer feedforward network has become the major and most widely used for the architecture of the neural network. In the feed forward networks all the connections are acyclic or indirected from the input to the output layer.

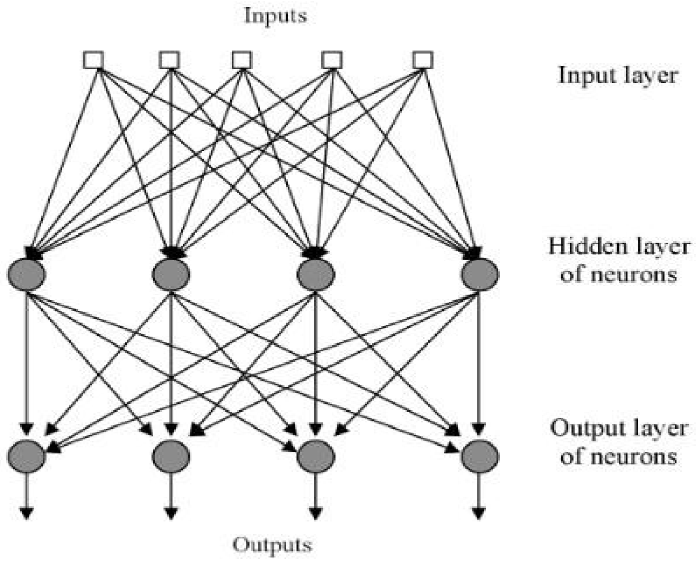

Figure (3.5) multilayer feedforward neural network with one hidden layer

Multilayer network in figure (3.5) consist of one or more layers of neurons between input and output layer, called the hidden layer. The neurons in the hidden layers are called hidden neurons. The network is called fully connected when every the neurons in one layer is connected to every neuron in the next layer.

3.3.1.5 Recurrent neural network

A recurrent network is a special form of neural networks. It can be a single layer or a multiple hidden layer neural network. The basic difference between this network and feedforward network is that it has one or more feedback loops as shown in Figure (3.6). The feedback loops can appear in many forms between any two neurons or layers. It typically involve unites delay elements denoted by (z^{-1}). Recurrent neural networks exhibit complex dynamics because of the large number of feedforward feedback connections. This characteristic provides them extra advantages in handling time series related and dynamical problems over feedforward networks. Recurrent networks are also useful for processing special data such as graph structure data. A recurrent small size network with size may be equivalent to complicated type of feedforward network.

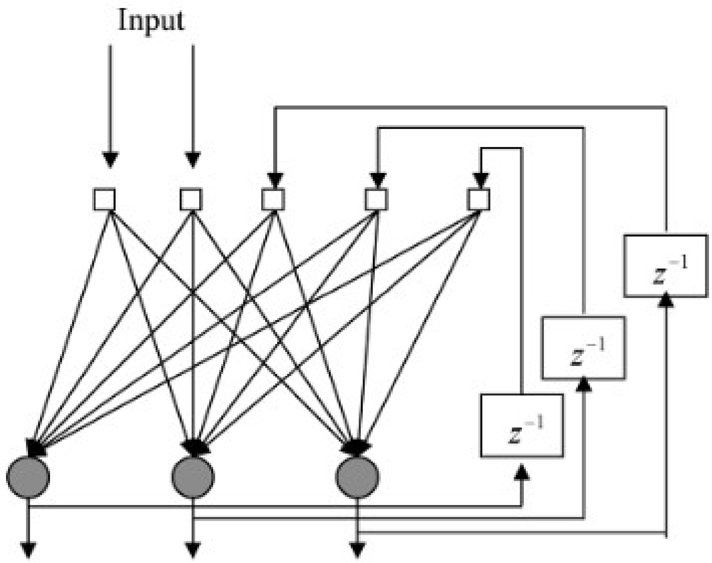

Figure (3.6) Recurrent neural

3.3.2 Unsupervised neural networks

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 (3.7).As shown in the figure 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,

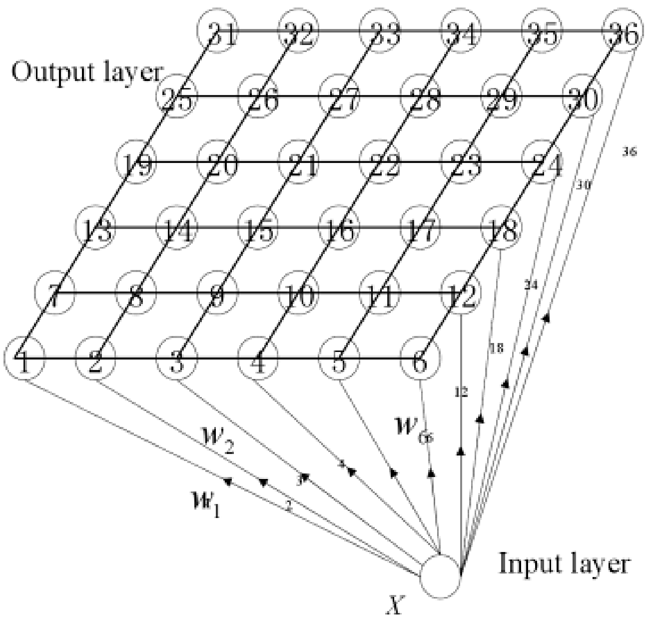

Figure (3.7) SOM network architecture

3.4 Training algorithms

Many training algorithms had been developed since the 1950's, here are some examples for these algorithms.

3.4.1 Conjugate gradient descent

The conjugate gradient-descent optimization technique was developed by Hestenes and Stiefel. As an optimization technique, the conjugate gradient descent can be the applied to neural network training by adopting weights as was in back propagation. In addition, the conjugate gradient descent has the ability to work with a large number of weights

Conjugate gradient descent performs a series of line searches across the error surface. It determines the direction of the steepest descent and projects a line in that direction to locate the minimum, after which it update in the weights once per epoch. Another search is then preformed along a conjugate direction from that point. This direction is been chosen to insure that all direction that have been minimized stay minimized. It does this in the assumption that the error surface is quadratic. If the quadratic assumption was wrong and the chosen slope direction doesn't slope downwards, it will then calculate a line of steepest descent and search that direction. Each epoch involves searching in specific direction these results in a search that doesn't generally follow the steepest descent, but it often produces a faster convergence than a search along the steepest decent direction because it is only searches one direction at a time. As the algorithm moves closer to the minimum point the quadratic assumption is more likely to be true and the minimum is then located quickly.

3.4.2 Back propagation

Since 1989, learning by back propagation has become the most popular method of training neural networks. The reason for this popularity is the underlying simplicity and the relevant power of the algorithm. Its power derives from the fact that, unlike its precursors, the perceptron learning rule and the Widrow-Hoff learning rule can be employed for training nonlinear networks of arbitrary connectivity. Since such networks are often required for real world application, such a learning procedure is critical. Nearly as important as its power in explaining its popularity is its simplicity. The basic idea is old and simple, namely define an error function and use a gradient descent to find a set of weights which optimize performance of particular task. This algorithm is to a degree that simple so it can be implemented in few lines of code.

3.4.3 Quick propagation

The quick propagation algorithm is a variation of the standard back-propagation algorithm developed by Scott Fahlman in 1989. It assumes that the local is quadratic and employs an approximation to the second order derivatives of the quadratic to make weight changes. The algorithm is generally not fast but has shown that to be faster than back-propagation for some applications, but is not generally faster. It can also get trapped in local minima or become unstable in a manner similar to back-propagation. For these reasons it is not considered a general purpose method for training feedforward networks, but can treated as specialized technique that can , sometimes, produce rapid training.

3.4.4 Quasi-Newton

The Quasi-Newton method is a popular algorithm for nonlinear optimization. It uses second order derivatives to find an optimal solution. They generally converge faster than first order techniques such as the gradient method used in back-propagation. However, its memory requirements and computation complexity scale as the squire of the number and weights. For these reasons it is generally not suited for training networks with many weights.

3.4.5 Levenberg-Marquardt

This is another nonlinear optimization algorithm based on second order derivatives. It has been adopted for training feedforward neural networks. It is however more restrict than back-propagation. Like quasi-newton method, the memory requirements for the LM algorithm scales as a function of the squire of numbers and weights, and their for restricted to smaller networks, typically, on the order of few hundred weights. It works only with summed squire error functions.

3.5 Neural network learning laws

Learning laws describe the weight vector for the ith processing units at time instant $(t + 1)$ in the terms of the weight vector at time instant (t) , it is formulated as follows :

$$w_i(t + 1) = w_i(t) + \Delta w_i(t) \quad \textbf{(3.11)}$$

where$\Delta w_i(t)$ is the change in the vector between*(t)* and *(t+1)* instant of time .

There are different methods for implementing the learning feature of a neural network, leading to several learning laws. Some basic learning laws are discussed below. All these learning laws use local information for adjusting the weight of the connection between two units

3.5.1 Hebb's law

Here the change in the weight vector is given by

$$\Delta w_i = \eta f\left(w_i^T a\right) a \quad \textbf{(3.12)}$$

Therefore, the jth component of Δw_i is given by

$$\Delta w_{ij} = \eta f\left(w_i^T a\right) a_j \quad \textbf{(3.13)}$$

$= \eta s_i a_i,$ for $j = 1,2, \dots, M$ **(3.14)**

wheres_i is the output signal of the ith unite. This law states that a weight increment is proportional to the product of the input data and the resulting output signal of the unit. It requires weight initialization of small random values around $w_{ij} = 0$ prior to learning. It represents an unsupervised learning.

3.5.2 Perceptron law

Here the change in the weight vector is given by

$$\Delta w = \eta[b_i - sng(w_i^T a)]a \qquad \textbf{(3.15)}$$

There for we have

$$\Delta w_{ij} = \eta[b_i - sng(w_i^T a)]a_j \qquad \textbf{(3.16)}$$

$$= \eta\ (b_i - s_i)a_j \qquad \text{for j} = 1,2, \dots, M \qquad \textbf{(3.17)}$$

This law is applicable only for bipolar output functions$f(.)$. This law is also called discrete perceptron learning law. The expression for Δw_{ij} shows that the weights are adjusted only if the actual output s_i is incorrect, since the term between the brackets is zero for a correct output. This is a supervised learning law, as the law requires a desired output for each input. In implementing the law, the weights can be initialized by any random initial values, as they are not critical. The weights converge to the final values, eventually, by repeated use of the input-output pattern pairs, provided the pattern pairs are representable in the system.

3.5.3 Delta law

Here the change in the weight vector is given by:

$$\Delta w_i = \eta[b_i - f(w_i^T a)]\dot{f}(w_i^T a)a \qquad \textbf{(3.18)}$$

Where $f(\dot{x})$ is the first derivative with respect to x. Hence

$$\Delta w_{ij} = \eta[b_i - f(w_i^T a)]\dot{f}(w_i^T a)a_j$$

$= \eta[b_j - s_i]\dot{f}(x_i)a_j$ for j= 1,2,…M **(3.19)**This law is valid only for a differentiable output function, as it depend on .the derivative of the output function (.). It is a supervised learning law since the change in the weight is based on the error between the desired and the actual output values for the given input. Delta learning law can also be viewed as a continuous perceptron learning law.

3.5.4Widrow and Hoff LMS law

Here the change in the weight vector is given by:

$\Delta w_i = \eta[b_i - w_i^T a]a$ **(3.20)**$\Delta w = \eta[b_i - w_i^T a]a_j$ for j=1,2,..,M **(3.21)**

This is a supervised learning law and is a special case of the delta learning law where the output function is assumed to be linear, i.e .$f(x_i) = x_i$. In this case the change in the weight is made proportional to the negative gradient of the error between the desired output and the continuous activation value, which is also the continuous output of output signal due to linearity of the output function.

3.6Activation function

The sigmoidal activation function plays a critical role in neural network modelling. However, selecting the correct sigmoidal function to apply as the transfer function or activation function is not important in neural network designs. The purpose of the sigmoidal transfer function to the neural network design is to normalize and shrink the weight estimates in the hidden layer to the output layer with a distribution that is centred about the zero in order to assure convergence to the correct values. A sigmoidal function has an S-shaped distribution as illustrated in Figure

(3.8). The beauty of the sigmoidal function lies in the fact that it is the first derivative of the function itself given by

$$f^{'}(x) = f(x)(1 - f(x) \quad \textbf{(3.22)}$$

The most common sigmoidal functions is the logistic function that given by the following equation

$$f(x) = 1/1 - e^{-x} \quad \textbf{(3.23)}$$

This link functions redefines the target variables from $(\infty, -\infty)$ interval to a [0, 1] interval. However, the default link function of SAS Enterprise Miner is a hyperbolic tangent $(tanh)$ activation function that is defined by

$$f(x) = (e^{x} - e^{-x})/(e^{x} + e^{-x}) \quad \textbf{(3.24)}$$

The function actually has an exponential distribution that is used as a transfer function applied to the input-to-hidden layer weights. The difference between the two sigmoidal distributions is the range values of the output responses. The hyperbolic tangent has a range between $[-1, 1]$ compared to the logistic function which has the rang between $[0, 1]$. The hyperbolic tangent function has an ideal network modelling property. It leads to faster a convergence in the optimization process in comparison to the various logistic functions given a sufficiently large sample size. At times, other functions such as the arctan and Elliott functions, given by equations (3.25), and (3.26) can be used

$$f(x) = (2/\pi)tan^{-1}(x) \quad \textbf{(3.25)}$$

$$f(x) = x/(1 + |x|) \quad \textbf{(3.26)}$$

The Elliot function can often produce similar results as those obtained using the hyperbolic tangent function. The sigmoidal activation function applied to the hidden-to -target layer depends on the level of measurements of the target variable, typically, a nonlinear design. However, one is encouraged to try other output activation function in order to increase the precision of the neural model. The coefficients of the inputs weights determine the steepness or the slop of the curve as either increasing or decreasing.

The sigmoidal function is linear when the input layer weight estimates are close to zero. The hidden unit bias determines the location of the inflection point or the centre of the curve changes. The weights and biases from the output layer determine the upper and lower asymptotes or tails of thesigmoidal function.

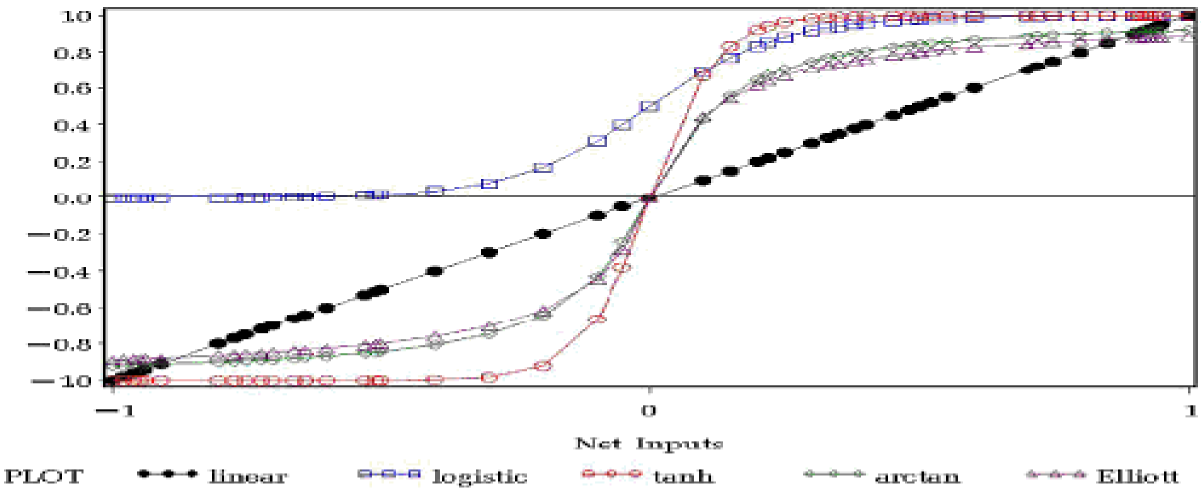

Figure 3.8 Common activation function

CHAPTER FOUR

METHODOLOGY AND RESULTS

4.1 Study Area

In this study a network consist of 73 control points distributed in Khartoum state (Omdurman and Bahri).63point were used as data(known)points and 10 points used as computation (unknown points) Figure 4,1 shows the study area and the distribution of these points .

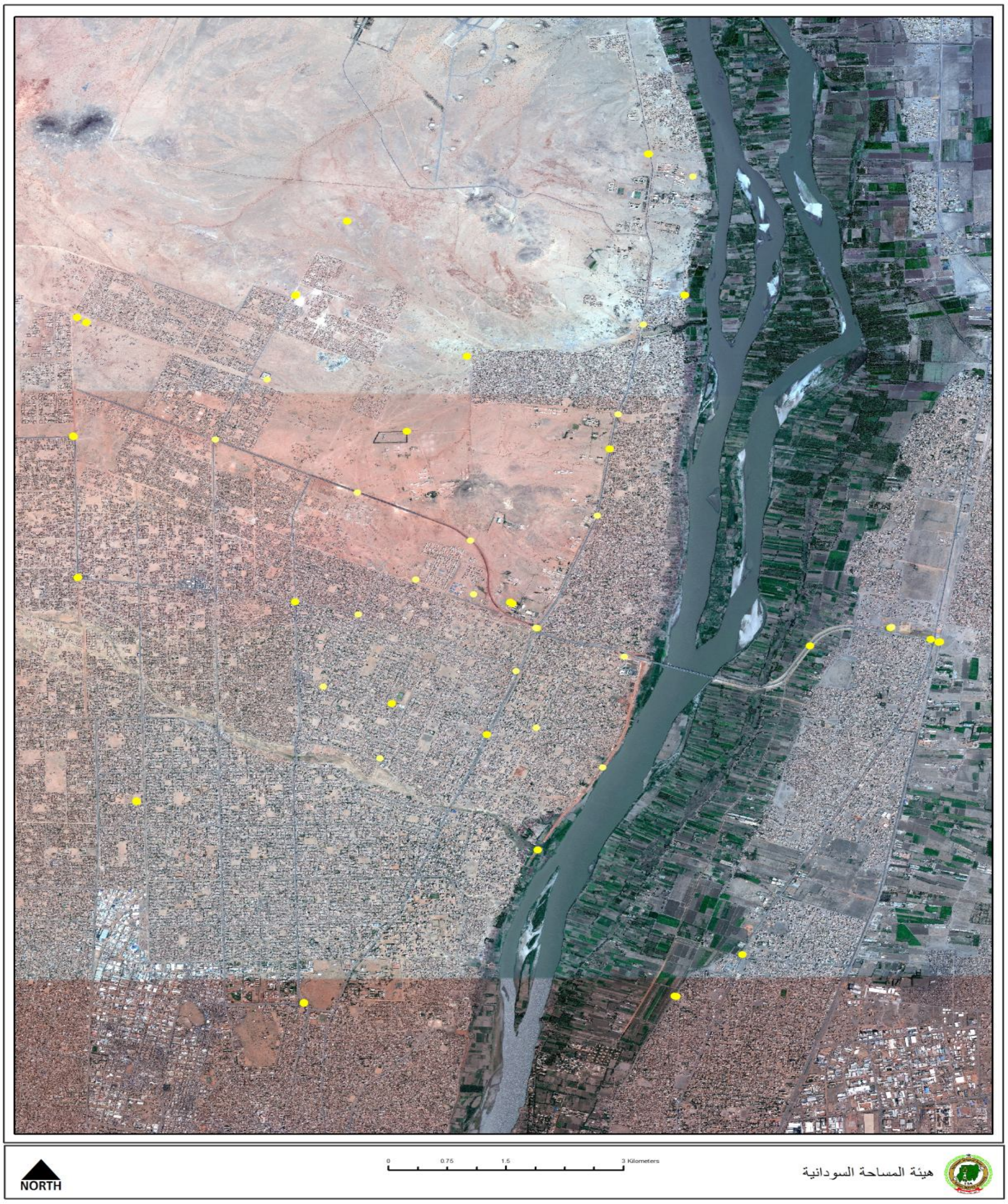

Figure 4.1 Study area

4.2 Materials of the test

Two sets of observations was done at each station at the same time by using Logistic Trimble R8And navigation Garmin GPS Map 60 CSX and the difference between each set of observations at each station was computed.Table (4.1)shows the observation and their differences and the root mean square error for the ten check points.

Table (4.1) Observations and differences

Point ID	RTK.Reading E (m)	RTK.Reading N(m)	Nav.Reading E(m)	Nav.Reading N(m)	Difference E(m)	Difference N(m)
1	447631.038	1738404.990	447629	1738404	-2.038	-0.990
2	451459.138	1737728.699	451460	1737729	0.862	0.301
3	452997.665	1737834.046	452996	1737839	-1.665	4.954
4	450592.292	1732892.574	450589	1732893	-3.292	0.426
5	447691.759	1729486.443	447688	1729492	-3.759	5.557
6	447982.455	1734530.150	447980	1734534	-2.455	3.850
7	447331.958	1736343.947	447328	1736345	-3.958	1.053
8	444882.893	1738419.372	444883	1738421	0.107	1.628
9	442103.266	1738796.113	442100	1738796	-3.266	-0.113
10	442048.505	1741025.267	442051	1741027	2.495	1.733
11	442220.826	1742797.512	442225	1742799	4.174	1.488
12	444886.010	1743220.449	444886	1743217	-0.010	-3.449
13	447075.654	1742269.229	447080	1742268	4.346	-1.229
14	449394.794	1745437.614	449395	1745434	0.206	-3.614
15	448898.395	1740813.273	448898	1740810	-0.395	-3.273
16	447662.969	1738379.504	447660	1738379	-2.969	-0.504
17	453103.958	1737782.686	453100	1737782	-3.958	0.686-
18	449736.453	1732234.916	449736	1732231	-0.453	-3.916
19	447677.605	1729476.068	447678	1729480	0.395	3.932
20	444999.268	1732132.859	444998	1732128	-1.268	-4.859
21	442858.998	1735293.012	442859	1735295	0.002	1.988
22	442051.933	1741004.437	442052	1741006	0.067	1.563
23	445554.890	1744373.644	445552	1744376	-2.890	2.356
24	449393.661	1745428.791	449396	1745433	2.339	4.209
25	449858.471	1743218.490	449858	1743222	-0.471	3.510
26	447663.823	1738381.600	447665	1738379	1.177	-2.600
27	453104.751	1737784.633	453103	1737780	-1.751	-4.633
28	444999.269	1732132.857	444997	1732135	-2.269	2.143
29	442859.941	1735295.077	442860	1735292	0.059	-3.077
30	442052.871	1741006.489	442050	1741003	-2.871	-3.489
31	445555.775	1744375.753	445556	1744374	0.225	-1.753
32	449394.466	1745430.870	449394	1745429	-0.466	-1.870

Point ID	RTK.Reading E (m)	RTK. Reading N(m)	Nav. Reading E(m)	Nav. Reading N(m)	Difference E(m)	Difference N(m)
33	449859.390	1743220.607	449860	1743219	0.610	-1.607
34	447662.962	1738380.661	447663	1738379	0.038	-1.661
35	453103.888	1737783.785	453101	1737783	-2.88	-0.785
36	449734.137	1732234.910	449735	1732235	0.862	0.090
37	447677.583	1729477.141	447678	1729478	0.417	0.859
38	444999.267	1732132.858	444996	1732137	-3.267	4.142
39	442858.964	1735294.115	442858	1735294	-0.964	-0.115
40	442051.832	1741005.571	442053	1741004	1.168	-1.571
41	445554.860	1744374.804	445554	1744374	-0.860	-0.804
42	449393.512	1745429.933	449392	1745432	-1.512	2.067
43	449858.438	1743219.568	449857	1743219	-1.438	-0.568
44	447662.990	1738380.493	447659	1738383	-3.990	2.507
45	453103.862	1737783.802	453102	1737779	-1.862	-4.802
46	449736.415	1732235.998	449733	1732235	-3.415	-0.998
47	447677.574	1729477.216	447676	1729478	-1.574	0.784
48	444999.283	1732132.930	444995	1732136	-4.283	3.070
49	442858.979	1735294.158	442855	1735294	-3.979	-0.158
50	442051.902	1741005.525	442047	1741005	-4.902	-0.525
51	445554.857	1744374.678	445550	1744374	-4.857	-0.678
52	449393.479	1745429.967	449392	1745428	-1.479	-1.967
53	449858.433	1743219.598	449856	1743216	-2.433	-3.598
54	447960.393	1738004.080	447959	1738001	-1.393	-3.080
55	452499.678	1738015.578	452501	1738014	1.322	-1.578
56	449086.278	1737554.669	449085	1737553	-1.278	-1.669
57	444524.607	1741892.738	444528	1741895	3.393	2.262
58	444906.291	1743236.481	444907	1743236	0.709	-0.481
59	443863.103	1740951.623	443865	1740950	1.897	-1.623
60	445677.667	1740121.506	445680	1740120	2.333	-1.506
61	447119.611	1739367.480	447122	1739367	2.389	-0.480
62	448744.219	1739754.649	448745	1739752	0.781	-2.649
63	449004.756	1741345.549	449006	1741345	1.244	-0.549
64	449329.974	1742752.391	449330	1742753	0.026	0.609
65	449960.305	1745075.793	449962	1745077	1.695	1.207
66	447706.867	1737325.528	447705	1737326	-1.867	0.472
67	447169.546	1738525.332	447168	1738526	-1.546	0.668
68	446425.540	1738760.638	446422	1738761	-3.540	0.362
69	445689.100	1738215.514	445688	1738213	-1.100	-2.5`14
70	445244.834	1737087.129	445241	1737084	-3.834	-3.129
71	445969.011	1735958.837	445966	1735958	-3.011	-0.837
72	448807.648	1735820.650	448809	1735821	1.352	0.350
73	447966.596	1736437.420	447963	1736440	-3.596	2.580
RMSE					0.886	0.373

Figure (4-2a) and (4-2b) shows the relationships between differencein easting and northing at the 10 points computation.

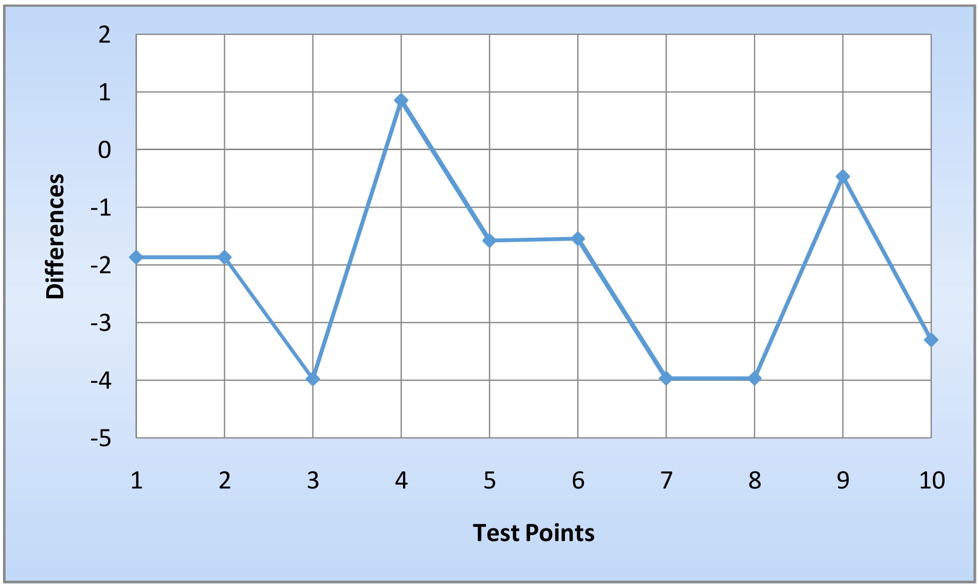

Figure (4-2a)

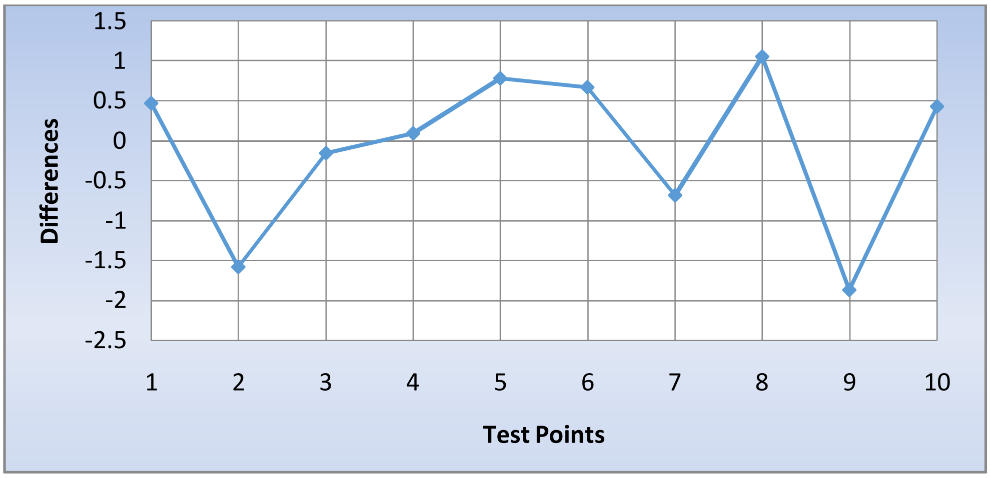

Figure (4-2b)

4.3 Procedures

In order to test the possibility of enhancing thelow cost navigater observationby using artificial neural network (softwareAluydaNeurolntelligence Version2.2(577) was used for the test according to the following criteria . table 4.2 shows the test criteria at ten points were obtained.

Table (4.2) tests criteria easting

Training	Conjugate gradient
Random seed number	50
Iterations	1000
Input activation function	Logistic
Output activation function	Linear
Output error function	sum-of-squares

Table (4.3) tests criteria northing

Training	Conjugate gradient
Random seed number	20
Iterations	1000
Input activation function	Logistic
Output activation function	Linear
Output error function	Sum-of-squares

4.4 Results

The results at ten points were obtained at Table (a,b) shows the results with thereroot mean square error.

Table (4.4) The Result for Easting

	Row	Target	Output	Difference (m)
TST	66	447170.0	447170.6	0.522
TST	55	449086.8	449084.6	2.142
TST	49	442052.4	442050.5	1.848
TST	36	447678.1	447679.3	1.241
TST	47	444999.8	444997.1	2.722
TST	67	446426.0	446425.9	0.189
TST	17	449737.0	449736.8	0.137
TST	7	444883.4	444884.7	1.286
TST	32	449859.9	449861.2	1.303
TST	4	447692.3	447689.3	2.959
RMSE				0.571

Table (4.5) the result for northing

	Row	Target	Output	Difference (m)
TST	66	1737325.528	1737326.456	0.928
TST	55	1738015.578	1738014.663	-0.915
TST	49	1735294.158	1735293.874	-0.284
TST	36	1735294.115	1735293.874	-0.241
TST	47	1729477.216	1729476.118	-1.098
TST	67	1738525.332	1738526.831	1.499
TST	17	1737782.686	1736345.181	-0.095
TST	7	1736343.947	1745427.455	1.234
TST	32	1745430.870	1732891.936	-0.950
TST	4	1732892.574	1737326.456	-0.638
RMSE				0.300

A graph showing the relationship between enhanced values for E and N at the 10 points.Figure (4-2a) and (4-2b)

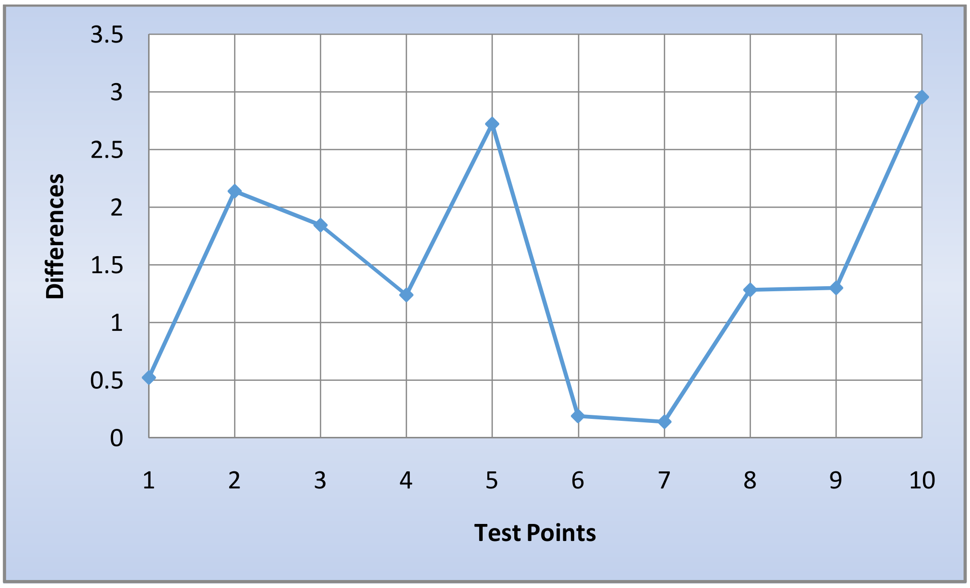

Figure (4-2c)

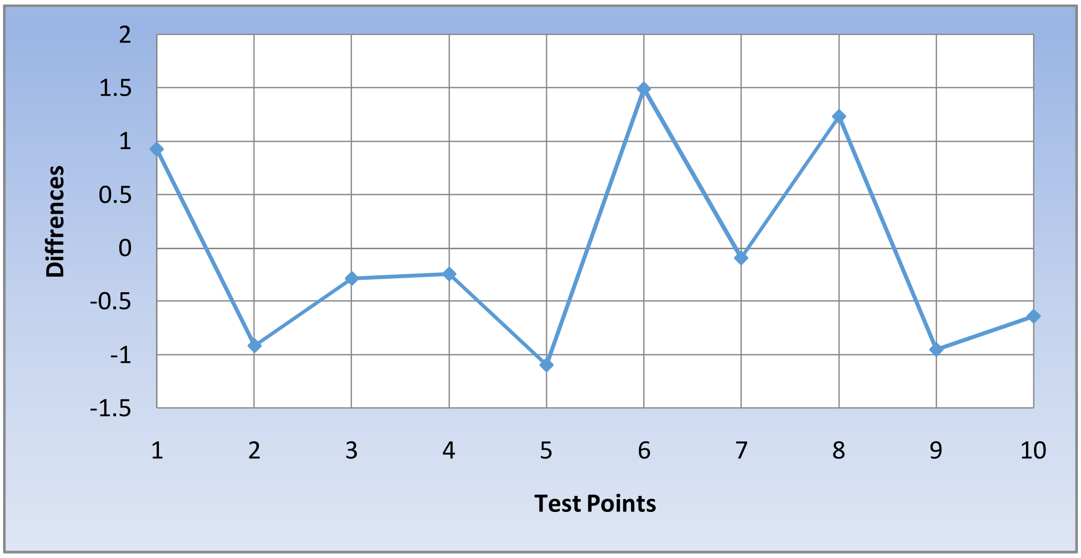

Figure (4-2d)

A graph of a comparisons of differences before and after the enhancement is shows in fig (4.3a , and 4.3b).

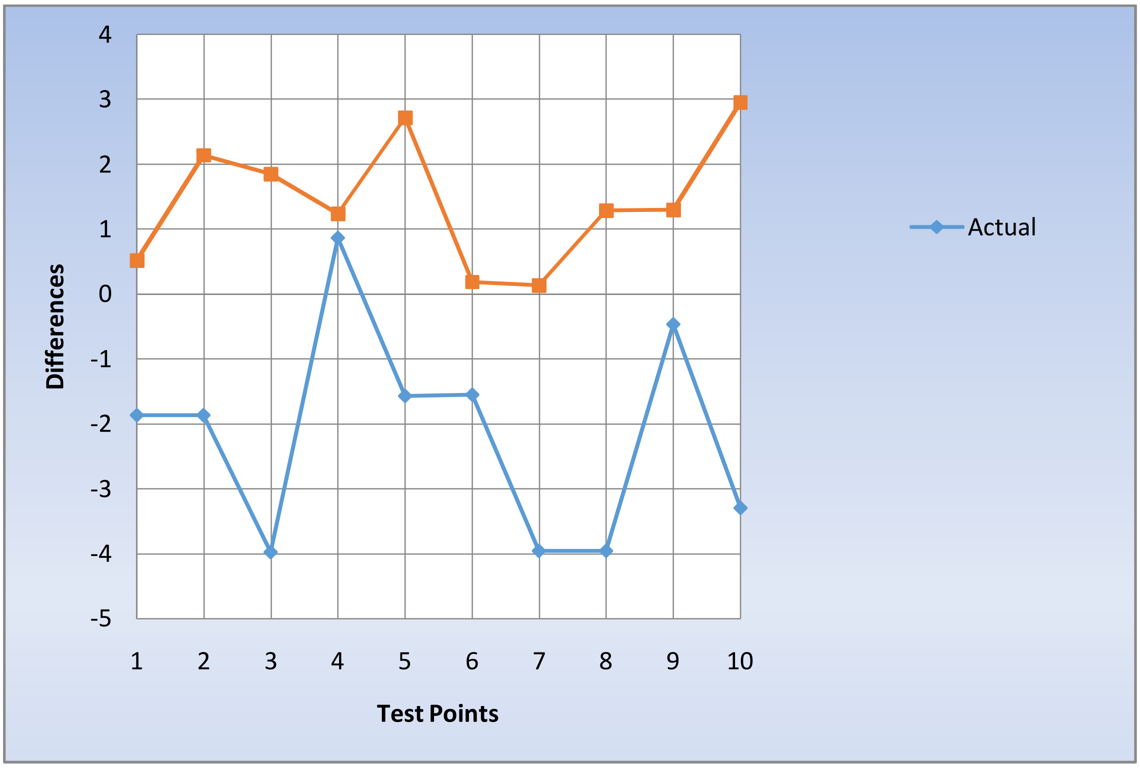

Figure (4-3a)

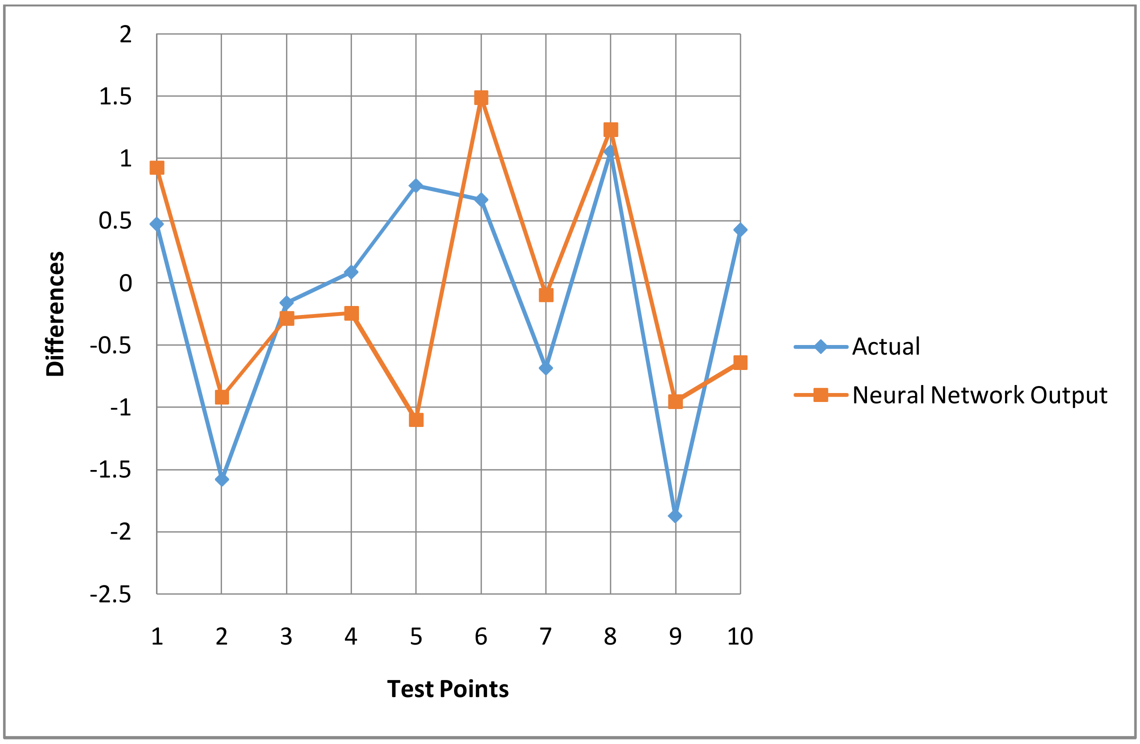

Figure (4-3b)

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

According of the test correct out in the study it could be conclude that:

1. The Planimetic accuracy of the absolute posting technique were found to be ±3 meter.
2. The accuracy figure was improved (±5) meter when the ANN model was used as an integrated solution.
3. The ANN model was able to proceed all test pattern successfully
4. The training session of the ANN model took 5minutes.

5.2 Recommendations

- Testing effect of the (distribution of data control points).
- Testing possibility of linking the ANN to GIS software

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