CELLULAR POSITIONING BY LOCATION FINGERPRINTING WITH THE AID OF PROPAGATION MODELS

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Abstract

The Fingerprinting method or the Database Correlation Method (DCM) is a network based positioning technique which has shown superior accuracy. DCM is based on a pre-measured database of location dependent variables such as Received Signal Strength (RSS). The major challenge of the technique is the effort involved in forming the database, which prevents it being deployed in large, dynamic networks.

The work presented in this thesis investigates the possibility of using network planning tool predictions instead of field measurements to create the fingerprint database for DCM. While the accuracy of this approach is lower than the DCM method with field measurements, further tuning of the predictions in order to improve the performance is proposed. The tuning method is defined as cell-wise calibration, which calibrates the predictions by using a lesser number of field measurements in a cell-by-cell basis. In addition, a novel fingerprint filtering approach and a fingerprint matching technique (a cost function) are proposed.

The trial results show that, the performance of DCM using the proposed database is inferior to that using a measured database. However, the application of calibration process for predictions improves the performance up to an acceptable level. The calibration method, designed for the bad urban scenario is based on curve fitting whereas that for urban, suburban and rural environments is based on neural networks. In addition, the novel fingerprint filtering approach is robust for the bad urban environment while the novel cost function shows higher performance with the proposed database.

The best positioning accuracy for the. bad urban environment is 200m in 80% of the estimates and that for the urban environment is 125m (80%). Remarkable performance improvement can be observed in the rural environment giving a positioning error less than 385m in 80% of the estimates. The performance in

suburban environment is inferior to that-in both urban and rural, with an error less than 550m in 80% of the time.

The proposed solution for positioning is best suited for the deployment in large dynamic networks as a network-based method to provide basic information services, such as nearest ATM machine, petrol. station or hospital, traffic information and location based advertising.

The work presented in this thesis in part or whole has not been submitted for any other academic qualification at any institution.

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CONTENTS

LIST OF FIGURES

LIST OF TABLES

Chapter 1

Introduction

Being small and handy, the mobile phone has become a regular part in day today life, and the addition of novel applications and capabilities makes it even more personal and trusted. As a result, the mobile service providers are striving to introduce value added features to attract potential customers. Location-aware service is one such application, which offers enormous possibilities to bring in novel services for 2G and 3G mobile networks. For some Location Based Services (LBS) it is sufficient to determine the cell of the mobile terminal but other services such as emergency calls or navigation systems require more accurate position determination techniques. Unfortunately, the GSM Network lacks positioning functionality; hence a separate positioning technology should be integrated to the network.

On the other hand, Global Positioning System (GPS) has proven to be the most accurate with an average accuracy less than 10m. However, some challenging issues regarding GPS positioning exist, such as the non-availability of GPS enabled mobile devices, the poor estimation in harsh environmental conditions and the poor indoor coverage, which make the system inappropriate for commercial applications such as localized information services.

Thus, the estimation of the user's location from data that is inherently available in the cellular network, also known as cellular positioning, has become a key technology in mobile communications.

1.1 Current status in the field of cellular positioning

The market for location-based services holds enormous potential. The ability to tell users where they are, and how to get where they want to go as well as how long it will take to get there and what else is close by can enhance a wide array of applications. In addition, LBS tools have the ability to create geo-fences, the alerts issued via SMS or voice when a user has entered or exited a specified area [1]. However, the reality of this LBS glory relies heavily on precise location determination techniques.

In the United States, people facing a critical emergency situation can request assistance through dialing 911 emergency assistance services. Most of theses calls are made from mobile phones with the user being unaware of his or her whereabouts. Hence, Federal Communication Commission (FCC) has imposed, through E-911 mandate, the mobile operators to precisely locate the callers requesting emergency assistance via 911 [2, 3]. Phase II of this regulation imposes accuracy levels for different location technologies based on their implementation as set out by Table 1.1 [2]. This was the wake up call for high enthusiasm in cellular positioning.

Table 1.1: FCC guidelines for location accuracy

Source: [2]

Type of location solution	67% of locations must be	95% of locations must be
Handset-based	<50m	<150m
Network-based	<100m	<300m

Furthermore, a recommendation has been issued for the optimal planning and implementation of emergency wireless location service, called E-112, for the European Union in 2004 [4]. Accordingly, in order to provide effective service, location accuracy should be 50m or less in urban corridors/centers and the requirements for accuracy diminish as the distance from urban centers increases. i.e. the need for high accuracy is less stringent in rural environments [4].

As a result, several commercial positioning systems have been developed all over the world, namely, CellPoint [5], SnapTrack [6], Ericsson Mobile Positioning System [7] and BT-Cellnet [8], which are based on Assisted GPS (A-GPS) and Enhance Observed Time Difference (E-OTD) positioning methods. The facts that these commercial systems are highly expensive and the upgrades to be done in the network in deployment prevent them being purchased by most of the mobile operators in countries like us.

Hence there exists a need to come-up with more accurate and cost effective solution for location estimation in cellular networks. A technique based on existing radio signal data from a series of base stations would be a feasible solution. However, significant signal level variations and multi-path effects have proved a major obstacle in many developments.

1.2 LBS applications and Performance requirements

Some of the applications that have taken major attention in commercial location based services are illustrated in Figure1.1.

Figure 1.1: Commercial LBS applications

Information services are defined to provide the nearest service such as ATM machine, petrol station or hospital, to provide traffic information and for advertising purposes. Navigation services could provide street-by-street turn-by-turn directions to a destination while tracking services include lone-worker tracking in high risk locations, criminal tracking and child tracking services to alert when the child moves away from a pre-defined area. Monitoring applications, like field force automation, mobile worker management and taxi fleet management are promising in most of the industries.

The reliability of the above mentioned applications rely on the performance of the positioning technology. Accuracy and yield are the two principal measurements of the performance of location technologies. Accuracy refers to the radius in which a location technology can pinpoint the location of a mobile phone, while yield refers to the location technology's ability to obtain a location fix, expressed as a percentage success rate [9]. In addition, the performance requirements of applications are partially dependent on where the Mobile Station (MS) to be located happens to be at that time. This represents whether the MS is inside a building (indoor), or outside in urban, suburban or rural environment.

Table 1.2 summarizes the performance requirements of above mentioned applications, based on research conducted among key application developers [9].

Table 1.2: Performance requirements of selected Location Based Applications

Source: [9]

	Indoor		Urban		Suburban		Rural	
	Accuracy (m)	Yield (%)	Accuracy (m)	Yield (%)	Accuracy (m)	Yield (%)	Accuracy (m)	Yield (%)
Information Services								
- Basic	50-100	80	500	80	1000	80	5000	80
- Enhanced	20-50	90	50	90	50	90	50-100	90
Navigation	10	95	10	99.9	10	99.9	20	99.9
Field force automation/ work force management	50	95	50	95	50	95	100	95
Lone-worker tracking	50	99.9	50	99.9	50	99.9	100	99.9
Taxi dispatch	n/a	n/a	50	90	50	90	50	90
Child tracking	50	99.9	50	99.9	50-100	99.9	50-100	99.9
Medical alert	50	99.9	50	99.9	50-100	99.9	50-100	99.9

1.3 Motivation

A range of cellular positioning technologies have been researched all over the world, yet, none of them have proven superior in terms of accuracy for all environments worldwide [10-28]. This opens the path to research on precise location estimation technologies. In addition, the lack of evidence in researching on cellular positioning techniques for improved accuracy in local environment provides a strong motivation to research on such techniques applicable for local context.

During the author's final year project, done as a partial fulfillment of the B.Sc. degree, different cellular positioning techniques were investigated and the accuracies of three of them, namely, the Geometrical Method, Statistical Method and the Database Correlation Method (DCM), were verified in local environment [29, 30]. Consequently, the Database Correlation Method was proven to be more accurate in all three environments, urban, sub urban and rural.

Even though the database correlation method has the potential for higher accuracies in all three local environments, the difficulty of creating the database with field test measurements has become a big challenge when deploying this technique in large, dynamic networks. Thus, there exist a need to come-up with a remedy for this deployment challenge and that paved the path for this particular research.

1.4 Research Objectives and Contributions

The principal objective of this research is to find a more practical method of applying the Database Correlation Method for location estimation in cellular networks, with less field measurements. In order to do this, the use of theoretical propagation models and/or Network Planning Tools to create a fingerprint database in local mobile network will be investigated. While the accuracy of this approach may be lower than the DCM method with field measurements, further tuning of the results in order to improve accuracy will be studied.

The major contributions include:

- Survey on fingerprinting methods for location estimation in cellular networks.
- Study comprehensively the propagation modeling done by Service Providers and the tools used.
- Develop the DCM by obtaining fingerprints through an appropriate propagation model and verify the accuracies of the method in all three environments, urban, suburban and rural.
- Carry out drive tests in three different environments to obtain sample test data for deviation analysis, calibration and location estimation phases.
- Analyze the deviations of the predictions from actual measurements.

- Study the deviation of accuracy from the DCM implemented by field test measurements.
- Design and develop a calibration method to tune the created database in order to minimize the above deviation. This includes calibrating the predictions using lesser number of field test measurements.

1.5 Organization of the Thesis

This dissertation is a systematic study for applying location fingerprinting method for cellular positioning with the aid of propagation models.

Chapter-2 is devoted for the literature review of cellular positioning techniques, specially fingerprinting method, radio wave propagation models and tools, and the techniques used for calibration such as neural networks. Next, in Chapter-3, the methodology applied in achieving the research objectives is presented comprehensively. This is followed by a detailed description of the environments, used for testing the developed methods for location estimation. Chapter-5 is devoted for an inclusive analysis of the outcomes of this work and finally, Chapter-6 concludes by discussing the achievements, commercialization aspects and future work.

Chapter -2

Literature Review

2.1 Cellular Positioning

Cellular positioning is merely the estimation of the locations of Mobile Stations (MS) using location sensitive parameters. While third generation mobile networks are enriched with positioning functionality, GSM networks should be integrated with a separate positioning unit as positioning functionality is deficient in GSM.

Cellular positioning can be achieved in variety of ways. All of these various techniques differ in accuracy, cost, and ease of implementation. Because of this operators have to weigh the tradeoffs among several methods. While all of these methods apply to terrestrial cellular systems, some require modifications to network infrastructure only, whereas others require new technology in the subscriber units as well.

Basically, all cellular positioning techniques have two roles, namely, Parameter Measurement (Location Measurement) and Position Determination (Location Estimation). These functions are performed by either MS or network. Consequently, cellular positioning systems are divided into three categories based on the role of the MS and the network. Those are Mobile based solutions, network based solutions and mobile-assisted network based solutions.

In mobile based solutions, both parameter measurement and location determination are performed by the MS. Still, some assisting information (BS coordinates) might be needed from the network to enable location determination in the MS. Mobile-based implementation does not support legacy handsets [31].

On the other hand, in network-based implementation one or more base stations (BSs) make the parameter measurements and send the measurement results to a location centre where the position is computed. This does not require any changes to existing handsets, which is a significant advantage compared to mobile-based or most mobile-assisted solutions [31].

When the MS makes positioning measurements and sends the results to a positioning element located in the network for position determination, the system is called mobile-assisted network based solution. Thus, the computational burden in mobile-based implementation is transferred to the positioning element; however, signaling delay and signaling load increase, especially when the estimated location information should be available at the MS.

2.1.1 Positioning Parameters

A. Cell ID

Cell-ID is the simplest positioning parameter, which gives cell sector information of serving cell in cellular networks. In current cellular networks, coverage is provided by a number of distributed cells. Each cell is normally divided into three sectors. Cell size varies from 300m to 3 km in urban areas and 3–20 km in suburban/rural areas. Hence, the accuracy of a positioning method, which gives the location of the BS as the estimated location, is based on the coverage area of the cell. This parameter is advantageous in the way that it doesn't require air interface resources and handset modifications in measurement procedure [14]. Cell ID of the serve cell could be obtained in the idle mode of the hand-set.

B. Timing Advance (TA)

Timing Advance is a parameter used to synchronize the time frame of each mobile station at the BS. It gives a distance estimate between the BS and the MS. TA is calculated at the BS and sent it back to the MS, which is then made available in the Network Measurement Report (NMR) at the mobile. Timing Advance value ranges from 0 to 63 and each value represents a range of distance from MS to BS, where the mobile can locate. This distance range is given by Equation (2.1).

$$\begin{aligned} &550.(TA-\frac{1}{2}) \leq d \leq 550.(TA+\frac{1}{2}); TA > 0 \\ &0 \leq d \leq 275m; TA = 0 \end{aligned} \tag{2.1}$$

Since the TA value is known only in the dedicated mode (call on) this cannot be used to locate a MS in idle mode. The accuracy of the positioning method, that considers TA alone, decreases when the MS is far away from the BS. Therefore, TA is used combination with the other methods to improve the accuracy [32].

C. Received Signal Strength (RSS)

In cellular environment, MS can measure signals from several surrounding BSs. These signal strength measurements provide a distance estimate between the MS and BS (with the aid of propagation models) and the MS must lie on a circle centered at the BS (With the use of Cell-ID the BS location could be identified).

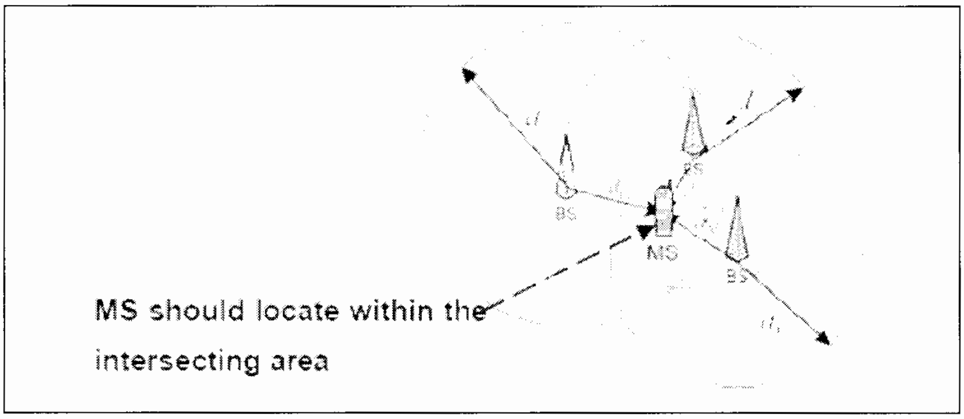


Figure 2.1: Distance to MS from several BSs using propagation models
Source: [29]

The received signal strengths from serving cell and the neighboring cell(s) are available in the NMR at the mobile. By using this information at the mobile itself or by transmitting them back to the network, either a terminal based solution or a network based solution can be implemented. Received Signal Strength of the serve cell and neighboring cells could be obtained through the Broadcast Control Channel (BCCH) in idle mode as well.

D. Angle of Arrival (AOA)

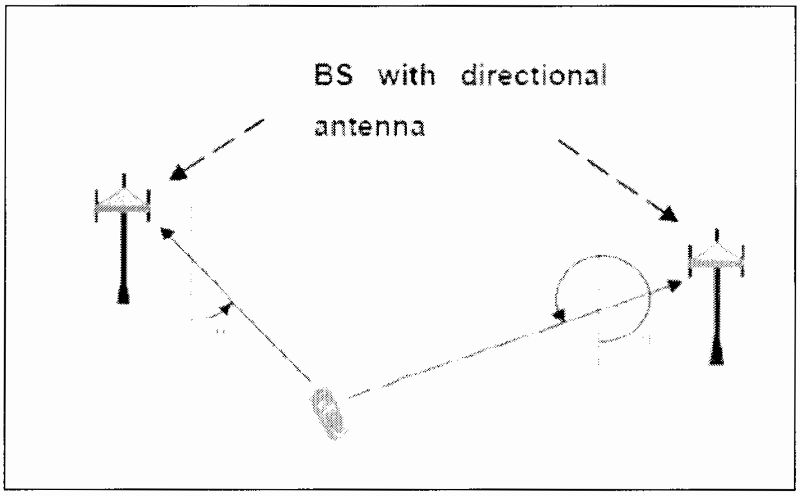


Figure 2.2: Angle of arrival parameter in GSM
Source: [29]

AOA parameter defines the angle of arrival of a signal from a MS at several BSs and could be measured through the use of antenna arrays. If a handset is within line-of-sight, the antenna array can determine the direction of the incoming signal from that hand-set. A second base station with the same technology would then also locate the direction of the handset and pinpoint the MS location with the use of data from the first base station and assuming 2-D geometry as shown in Figure 2.2 [29].

Line of sight between the MS and the BSs is essential for accurate measurement of the AOA. Hence, it is clearly not a parameter of choice in dense urban areas where line of sight scenario is seldom present. However, the AOA could be used as a location sensitive parameter in rural and suburban areas and it is an advantage to be able to locate a MS using measurements from a minimum of two BSs [31].

A major barrier to implement positioning techniques based on AOA in existing GSM networks is the need for an antenna array at each BS. It would be very expensive to build an overlay of AOA sensors to existing cellular network. However, since it is a network-based method and supports legacy handsets, it is developed by several companies as an E-911 solution [31]. In addition, applying AOA parameter in positioning techniques may introduce a capacity issues in cellular networks as the measurements taken at several BSs from a single MS requires time synchronization. This will result in the difficulty to serve a large number of simultaneous users.

E. Propagation Time

This is the one-way propagation time of a signal transmitted by the MS and received at multiple BSs. Alternatively; the measurement of the round-trip time of a signal gives a result twice that of the one-way measurement. The measurement of one-way propagation time requires the knowledge of the exact time at which the MS transmits and the BSs should have very stable and accurate clocks. But, the measuring of round-trip-time does not rely on such synchronization between the mobile and base station, and is the common means of measuring propagation time [18].

Since signals travel with a known velocity, the distance can be directly calculated from the propagation time. Geometrically, this provides a circle, centered at the BS, on which the MS must lie. By using at least three BSs to resolve ambiguities, the MS's position is given by trilateration.

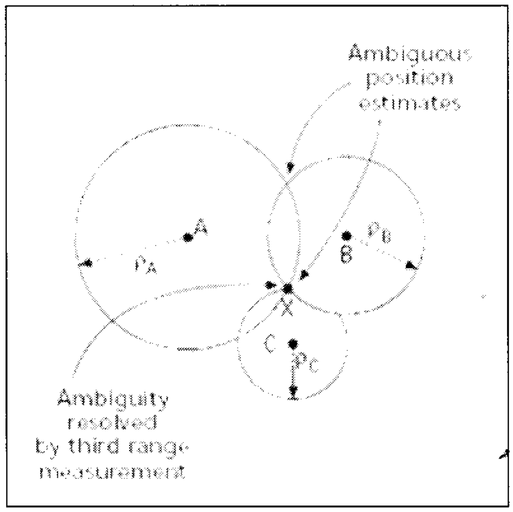


Figure 2.3: Propagation Time measurement
Source: [18]

Since the inaccuracy in timing synchronization translates directly to an imprecise location, the synchronization of the network base stations is very important when using propagation time as the location sensitive parameter. This is purely applicable for a network based solution, where the propagation time information at several base stations is taken in to consideration.

F. Time Difference of Arrival (TDOA)

This is the time difference of the arrival of a signal from the MS at a pair of BSs. This can be derived by measuring the Time of Arrival (TOA) of the signal at each BS and sending them to a central site to compute the time differences.

A TDOA measurement defines a hyperbolic locus around the BS on which the mobile telephone must lie. The intersection of the two hyperbolic loci (using three BSs) will define the position of the mobile telephone as shown in Figure 2.4.

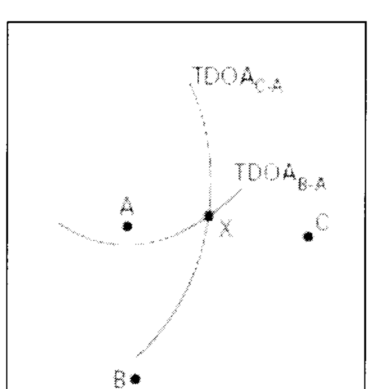


Figure 2.4: TDOA parameter
Source: [18]

A third TDOA measurement can be used to resolve the ambiguity of the hyperbolae intersecting at two locations.

The synchronization of the base stations is an important issue in implementing positioning systems using TDOA parameter. This is also purely applicable for network based solution where additional hardware is needed at the BS to implement [18, 29].

2.1.2 Positioning Techniques

Positioning techniques in cellular networks could be classified in to three major classes based on the approach used. They are;

- Geometrical Methods
- Statistical Methods
- Fingerprinting Methods

This section reviews the existing literature on first two approaches while the third approach is comprehensively discussed in Section 2.2 as it is the basis for the research work presented in this thesis.

A. Geometrical Methods

Geometrical method is a traditional positioning approach to location estimation based on standard geometry. Geometrical algorithms form circles, hyperbolae or angles centered at the hearable base stations and estimate the location by intersecting those in 2-dimension. Trilateration and triangulation are the basic geometry used in these methods. Different positioning parameters described in Section 2.1.1 can be used in triangulation and trilateration.

Two measurements of angle of arrival parameter from the MS at two different BSs could be triangulated to estimate the location of the mobile as shown in Figure 2.2 [31].

In addition, the distance estimate, which is computed using the received signal strength and propagation models suitable for the environment or using the propagation time parameter between BS and MS, defines a circle around the BS on which the MS may locate. Then the position of the MS could be estimated by trilaterating three such range circles at three hearable cells as shown in Figure 2.1. Theoretically, this would give a single intersection point, but due to multi-path effects and the constraints in propagation models, several intersection points will result. In such cases, the geometrical mean of all the intersection points could be taken as the estimated location as shown in Figure 2.5 [29].

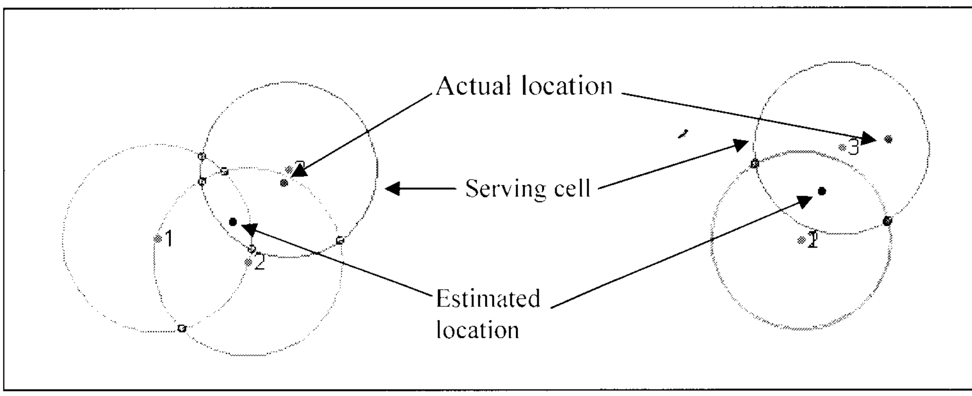


Figure 2.5: Geometrical mean of all intersection points in geometrical method
Source: [29]

Application of geometrical technique in location estimation is described in [29] together with accuracy results in three different environments. The results of that work shows, the 80% accuracy of geometrical method lies in the range of 500m in urban, 1000m in suburban and 1500m in rural environment. This is a low accuracy level for most of the location based services immerging today.

B. Statistical Methods

The second approach, which is based on statistical modeling, was first proposed by Teemu Roos, Petri Myllymäki and Henry Tirri in their paper, A Statistical Modeling Approach to Location Estimation [10]. The basic idea of this method is the construction of a statistical model which describes the distribution of signal strength at any given location, and to use the model to estimate the mobile unit's location when the signal strength is observed. The approach is strongly linked with propagation modeling.

The use of statistical modeling gives several feasible solutions over other approaches like geometrical approach. The key point in geometrical approach is mapping measured signal properties to the location. In contrast to this, statistical modeling approach emphasizes propagation modeling, in which the dependency of the measured signal properties on the location variable is considered. Here, the location estimation problem is solved as inference–problem, which is the kind of reasoning typical of statistics in general [10].

In this approach, first, a propagation model is selected for received signal strength at a distance *d* from the transmitter, and then, the probability distribution of the received signal strength around a specific area is defined. Then it requires a calibration of propagation parameters appearing in the propagation model equation, with respect to the environment. This is also a statistical estimation process, which uses a huge amount of field test data relative to a particular environment [33]. After estimating the propagation parameters, location estimation for a particular set of observed signal strengths at a specific location can be done as an inverse, or else, an inference problem.

Simulation results of this method for location estimation are given in [10] and [33], in which the positioning error is less than 620m in 95% of the estimates.

Furthermore, an enhancement to initial work in [10] has been proposed in [34], in which a directional propagation model is considered. According to the results demonstrated in [34] the best value of the average error is around 340m.

In addition, the statistical modeling approach has been tested in local context and the results are presented in [30]. Accordingly, the positioning error in local urban environment is less than 375m in 80% of the estimates.

A different approach for statistical estimation has been proposed in [35], which helps to reduce the error caused by the effect of signal fluctuations by acting as a filter for handling signal fluctuations. The simulation results show that the best average accuracy is around 260m.

2.1.3 Performance Measures

Commonly used accuracy measures in location estimation should be known in order to compare and understand the performance of different positioning technologies. This section reviews on different measures available in literature for this purpose.

A. Positioning error

Positioning error is the Euclidean distance between the estimated location and true location as given in Equation (2.2)

$$d = \sqrt{(x_t - x_e)^2 + (y_t - y_e)^2 + (z_t - z_e)^2} \qquad (2.2)$$

Where, $E(x_e, y_e, z_e)$ - estimated location

$T(x_t, y_t, z_t)$ - corresponding true location

The error in the altitude is often ignored in cellular positioning. In addition, the true location might be replaced with the location calculated with the GPS receiver [36].

B. Circular Error Probability (CEP)

Circular error probability or circular error probable (CEP) is the radius of a circle centered at the true position, containing the position estimate with a certain probability. Usually the radius of the 50% (R50) probability is used, but 67% (R67) and 95% (R95) probabilities are often quoted as in Figure 2.6.

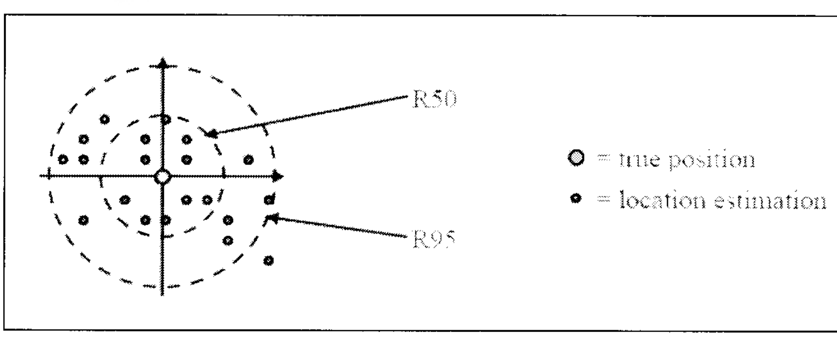


Figure 2.6: Circular Error Probability
Source: [36]

R50 equals the median of the positioning error distribution. A bit similar measure is the arithmetic mean which equals the sum of the positioning errors of the samples divided by the number of samples. The median is a much better measure than the arithmetic mean for highly asymmetrical distributions and hence more applicable in mobile positioning [36].

In case of three-dimensional accuracy, a common measure is Spherical Error Probability (SEP), which also takes the error in the altitude into account.

C. Cumulative Distribution Function (CDF)

Cumulative Distribution Function (CDF) is often used in visualizing the positioning error. A general impression of the error distribution can be obtained quickly by looking at the CDF graph. The X-axis represents the positioning error in meters and the percentage of all samples is depicted in the Y-axis.

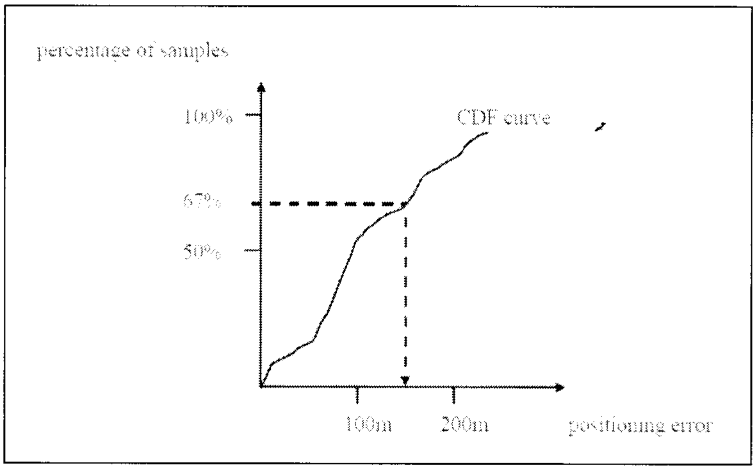


Figure 2.7: Cumulative Distribution Function
Source: [36]

Median, R67 and R95 values can be approximated from the CDF graph by ocular estimation.

D. Root Mean Square (RMS) Error

The Root Mean Square error is defined by Equation (2.3).

$$R.M.S. = \sqrt{\frac{1}{n}\sum_{i=1}^{n} d_i^{\,2}} \tag{2.3}$$

Where, n - Number of position samples

d_i - Positioning error of i^{th} sample

This measure represents the whole error distribution with one value and hence more comprehensive.

Consequently, the most illustrative measure is CDF because it shows the whole error distribution, while the numerical values are used to simplify the representation [36].

2.2 Fingerprinting Method

Fingerprinting method for location estimation in mobile networks is also known as Database Correlation Method (DCM). This technique was first proposed by Heikki Laitinen, Jaakko Lahteenmaki and Tero Nordstrom in their paper, "Database Correlation Method for GSM Location", [12]. Fingerprinting Technique relies on a pre-measured database of a location dependent variable. In GSM networks, location dependent variable would be either the Received Signal Strength (RSS) or the Channel Impulse Response (CIR). Angle of Arrival can also be considered, but it requires additional hardware to perform the measurement.

The key idea of DCM is to store the signal information seen by the MS, within the coverage area, in a database as signal information samples called *Fingerprints* [12]. A fingerprint consists of signal information seen at a location together with the location coordinate. The measured signal information at the location to be estimated is compared with the fingerprints stored in the database and the location coordinate of the best matching fingerprint is taken as the estimated location.

DCM is a general approach for positioning and can be applied for any cellular network or WLAN. Since this method does not assume any line-of-site propagation condition, it is robust for urban environments, where the multi-path phenomenon is directly applied.

In general, fingerprinting technique involves two phases.

- ✓ Database preparation (Off-line phase)
- ✓ Location estimation (On-line phase)

2.2.1. Database Preparation

The heart of the fingerprinting method is the database which consists of pre-measured samples of location sensitive parameters. Hence, much attention should be given for database preparation.

RSS has been chosen as the location sensitive parameter in [12]. Then, the database consists of RSS fingerprints within the area. A single fingerprint is made up of;

- Cell ID of all hearable cells

- RSS of all hearable cells
- GPS coordinate of the measured location

The fingerprints can be formed using either real measurements or predictions from planning tools. The original work has used real measurement for this purpose. A method of collecting fingerprints is also proposed in [12]. There, the measurements are taken at a very low speed along the selected routes and two measured fingerprints per second are taken on average.

Besides, a more feasible approach for collecting database fingerprints is proposed in [30]. The novel method averages the signal strengths of ten consecutive measurements along the route while the median value of ten GPS coordinates is taken as the location coordinate. Further, it proposes a sliding window approach, such that the last five measurements of one fingerprint contribute to the first five measurements of the next fingerprint. This helps to increase the fingerprint resolution.

2.2.2 Location Estimation

Location estimation algorithm in fingerprinting method is a simple correlation algorithm, which matches the measured signal sample at the location to be estimated, with the fingerprints stored in the database, and outputs the location of the best matching fingerprint as the estimated location. The number of comparisons can be reduced by filtering the fingerprints using other parameters such as serving cell and timing advance [36].

In [12], the fingerprint matching was based on the least mean square approach, which uses Equation (2.4) to calculate a cost for each fingerprint.

$$d(k) = \sum_i (f_i - g_i(k))^2 + p(k) \tag{2.4}$$

Where f_i is the signal strength of the measured sample on the i^{th} cell, $g_i(k)$ is the signal strength of the k^{th} fingerprint on the same cell. The summation is taken over the hearable cells that are found in both of the fingerprints. A penalty term $p(k)$ is introduced for each cell that is found in only one of the fingerprints. The database fingerprint with the lowest value for $d(k)$ is set to be the best match for the measured sample.

The trail results in urban and suburban areas in Finland [12] show that the above algorithm can provide a positioning error less than 90m (90%) in urban whereas the error for suburban is 190m (90%).

Some what different approach is presented in [23]. Instead of using the LMS, another method (EXP) motivated by the Gaussian probability distribution is introduced as shown in Equation (2.5).

$$P = \sqrt{P_{EXP} * P_{Pen}} = \sqrt{\sqrt[n]{\prod_i e^{-(\frac{f_i - g_i(k)}{\sigma})^2}} * \sqrt[m]{\prod_i e^{-(\frac{f_i - g(k)_{min}}{\sigma})^2}}} \quad (2.5)$$

Where P_{EXP} is the probability computed for n cells to match the measured sample with the k[th] database fingerprint and P_{Pen} is the penalty term consists of all the penalty contributions computed for cells, which do not exist in the database fingerprint. f_i is the signal strength of the measured sample on the i^{th} cell, $g_i(k)$ is the signal strength of the k[th] database fingerprint on the same cell and $g(k)_{min}$ is the weakest signal level in the database fingerprint. The parameter σ characterizes the deviation between the signal strength values. The database fingerprint with the highest probability P is set to be the best match for the measured sample.

The positioning trial carried out in the urban area of Germany yields positioning accuracy of 98m (67%) for LMS approach and 83m (67%) for EXP approach whereas that of suburban area is 602m (67%) for LMS and 607m (67%) for EXP approach.

In addition a different way of calculating the penalty term for Equation (2.3) is proposed in [36]. The modified equation is given in Equation (2.6).

$$d(k) = \sum_i (f_i - g_i(k))^2 + \sum_j (f_j - l_{max})^2 + \sum_l (l_{max} - g_l(k))^2 \quad (2.6)$$

Where. f_i is the RSS of the i[th] cell in the measured sample, $g_i(k)$ is corresponding RSS value of the k[th] database fingerprint, f_j is the RSS of the j[th] hearable cell in the measured sample which is not hearable in the k[th] database fingerprint, $g_l(k)$ is the RSS of the l[th] hearable cell in the database fingerprint which is not hearable in the required location and l_{max} replaces the missing signal strength values.

The trial results presented in [36] demonstrates that the positioning error is less than 67m in 67% of the time and less than 277m in 95% of the time in urban environment of Finland.

More recent approaches involve the application of Neural Networks (NN) for fingerprint matching [22, 24, 25, 28, 37]. In [37], a multi-layer perceptron architecture with 22 inputs, 2 hidden layers and 2 outputs has been proposed for location estimation in fingerprinting methods. The work done in [24] is based on a Feed forward neural network, which has been trained using Extended Kalman Filtering Method. In [25], the positioning using NN has been tackled in two ways; as a function approximation problem and as a multi-class classification problem.

2.2.3 Related Work

As explained in Section 1.4, the major objective of this research is to investigate the possibility of using propagations models/tools to form the fingerprint database in local context and come up with a more practicable solution for deployment of fingerprinting technique in large dynamic networks. Number of research has been carried out in this regard and this section reviews them briefly.

The work presented in [23] involves the use of propagation models (Hata-Okumura for suburban/rural scenario and Extended Walfisch-Ikegami model for urban scenario) for the formation of database. The results show that the positioning error is less than 282m (95%) in urban while that is less than 1023m (95%) in suburban/rural. A prediction model based on Outdoor and Outdoor-to-indoor coverage in urban areas at 1.8 GHz, has been used in [37] to form the fingerprint database. Further, the predicted data has been calibrated with the aid of a neural network. The NN used for calibration consists of 24 inputs and 22 outputs. The inputs correspond to the predicted RSS values for all the cells (22) within the area and the location coordinates while the outputs correspond to the corrected RSS values of 22 cells. This includes only one NN for calibration of the prediction in the whole area. Since the number of inputs and the outputs are high, the computational burden involved in training phase is large. In addition, the structure of the NN changes when new cells are added to the network, which requires training of the NN again for whole environment, calibrating all predictions and replacing of the database with newly, calibrated values. Hence the maintenance load is high with this type of a structure. A positioning trial carried out in an urban environment in Germany has shown that, the positioning error is less than 175m in 67% of the time while that is less than 220m in 95% of the time.

2.3 Radio Wave Propagation Models and Tools

A Propagation Model is a mathematical formulation for characterization of radio wave propagation within the environment, as a function of frequency, distance and other environmental parameters such as, terrain profile, clutter, etc [38]. Propagation Models are useful in predicting the path loss or the received power of the signals transmitted by a far away transmitter, at a specific location.

The mechanisms which govern radio wave propagation are complex and diverse. They can be attributed to three basic phenomena, namely, reflection, diffraction and scattering. Reflection occurs when the radio wave impinges upon obstructions whose dimensions are very large compared to the wave length of the radio wave. Diffraction explains how the radio waves can travel in urban and rural environments without a line-of-sight path. Scattering occurs when the radio path contains objects with dimensions that are on the order of the wave lengths or less of the propagation wave [39].

Propagation models can be either Empirical or Deterministic or a combination of these two. While the empirical models are based on the measurements, deterministic models deal with the fundamental principles of radio wave propagation. Empirical models implicitly take all the environmental influences into account, which is the major advantage. However the accuracy of these models depends not only on the accuracy of the measurements, but also on the similarities between the environment to be analyzed and the environment where the measurements are carried out [40]. On the other hand, deterministic models can be applied to different environments without affecting the accuracy since they are based on the principles of physics. But, the deterministic algorithms are very complex and lack computational efficiency [40].

The prediction models are classified into two major categories on the basis of the radio environment. They are Indoor propagation models and Outdoor Propagation models. Further, in respect of the size of the coverage area, the outdoor propagation models are sub divided into two additional classes, macro cell and micro cell prediction models [40].

This section briefly describes some available propagation models for cellular environment and a detailed description of them are given in Appendix A.

2.3.1 Hata-Okumura Model

This is a totally empirical model which uses four parameters, namely, the frequency (f), distance (d), base station Antenna height (h_{BS}) and the height of the mobile antenna (h_{MS}), for the estimation of the propagation loss [41].

The median Path Loss equation of Hata-Okumura model is given in Appendix A.

The model predictions are mainly applicable for macro cellular environments, which is usually the case in most sub urban and rural environments. Urban environment mainly consists of micro cells; hence this model is not valid.

2.3.2 Walfisch-Ikegami Model

The dominant Propagation Mechanism in Walfisch-Ikegami Model is the propagation over the rooftops with diffraction into street canyons [41, 42]. This model is mainly suitable for medium cells in built-up areas. The model allows improved path-loss estimation by considering the profile of the environment including;

- Heights of buildings
- Widths of roads
- building separation
- Road orientation with respect to the direct radio path

However this model is still statistical and not deterministic because a topographical database of the buildings cannot be considered.

More details on Walfisch-Ikegami Model including path loss equation are given in Appendix A.

2.3.3 Outdoor and Outdoor-to-Indoor Coverage in urban areas at 1.8 GHz

This is a run-time efficient three-dimensional propagation model for the prediction of outdoor-to-indoor coverage of small macro cells in urban areas at 1.8GHz based on high resolution building data [43].

Outdoor Prediction method

The model has been designed to predict the coverage for small macro cells in dense urban areas where the BS antenna is mounted above the rooftop level. In such case, the propagation paths are divided into two models for analysis, namely, Vertical Plane Model (VPM) and Multi-path Model (MPM). If the vegetation obstructs the propagation path of each ray, an additional vegetation loss is computed based on a vegetation model for the environment. The effect of the terrain height variation is considered by using the effective antenna height and the absolute building height when diffraction losses are calculated.

Outdoor-to-Indoor Prediction Method

An important feature of this model is the prediction of propagation at indoor areas from Outdoor BSs. The model uses two approaches to predict indoor coverage from outdoor BSs. The first approach is an empirical model, where the indoor coverage at ground floor is derived from the outdoor path loss outside the building at a height of 2m and the predictions for the higher floors are derived using a height gain model. Then a semi-empirical model is used including more deterministic components such as angle of incidence, as a further refinement.

2.3.4 CRC- Predict Propagation Model

CRC- Predict is a VHF/UHF Propagation Prediction Model, used for estimating radio signal strengths on terrestrial paths at VHF and UHF, given a transmitter location, power, and a receiver location(s) [44]. Since transmission paths are often obstructed by terrain, the model can operate on a topographic database consisting of terrain data to count the effect of the obstruction. The calculation includes diffraction losses due to terrain obstacles (e.g. Hills, trees, buildings, etc.). The diffraction calculation is done by starting at the transmitting antenna and finding the radio field at progressively greater distances. At each step, the field at a point is found by a numerical integration over the field values found in the previous step.

CRC-Predict model is the most widely used propagation prediction model in the suite of PlanetEV Network Planning Tools.

The model equation is given in Appendix A.

The special features of this model include;

- ✓ The model dynamically takes the terrain profile (through the diffraction loss) of the area into account and provides the facility of optimizing the model for specific area by tuning for the local terrain profile.
- ✓ Also includes the clutter information of the environment to calculation
- ✓ Can be optimized for a specific environment

2.4 Neural Network Techniques

A neural network is an intellectual abstraction which would enable a computer to work in a similar way to that in which the human brain works [45]. It has been developed as a tool to mimic some unique characteristics of a human brain such as the ability to learn general mechanisms from presentation of a reduced set of examples, or to retrieve correct information from missing or distorted input data.

The biological neuron has two parts, Dendrites and Synapses. Dendrites are extensions of a neuron which connect to other neurons to form a neural network whereas the synapses are the gateways which connect to dendrites that come from other neurons. Figure 2.8 depicts the structure of a biological neuron.

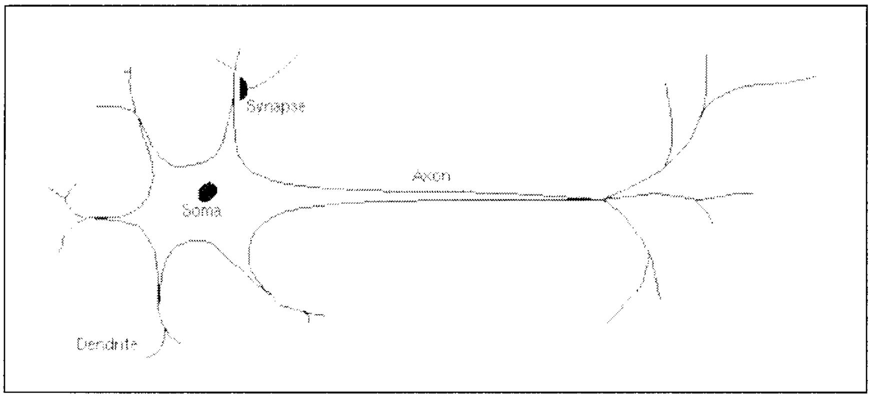


Figure 2.8: A Biological Neuron
Source: [46]

Neuron receives information from other neurons, processes it and then relays this information to other neurons. It integrates the pulses that arrive and when this integration exceeds a certain limit, neuron in turn emits a pulse. Dendrites modify the amplitude of the pulses traveling through them. This modification varies with time, as the network 'learns'. The neural network stores information in the pattern of connection weights. When a connection (dendrite) is very strong, the importance of the neuron from which this connection comes has an important role in the network.

2.4.1 The mathematical representation of a neuron

A first-order mathematical model for a neuron is shown in Figure 2.9. The neuron itself only performs accumulation and thresholding for incoming pulses. When a pulse comes from a connection, it is first multiplied by a number called the weight of the connection which assigns a certain importance to the connection, and then accumulates the overall result. The accumulated result is passed through a threshold which emits a pulse when a certain value is reached. The output of the threshold stage is in turn connected to the inputs to several other neurons.

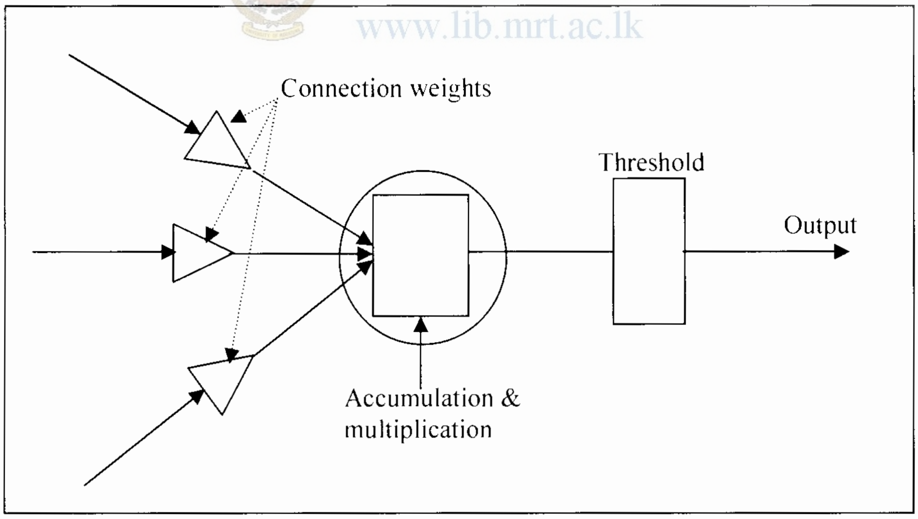


Figure 2.9: Mathematical Representation of a Neuron

The signals transmitted through biological neurons are in the form of pulses. Hence, a further simplification is adopted assuming a set of real numbers are fed in and a single real number is generated at the output. Instead of a biological threshold function, a mathematical function such as the sigmoid function, arctangent, arcsine, etc is used. It is normally called *node transfer function.*

Node Transfer Functions should be smooth and continuous (i.e. should not be piecewise linear or step function) with an absolute upper and lower limits. It should be differentiable too. It is desirable that the derivative can be re-written in terms of the function itself, which simplifies the mathematics and improves the efficiency.

2.4.2 Neural Network Topology

The principal importance of a neural network is not only the way a neuron is implemented but also how their interconnections (topology) are made. The topology of a human brain is too complicated to be used as a model because a brain is made of hundreds of billions of connections which can't be effectively described using such a low-level and highly simplified model.

Thus a simple topology for easy implementation on a digital computer is defined with three layers, namely, input layer, hidden layer and output layer. All neurons from one layer are connected to all neurons in the next layer.

This can be represented in mathematical notation as given in Figure 2.10.

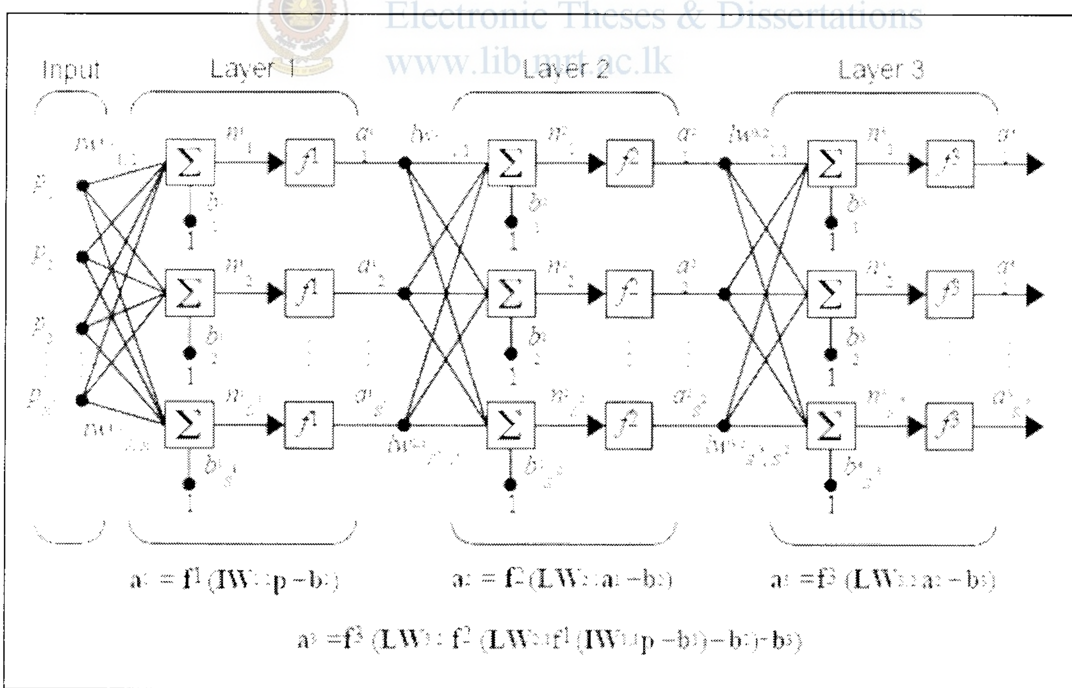


Figure 2.10: Mathematical Notation for Neural Networks

Source: [47]

2.4.3 Training a neural network

A neural network is unable to solve any particular problem until it is trained. Like a little baby, whose brain is fully developed and ready for work but who is not able to do anything because it has not experienced any stimulus. So a neural network without learning is analogous to a human without education.

In training stage, the network is fed with a set of numbers and the result is obtained from the output layer. The weights of the connections are initially in a random state; hence, the result at the beginning is not the exact one expected. Therefore, the weights of the connections are changed until the desired result is obtained (Trained). Next, another input is fed and the weights are adjusted continuously, until the desired output is obtained for each and every input. The entire set of training examples must be shown to the network many times in order to get a satisfactory result.

After all of this training, the network is able to solve the particular problem and it is said that the network has learned, and its 'knowledge' is stored by all the different connection weights.

It is necessary that the sufficient training examples are available to train the neural network weights and biases. A generally accepted guideline is to have the number of training examples more than or equal to five times the number of parameters to be adjusted during training [48].

$$S \geq 5.N \tag{2.7}$$

Where, N - Total number of parameters to be adjusted

S - Number of training samples.

If the number of training samples is less, the network will learn the training set rather than building a statistical model for the problem being discussed. In this case NN will lose the ability to generalize and this is known as over fitting. Two methods have been described in [47] to reduce over fitting when a lesser number of training data is available. These are called, Regularization and Early Stopping.

Selection of an algorithm for training is also a key factor in neural network design. A number of training algorithms are available; however, none of them have proven superior for all the problems. Some training algorithms used during this work have been described in Appendix B.

2.4.4 Neural Networks for Calibration

Neural Networks are universal approximators, which can be used to fit any continuous function defined on bounded inputs to a pre-defined arbitrary degree of accuracy. It has the flexibility & the ability of dealing with uncertain data. Due to these facts, neural networks are applicable in calibration, which tries to model a relationship between corrupted data and real data.

The application of neural networks for multivariate calibration with chemical data has been widely discussed in [49]. Multi-layer Perceptrons with Back Propagation training algorithm has been adopted in that work. In addition, neural networks have been used to correct the RSS predictions obtained from propagation models, in [37]. A Multi-layer feed forward neural network with 24 inputs and 22 outputs has been applied for calibration in that work. The calibrated prediction data are applied for fingerprinting and the results show a significant improvement in positioning accuracy after calibration.

Chapter 3

Methodology

The methodology applied towards achieving the goals of the research is described comprehensively in this section.

The Figure 3.1 shows a summary of the methodology in block diagram form.

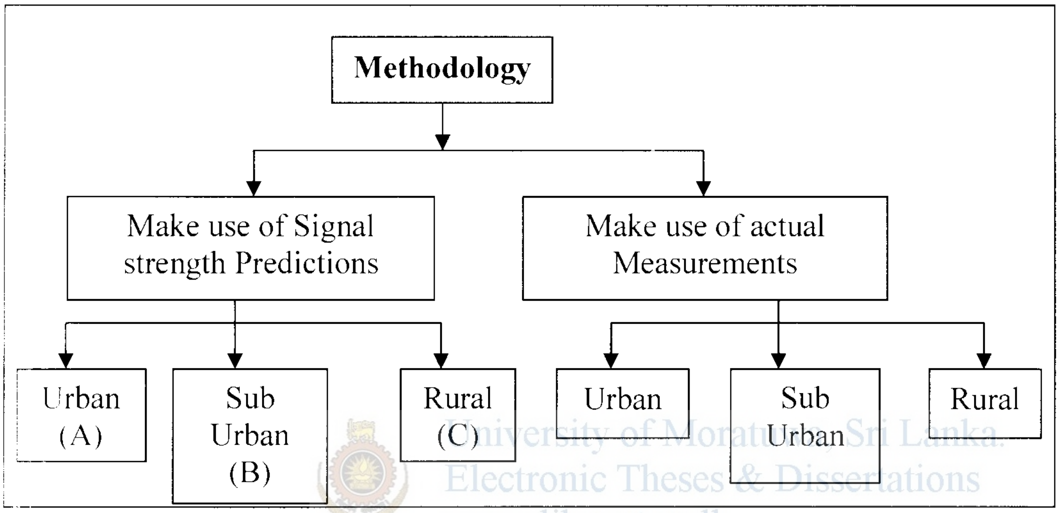


Figure 3.1: Summary of Methodology

The major goal is to investigate the possibility of using predictions obtained from propagation models to create the database and come up with a best solution for location estimation with improved accuracy. This is accompanied by the comparison of the performance of DCM algorithms using a predicted database and a measured database and make use of a lesser number of field measurements to tune the predictions in order to reduce the deviation between the measurements and the predictions. Hence, the research deals with both actual and predicted strengths. As illustrated in Figure 3.1, the performance of fingerprinting method will be investigated for three different environments, namely, urban, suburban and rural, using predicted fingerprints as well as measured fingerprints.

The methodology involved in applying the techniques for a particular environment is illustrated in Figure 3.2.

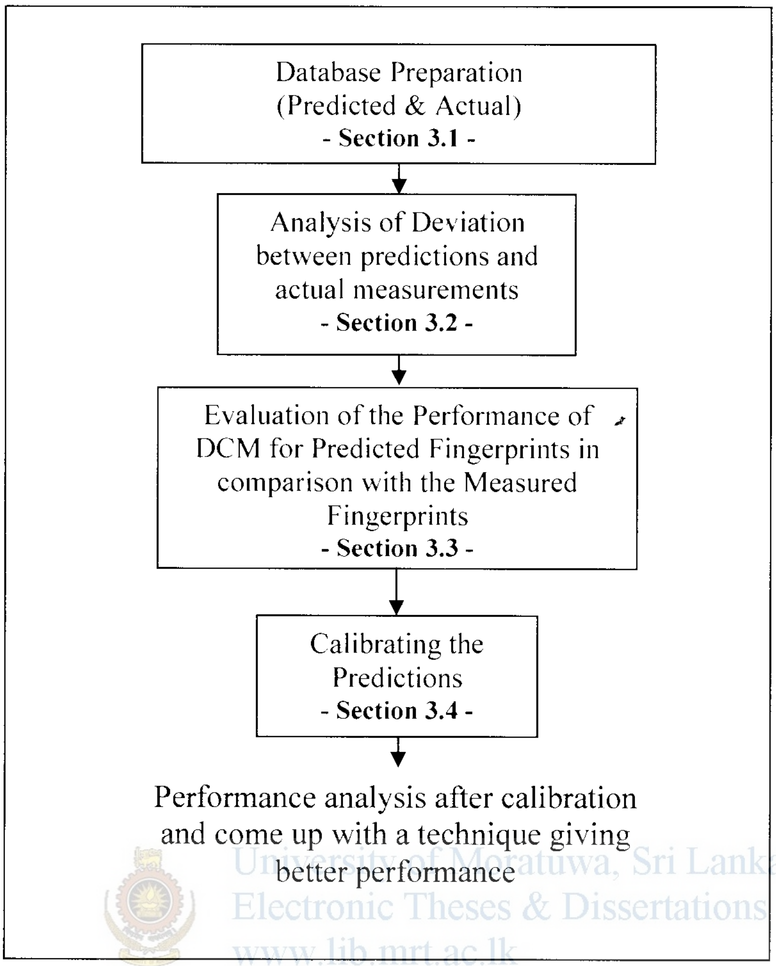


Figure 3.2: Methodology for a selected environment

Each step of the methodology in Figure 3.2 will be described comprehensively in the next sections.

3.1 Database Preparation

The database is the key element in any positioning technique based on fingerprinting. This reference database consists of location sensitive parameters observed by the mobile station at different locations together with the location coordinates, called fingerprints. RSS being selected as the location sensitive parameter, a fingerprint consists of the RSS values from all hearable cells at a location together with the cell ID and the GPS coordinates of that location.

This research involves two databases, namely Predicted Database and Measured Database. Fingerprints of predicted database are created using the signal strength predictions and that of the measured database are created using the field test trials.

3.1.1 Predicted Database

During the planning process of wireless networks, propagation predictions are computed for each base station within the whole range considering the type of the environment, clutter information and topography in order to analyze the coverage and interference scenario. This research makes use of such a model, called CRC-Predict propagation model, described in Section 2.3.4, to obtain predictions.

In addition to the specific features of CRC-Predict propagation model, the fact that it is used in the Network Planning Tool available at a local service provider would enable obtaining predictions tuned to the local environment.

A. Interfacing to the Planning Tool

Even though, the planning tool available at the local mobile network readily provides the predictions for a given location, the challenge was to read those predictions to positioning application. The interfacing methodology applied for this task is illustrated in Figure 3.3.

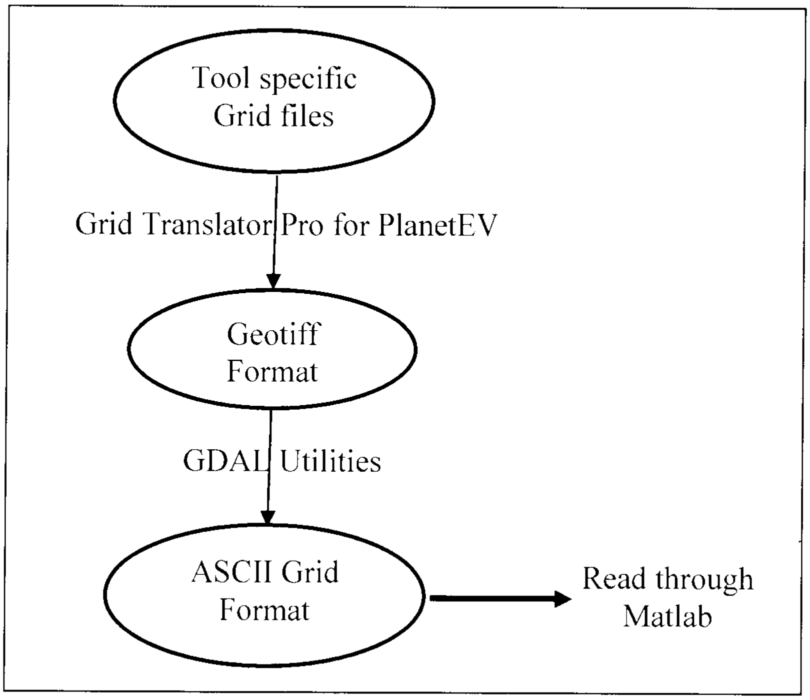


Figure 3.3: Methodology for interfacing to planning tool

The steps of interfacing to planning tool can be describes as below.

- Planning tool stores it's predictions in a grid file format which is specific to it. This grid file format is not compatible with the commonly used ASCII grid format. Therefore the Planning Tool specific grid files should be converted to ASCII grid file format.
- A Tool called "**Grid Translator Pro for PlanetEV**" (From Geomatics Systems), which is an add-on running on MapInfo Professionals, is used to convert planning tool grid files to Geotiff Format [50].
- Those Geotiff files are converted to ASCII grid files through GDAL (Geospatial Data Abstraction Library) Utilities [51].
- ASCII grid files are readable through Matlab

Figure 3.4 shows a snapshot of Grid Translator Pro for PlanetEV tool used to perform the conversion from planning tool specific grid files to Geotiff files.

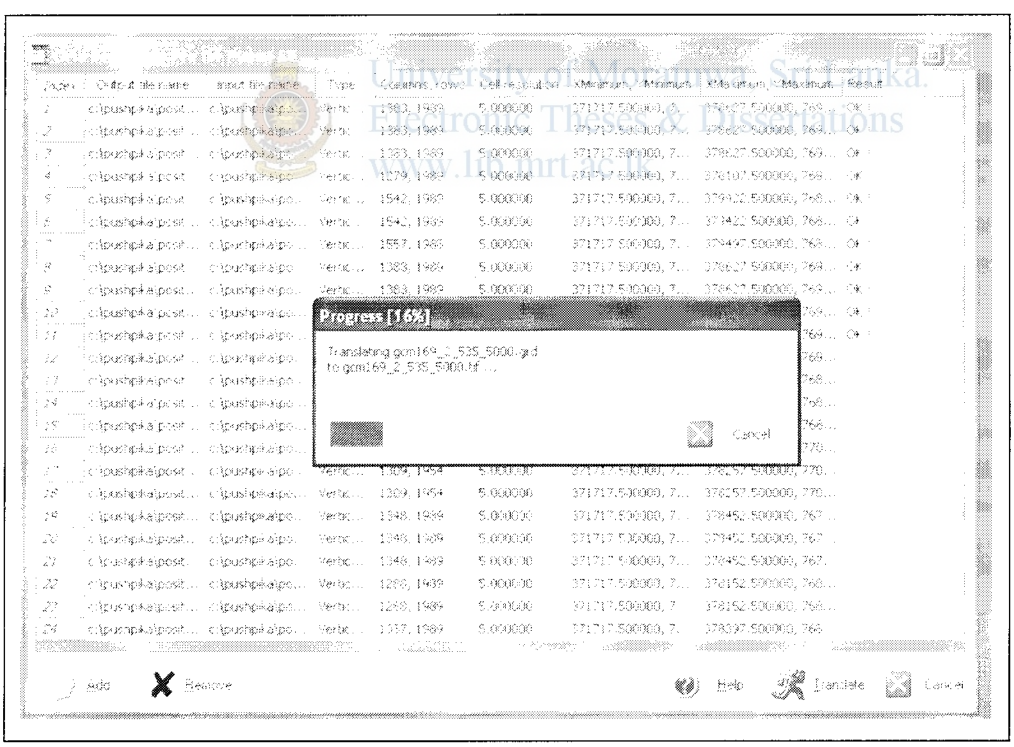


Figure 3.4: Grid Translator Pro for PlanetEV

B. Fingerprint Creation

The planning tool predicts the signal strength for the coverage area of the cell with a resolution of 5m in urban environment and that of 25m in suburban and rural environments. If the same resolution is used in this work, the database becomes unnecessarily large. Therefore the predictions along roads are used and this results in a predicted database with fingerprints along roads of the considered area.

The predicted strengths from different cells correspond to a particular location are collectively stored together with the location coordinate, as a fingerprint. The cell with the largest predicted strength in that collection is selected to be the serving cell. The information on serving cell is useful in location estimation process described in Section 3.3.1.The format for such a fingerprint database is shown in Figure 3.5.

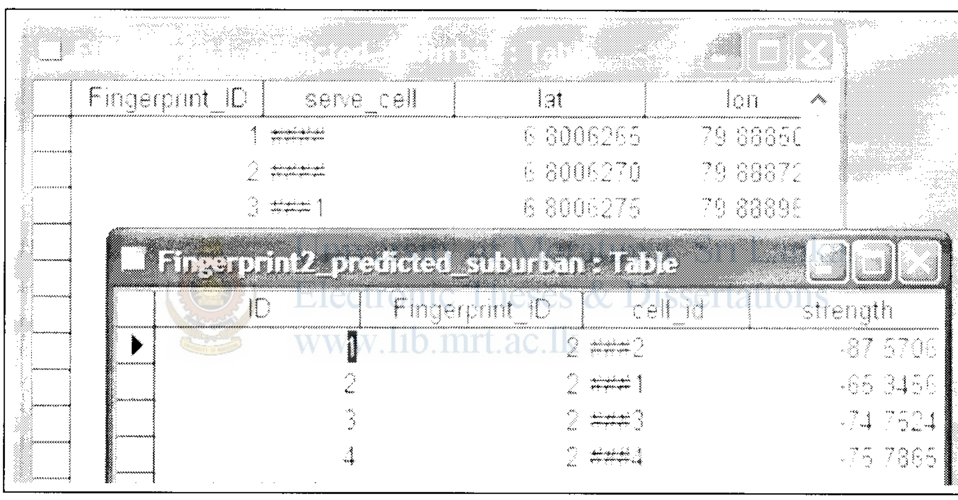


Figure 3.5: Format of the Fingerprint Database
Cell IDs have been changed for the purpose of reporting

3.1.2 Measured Database

The measured database consists of the fingerprints collected along the roads within the area.

A. Data Collection

Drive tests are performed along the roads with a speed less than 20 km/h and the measurements are taken by a mobile measurement unit interfaced to a laptop PC. Simultaneously, the coordinates of the measurement locations are taken using a GPS receiver interfaced to the same laptop PC. The GSM module inside the mobile measurement unit is capable of measuring signal strengths from six surrounding base stations including serving cell and five neighboring cells. Then a single measurement consists of received signal strength from up to six hearable cells and the location coordinates. The average time taken for one measurement is 15 seconds.

In addition, the measurements are performed in idle mode rather than in the active mode of the GSM module. This is to justify the error performance for the normal conditions as all the mobile stations are in idle state unless they are taking calls, receiving calls or performing other activities such as browsing the internet, video conferencing, which need the interaction with the network.

B. Fingerprint Creation

A possible method of creating fingerprints through drive tests is illustrated in [12]. Nevertheless, the author has taken a different and more practical approach suits for the local context.

In that, ten consecutive measurements along roads are taken to form a single fingerprint. Then, the fingerprint consists of the average Received Signal Strength of each cell appears in those ten measurements together with the median location coordinates corresponds to the ten locations. The cell having the largest average received signal strength is taken as the serving cell of the fingerprint. In addition a sliding window approach has been applied, as illustrated in Figure 3.6, in order to increase the fingerprint resolution. The last five measurements of the first fingerprint contribute to the first five measurements of the second fingerprint by increasing the fingerprint resolution by a factor of 2.

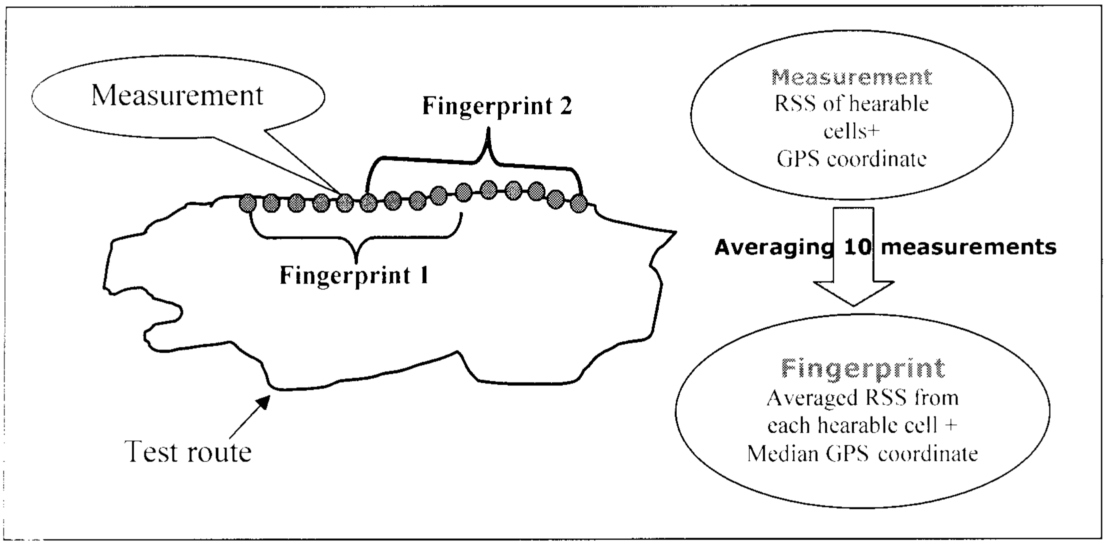


Figure 3.6: Methodology of fingerprint creation for measured database – Sliding Window

3.2 Deviation Analysis

Even though the planning tool predictions are tuned to the local environment, they still may differ from the actual measurements obtained in the same environment. Hence, one of the major activities of this research is to comprehensively analyze the deviation between predicted and actual measurements. This section describes the methodology used for that task.

The deviation analysis can be divided in to two methods.

I. Cell-wise analysis

II. Fingerprint-wise analysis

3.2.1 Cell-wise Analysis

The deviation is analyzed separately for each cell. This uses the measurements obtained at different locations within the coverage area of the cell and the predictions of the same locations.

This is done according to the Equation (3.1), which computes the Root Mean Square Error for a cell.

$$RMSE_k = \sqrt{\frac{1}{N_k}\sum_{i=1}^{N_k}(RSS_{k.i} - RSS'_{k.i})^2} \qquad (3.1)$$

Where $RMSE_k$ - Mean Square Error of kth cell

$RSS_{k.i}$ – Measured Received Signal Strength of kth cell at ith location

$RSS'_{k.i}$ – Predicted Received Signal Strength of kth cell at ith position

N_k - Total Number of test points for the kth cell

The RMSE per cell is calculated in two ways, which differ in the manner the values are substituted. In first, the RSS values are substituted in dBm for Equation 3.1 and the RMSE value is computed in dB. The next method involves substituting the RSS values in mW, and computing RMSE in mW which is then converted to dBm by taking log.

3.2.2 Fingerprint-wise analysis

Fingerprint-wise analysis includes calculating the root mean square error between the predicted and measured fingerprints at different locations, using the Equation (3.2) and (3.3).

$$RMSE_i = \sqrt{[RSS_{mean.i} - RSS'_{mean.i}]^2} \tag{3.2}$$

$$RSS_{mean.i} = \frac{1}{N}\sum_{k=1}^{N} RSS_{i,k} \tag{3.3}$$

Where $RMSE_i$ - Root Mean Square Error for ith fingerprint

$RSS_{mean.i}$ - Mean value of the measured signal strength of all cells at ith fingerprint

$RSS'_{mean.i}$ - Mean value of the predicted signal strength of all the cells at ith fingerprint, calculates similar to 3.3

N - Total number of cells per fingerprint

3.3 Positioning Algorithm

The basic steps of location estimation in fingerprinting methods are described in Section 2.2.2. The methodology applied for location estimation in this research is presented in this section.

The positioning algorithm consists of two phases, namely fingerprint filtering and location estimation.

3.3.1 Fingerprint Filtering

In order to reduce the burden encountered in correlation process, the number of database fingerprints to be correlated is limited using some filtering criteria. The idea of filtering is to sort out the potential solutions for the location estimation problem. In particular, the use of serving cell information is much applicable since the serving cell defines a probable area to locate the mobile station. In addition, Timing Advance parameter available in GSM networks [32] is another option, but the fact that the correct timing advance value can be measured only in active mode, prevents it being applied in this research (as the measurements are taken in idle mode).

A. Novel Filtering Approach

It was observed that, the measured database with high resolution contains a considerable number of fingerprints having same serving cell. This leads to the selection of a far away fingerprint as the estimated location by removing the closer ones in the matching process. This scenario is illustrated in Figure 3.7.

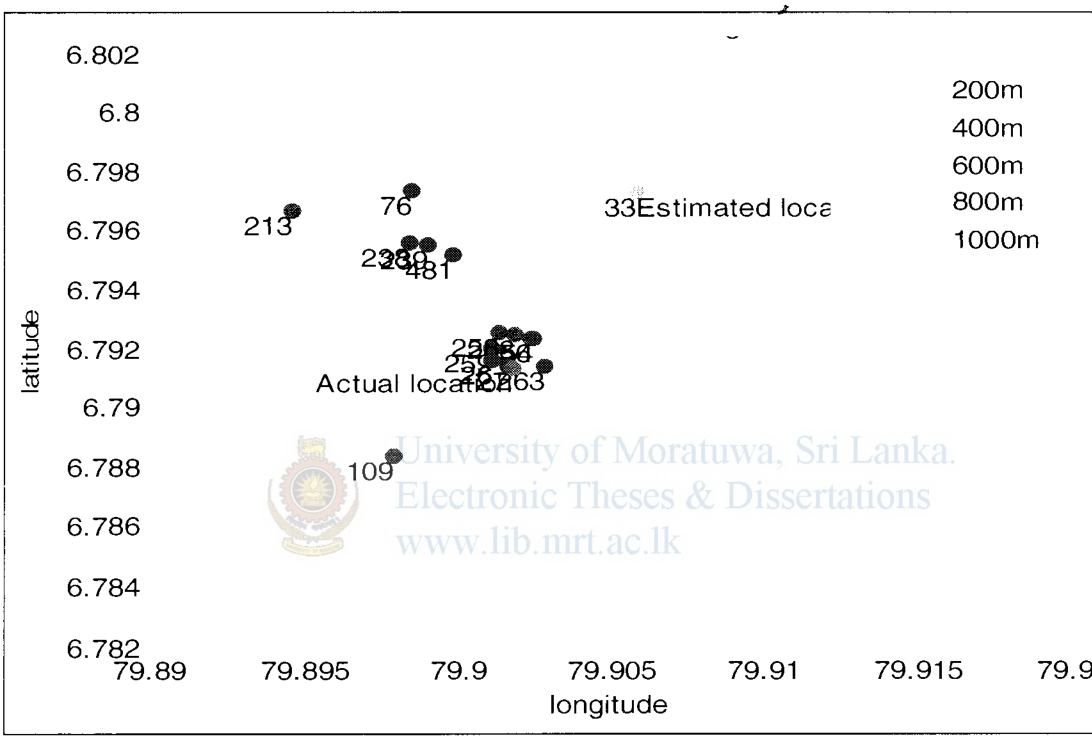


Figure 3.7: Far away estimation when filtering only by serving cell
Original is in colour

According to Figure 3.7, there are several fingerprints having same serving cell as the location measurement. Among them, the DCM with minimum cost estimation has selected a far away fingerprint as estimated location, when closer fingerprints exist. Therefore if those fingerprints are further filtered in order to select only the closest ones, then the estimation would be much accurate.

Hence, an extension to filtering approach is proposed in this research, in which the fingerprints are first filtered based on the serving cell and a score is calculated for each filtered fingerprint using Equation 3.4 .After that, the first K-number of fingerprints having the highest score values are selected as the neighbors of the location to be estimated.

$$Score\ (i) = \frac{(Number\ of\ matching\ cells\ in\ measurement\ \&\ the\ Fingerprint)}{Max(Number\ of\ cells\ in\ Measurement, Number\ of\ cells\ in\ Fingerprint)} \quad (3.4)$$

Where $score(i)$ – Score of the i^{th} Fingerprint

In Equation (3.4), the number of cells contributing to both fingerprint and the measurement is referred as matching cells.

The novel method is based on the assumption that if the number of matching cells are higher, the closer the fingerprint to the location to be estimated. This can be proved taking the same example illustrated in Figure 3.7.

In Figure 3.7, there exist a considerable number of fingerprints which are within 200m from the actual location. The Table 3.1 shows the score values and the cost values calculated for some fingerprints.

Table 3.1: Score values and cost values of fingerprints

FP_ID	# of matching cells	Score	Cost
26	5	0.833333	335.3153
27	5	0.833333	335.3667
259	5	0.625	330.3193
258	5	0.555556	330.5279
263	3	0.375	332.9468
213	4	0.363636	333.3909
254	3	0.333333	328.0078
33	2	0.285714	322.2937

Without the novel filtering method, the algorithm selects the Fingerprint 33 as the estimated location as it has the lowest cost among all. When the number of matching cells is considered, Fingerprints 26, 27, 259 and 258 proved to be closer than Fingerprint 33. Among them, Fingerprint 26 & 27 has the highest score and the novel filtering method selects those two as the potential solutions. Amongst, the fingerprint

26 has the lowest cost and the location of that is selected to be the estimated location with novel approach. This result is shown in Figure 3.8.

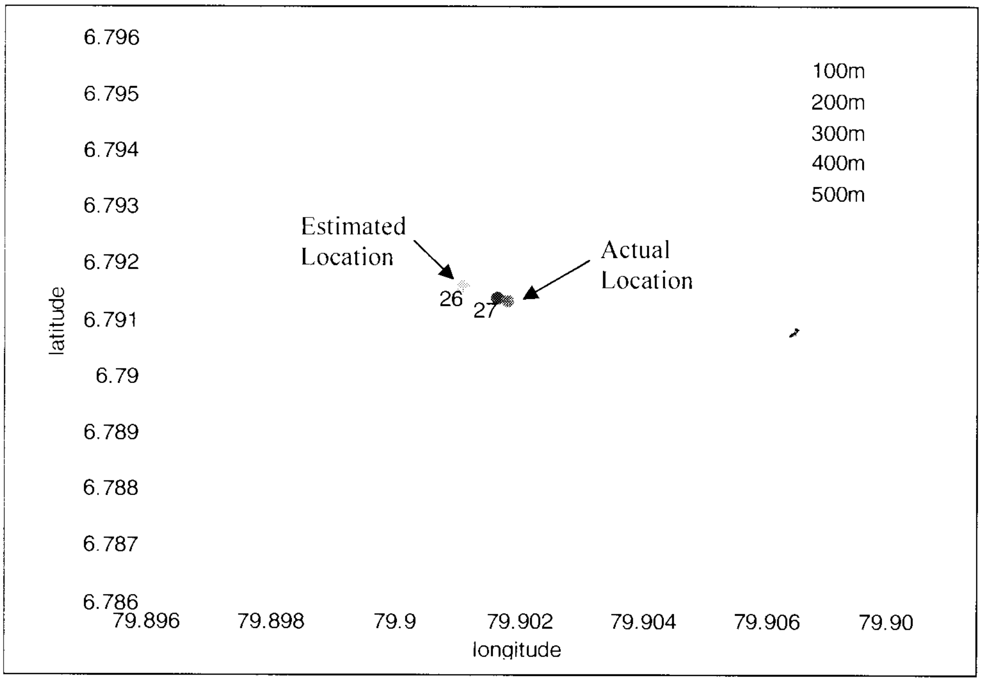


Figure 3.8: Results using novel filtering approach

Original is in colour

Hence, the novel filtering method has the ability of filtering outliers. This filtering method is tested with different K values for better performance.

3.3.2 Location Estimation

Location estimation phase includes finding the best solution out of potential solutions filtered in filtering process. This involves a correlation algorithm for fingerprint matching. As described in Section 2.2.2, several matching techniques are available in literature. This section describes the author's approaches in fingerprint matching.

The correlation function used for this purpose is known as Cost Function, and the correlation co-efficient is known as the cost. Altogether five Cost Functions have been used to come up with a best solution for each environment. Almost all the Cost Functions are based on the signal distance between the database fingerprint and the measurement taken at the location to be estimated.

Finally, the location of the database fingerprint giving a smallest distance from the measurement is taken as the estimated location.

A. Cost Function-0

This is the simplest form of the Cost Functions, which considers only the cells present in both fingerprint and the measurement. The function is defined in Equation 3.5.

$$d(k) = \sum_i (f_i - g_i(k))^2 \tag{3.5}$$

Where $d(k)$ - Cost for k^{th} fingerprint

f_i - RSS of i^{th} hearable cell in the location to be estimated

$g_i(k)$ - RSS of the same i^{th} cell in k^{th} database fingerprint

The summation is taken over the cells which are found in fingerprint and measurement both.

B. Cost Function -1

There exist situations where, some cells are hearable at the location to be estimated, but are not appearing in the fingerprint and the cells which are significant in the fingerprint are insignificant at the location to be estimated. In such cases the signal strengths of those cells can be added as a penalty for the cost calculated in Equation 3.5 giving a new Cost Function defined in Equation 3.6.

$$d(k) = \sum_i (f_i - g_i(k))^2 + \sum_j f_j + \sum_l g_l(k) \tag{3.6}$$

Where

f_j - RSS of the j^{th} hearable cell at location to be estimated which is not appearing in the k^{th} database fingerprint

$g_l(k)$ - RSS of the l^{th} hearable cell in the database fingerprint which is not hearable at the location to be estimated

The second and third parts of the Equation are known as *penalty terms*.

C. Cost Function -2

Cost Function-2 is a derivative of Cost Function-1 with a modified penalty term. In Cost Function -1, the RSS of a penalty cell is directly substituted as penalty. However, it is reasonable to think that a particular cell is not appearing in the fingerprint or the measurement because the signal strength from that cell is extremely low at those locations. Hence, those missing signal strengths in fingerprint or the measurement can be replaced by the threshold level of the receiver as shown in Equation 3.7. This form of the Cost Functions can be found in the literature as well [36].

$$d(k)=\sum_{i}(f_i-g_i(k))^2+\sum_{j}(f_j-l_m)^2+\sum_{l}(l_m-g_l(k))^2 \qquad (3.7)$$

Where l_m - Receiver Threshold (usually -100dBm)

D. Cost Function-3

Cost Function-3 is a modified version of Cost Function-0 by introducing the averaging of the cost over the number of matching cells in both fingerprint and the measurement and defined in Equation (3.8).

$$d(k)=\frac{\sum_{i=1}^{N1}(f_i-g_i(k))^2}{N1} \qquad (3.8)$$

Where: N1 – Number of cells present in both measurement and Fingerprint

The significance of this Cost Function is described below.

In signal strength matching scenario, it is reasonable to think that, if the number of matching cells for one fingerprint and the measurement is greater than that for another fingerprint and the measurement, then the former fingerprint is closer to the location to be estimated than the latter. Still, there is a possibility of selecting latter fingerprint as the estimated location when using Cost Function-0. This is shown in Figure 3.9.

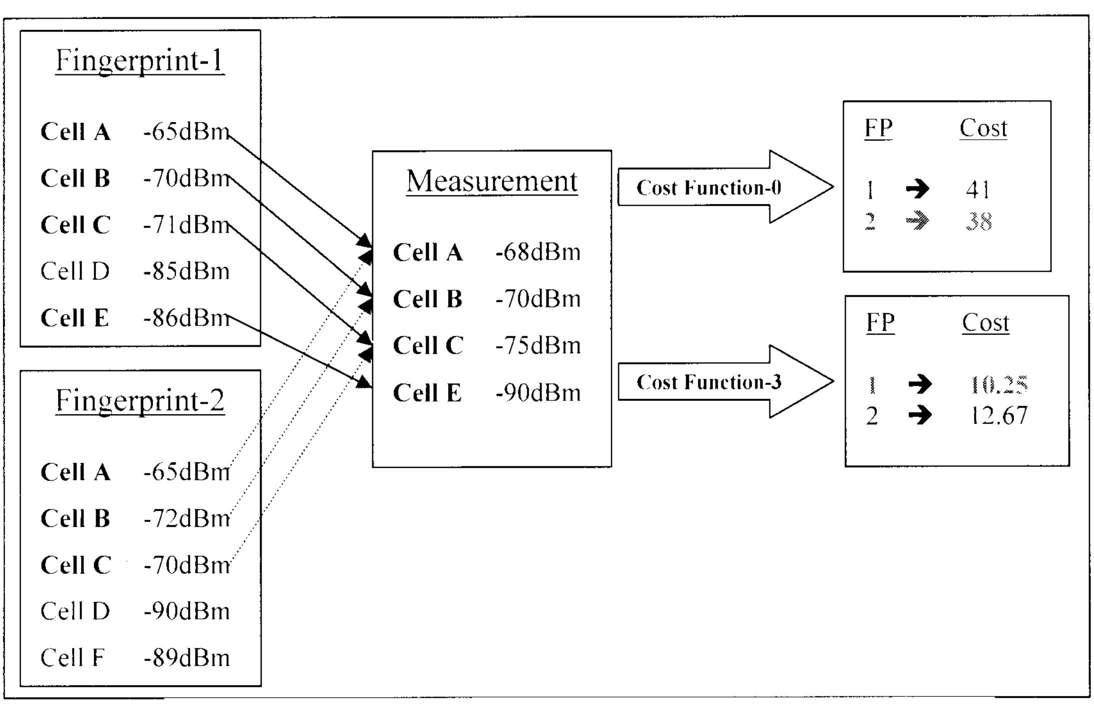


Figure 3.9: Significance of Cost Function-3

According to Figure 3.9, the number of matching cells in fingerprint 1 & the measurement is 4 and that in fingerprint 2 and measurement is 3. Hence it is reasonable to think that the fingerprint 1 is closer to the measurement location than fingerprint-2. However, the Cost Function -0 gives a lowest cost for fingerprint 2, selecting it to be the estimated location. When the newly defined Cost Function -3 is applied, it selects the fingerprint -2 as the best matching one, which is true according to above argument.

E. Cost Function-4

The author proposes another Cost Function which is a derivative of Cost Function-2. A similar argument as applied in relation to Cost Function-3 can be used to describe the validity of Cost Function-4 as well. The resulting Cost Function is given in Equation (3.9).

$$d(k) = \frac{\sum_{l=1}^{N1} (f_l - g_l(k))^2}{N1} + \frac{\sum_{l=1}^{N2} (f_l - l_m)^2}{N2} + \frac{\sum_{l=1}^{N3} (l_m - g_l(k))^2}{N3} \tag{3.9}$$

Where N1 – Number of cells present in both measurement and the fingerprint

N2 – Number of cells present in measurement but not in fingerprint

N3 – Number of cells present in Fingerprint but not in measurement

In the location estimation process all these five Cost Functions have been applied together with two filtering methods described in Section 3.3.1. Figure 3.10 illustrates all the approaches taken in location estimation process to come up with a best solution using a measured database.

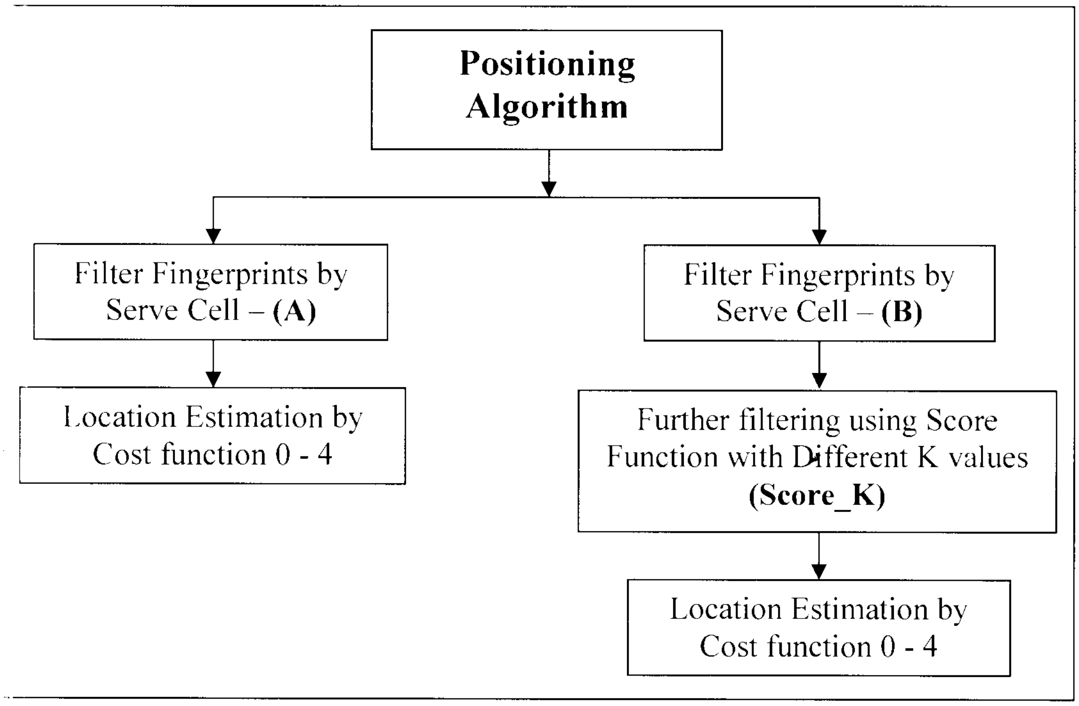


Figure 3.10: Different approaches of Positioning Algorithm

3.4 Calibration Process

According to the results shown in Section 5.1, it is evident that there exist a considerable deviation between the predicted signal strength and actual signal strength. Further, the results in Section 5.2 show that the performance of Database Correlation Method using a predicted database is inferior to that using a Measured Database in all three environments, urban, suburban & rural. Hence the author's objective is to develop a technique that can be used to minimize the deviation between measured and predicted signal strengths such that the performance of DCM is improved.

The approach of correcting predicted signal strengths using a lesser number of measured data is applied and this is referred to as *Calibration* throughout this thesis. The approaches taken in designing a calibration technique are comprehensively discussed in this section.

Two approaches have been taken, namely, Neural Network based Approach and Curve Fitting based approach. These two approaches will be discussed in Section 3.4.1 & 3.4.2 respectively.

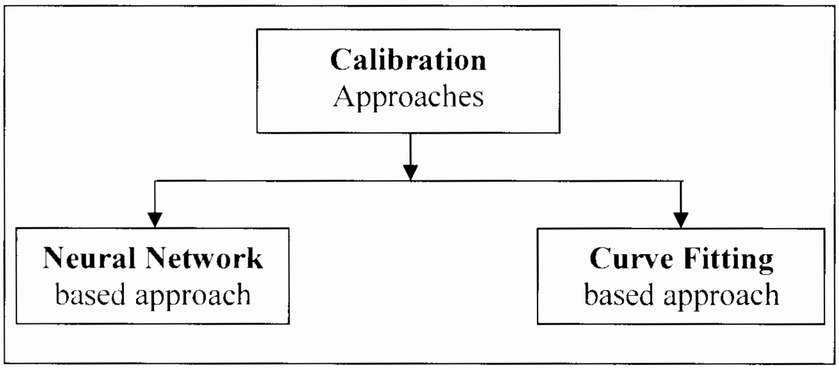


Figure 3.11: Approaches for calibration

Furthermore, the author has identified two variants of calibration process called, Cell-wise Calibration and Fingerprint-wise Calibration. Cell-wise Calibration is defined as correcting the predicted signal strengths of different cells separately. Here, a calibration technique based on neural networks or curve fitting is designed for each cell separately. In contrast to that, Fingerprint-wise Calibration involves designing a global calibration technique for a particular environment such that all the predicted fingerprints could be corrected together. The author has identified characteristics of both variants as listed in Table 3.2 and selected the one suitable in achieving goals.

A work similar to Fingerprint-wise calibration has been done [37] to calibrate predicted fingerprints using neural networks, in which all the fingerprints for the selected area are calibrated using a single neural network with 24 inputs and 22 outputs. 24 inputs consist of 22 predicted RSS from 22 distinct cells within the selected area and 2 location coordinates while 22 outputs correspond to the predicted RSS of each cell in the input. This kind of a topology has several drawbacks in practical implementation. Since the number of inputs and outputs are higher it requires more processing power in training the neural network for better approximation. In addition, if this is to be implemented in large, dynamic networks where the new cells are added frequently, the whole neural network should be re-trained for the entire area with the addition of new input and output, i.e. the topology of the neural network should be changed with the changes in network. In addition more work is needed in finding an optimum calibration technique.

Table 3.2: Characteristics of Cell-wise calibration and Fingerprint-wise calibration

Cell-wise Calibration	Fingerprint-wise Calibration
• Predictions of each cell are calibrated separately • If neural network techniques are used, the network topology is simple • Possibility of applying curve fitting techniques is there • The maintenance burden involved in adding new cells to the network is low • Possible to achieve higher accuracies as the predictions of each cell are optimized separately	• Predictions of all the cells are calibrated using a single technique • The network topology is complex in using neural networks • The possibility of applying curve fitting techniques is less • The work load involved in adding new cells to the network is high • Since the predictions of all cells are optimized together more sophisticated optimization techniques are needed for better optimization

Despite the fact that cell-wise calibration involves calibrating the predictions of each cell separately, it requires a lower maintenance work in adding new cells to the network after deployment. In addition, it has the potential for higher accuracies as the predictions are optimized per cell. Furthermore, it provides a simple but optimum solution for calibration than Fingerprint-wise approach. Due to these reasons, Cell-wise calibration is selected for calibration process of this research.

The following sections describe the application of neural networks and curve fitting for cell-wise calibration.

3.4.1 Neural Network based Approach

Neural Networks being universal approximators, makes them applicable for the calibration problem in this research as it also attempts to approximate a relationship between the predictions and actual signal strengths within the coverage range of a cell. The flexibility & the ability of dealing with uncertain data make the neural networks more robust in function approximation. The applicability of neural networks in calibration problem is proved in the literature [37, 49] as well.

A. Network Topology Design

Designing the topology of the neural networks involves deciding on number of inputs, number of outputs, number of hidden layers, and number of neurons to be used in each layer and transfer functions for each layer.

The number of inputs and the outputs should be selected appropriately for the problem. It is needed to identify the varying parameters related to the problem. Goal of the cell-wise calibration is to minimize the deviation between predicted strength and actual strength. The signal strength differs from location to location and varies with the distance from transmitter. Therefore the parameters applicable for this scenario are predicted signal strength, location of the prediction, location of the transmitter and distance from the transmitter. The output is obviously the corrected signal strength. Apart from this, it is possible to vary the format of the input and the output.

The number of hidden layers in neural network is related to the complexity of the network. More hidden layers provide better approximation to complex functions. It is said that a neural network with one hidden layer and appropriate number of hidden neurons is enough for most function approximations. Therefore, most of the topologies designed by the author consist of one hidden layer. In addition the number of neurons per layer is also an important parameter in neural network design. Increasing the number of neurons increases the number of weights to be trained. It is a fact that the number of training example should be five times greater than the number of weights and biases to be trained [48]. Hence, it should be careful when increasing the number of neurons as it may violate the previous rule.

In that view, the author has come up with five different neural network topologies to be used in this work. Those are categorized as Multi-Layer Feed Forward Neural Networks and are describe below.

1. Simple Neural Network-1 (simple_NN1)

This is a simple feed forward back propagation neural network with one hidden layer. The parameters for this are given below.

- One Input source
    - [Predicted Strength; Loc_lat; Loc_lon; Cell_lat; Cell_lon]
- One hidden layer (10 neurons with arctangent transfer function)
- One output (calibrated strength with linear transfer function)
- Performance function - Regularized Mean Square error

The input vector to this neural network consists of five inputs, including the predicted strength, latitude and longitude of the measurement location, and latitude and longitude of the location of the cell. The output of the neural network is the calibrated strength at the given location. The performance function is selected to be the regularized mean square error as it helps to improve the generalization [47]. The total number of weights to be adjusted is 60 in this neural network.

2. *Cell Neural Network-1 (cell_NN1)*

- One Input source
    - [Predicted Strength; Loc_lat; Loc_lon]
- One hidden layer (8 neurons with sigmoid transfer function)
- One output (calibrated strength with linear transfer function)
- Performance function - Regularized Mean Square error

This neural network reduces the number of inputs to 3 by eliminating the location of the transmitter. One hidden layer with 8 neurons is used to get the calibrated strength as the output. It consists of 32 weights.

3. *Custom Neural Network-1 (custom_NN1)*

The third topology is a custom topology, which deviates from the standard neural network structure [47]. It is a complex structure with following parameters.

- Three Input sources
    - Predicted Strength
    - [Latitude of Location ; Latitude of cell location]
    - [Longitude of Location ; Longitude of cell location]

- Five layers (3, 6, 6, 2, 3 neurons with arctangent, sigmoid, sigmoid, sigmoid transfer functions and random bias values)
- One output (calibrated strength with linear transfer function)
- Performance function - Regularized Mean Square error

The structure of the Custom neural network-1 is shown in Figure 3.12. The total number of weights and biases to be adjusted is 60.

4. *Custom Neural Nerwork-2 (custom_NN2)*

This is a derivative of custom neural network-1 with reduced number of inputs and layers.

- One Input source
  - [Predicted Strength; Loc_lat; Loc_lon; Cell_lat; Cell_lon]
- Two layers (5, 10 neurons with arctangent, arctangent transfer functions and -1 bias values)
- One output (calibrated strength with linear transfer function)
- Performance function - Regularized Mean Square error

This consists of 80 weights and biases and the structure of the neural network is shown in Figure 3.13.

5. *Loss Neural Network-1 (LossNN1)*

As mentioned earlier, the format of the input and the output of the neural network can be varied. As such, the LossNN1 has been designed to output the error in signal strength loss in predictions and actual measurements. This is defined in Equation 3.10-3.12.

$$Loss1 = Transmitted\ Power - Predicted\ Strength\ (dB) \tag{3.10}$$

$$Loss2 = Transmitted\ Power - Actual\ Strength\ (dB \tag{3.11}$$

$$Error = Loss1 - Loss2 = Actual\ strength - Predicted\ strength\ (dB) \tag{3.12}$$

Then the calibrated strength can be derived from Equation 3.13.

$$Calibrated\ Strength = Predicted\ Strength + Error \tag{3.13}$$

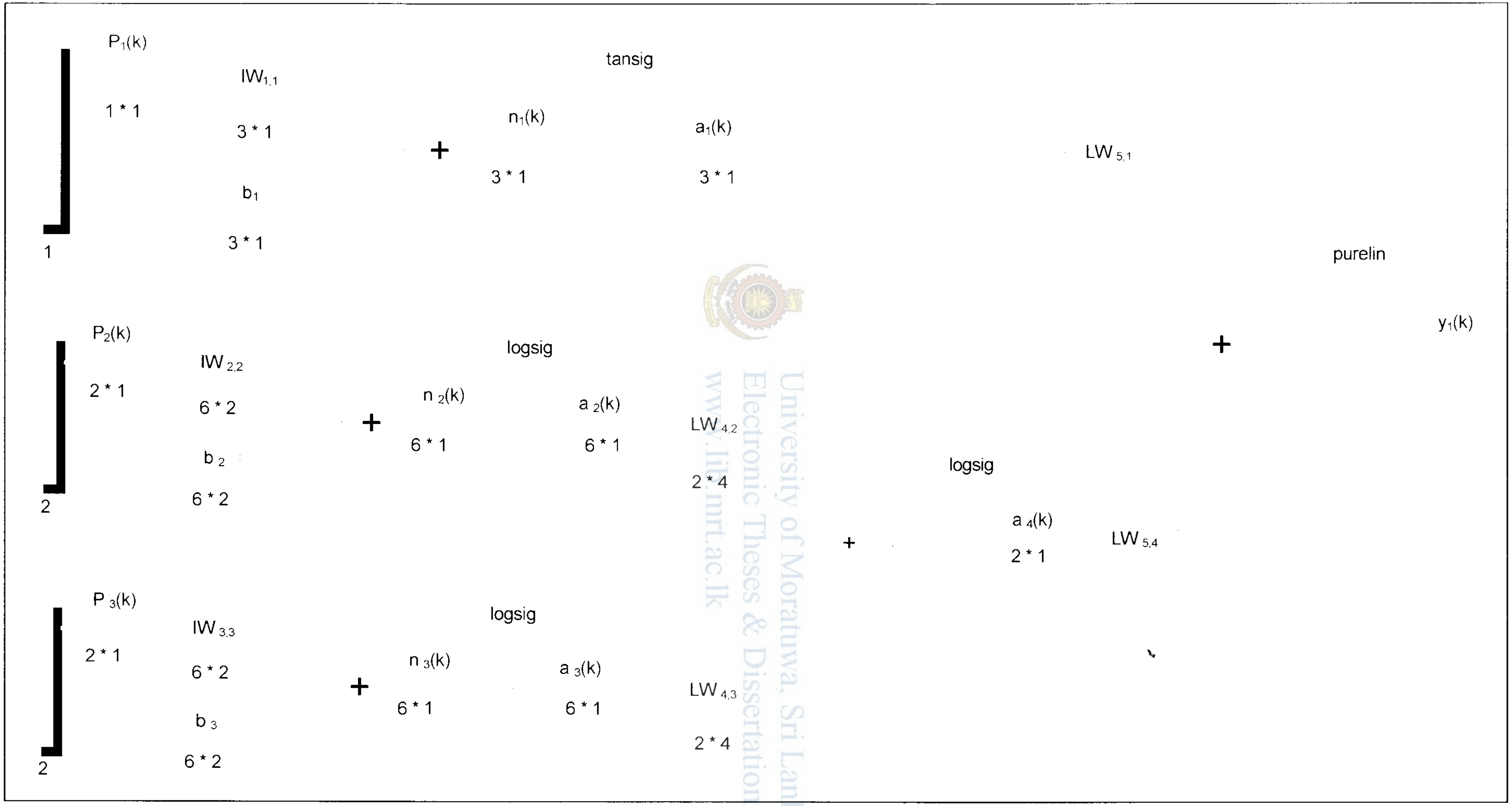


Figure 3.12: Topology of Custom Neural Network-1

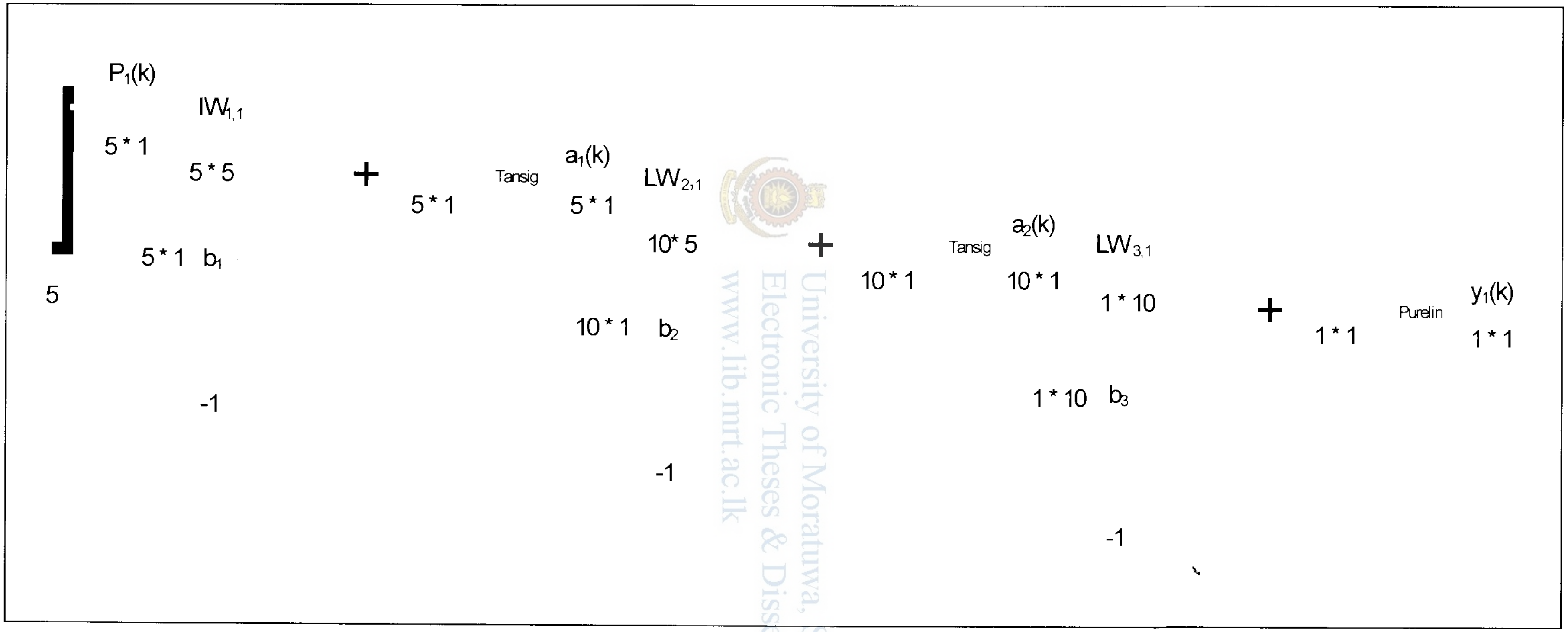


Figure 3.13: Topology of Custom Neural Network - 2

The parameters for the neural network are shown below.

- One Input source
    - [Loc_lat; Loc_lon]
- Output
    - [error in loss]
- One hidden layer (5 neurons with sigmoid transfer function)
- One output (error in loss with linear transfer function)
- Performance function - Regularized Mean Square error

The topology of the neural network is simple with the location coordinates being the two inputs and the error in loss as the output. The network consists of 15 parameters that should be trained before applied in calibration.

B. Training Neural Networks

Adjusting the weights and the biases of the neural network is referred to as training. During the training, the weights and the biases of the network are iteratively adjusted to minimize the performance function of the network. The network is trained by introducing known inputs and the target outputs to the network. A sufficient number of training samples should be available in order to obtain better performance. In additions the training samples should represent the overall problem space in order to reduce the over fitting.

Selecting a proper training algorithm is a key parameter in neural network training. Several training algorithms are available with different variants [47, 52], but none of them has proven superior for all the problems. Hence, selecting a proper training algorithm is more over less a trial and error approach.

During this work, the author uses five different types of training algorithms which are explained in Appendix B. Those are,

- Gradient Descent Algorithm
- Gradient Descent Algorithm with Momentum
- BFGS Algorithm
- Resilient Back propagation Algorithm

- Particle Swarm Optimization Algorithm

These algorithms have different parameter to be adjusted appropriately for the problem. Hence, all the neural networks are trained with different training algorithms by varying their parameter until a better solution for the calibration problem is obtained.

Furthermore, the sample data available for training are divided in to two sets, namely, training set and testing set, and the performance of the trained neural network is evaluated according to the mean square error computed for testing set.

3.4.2 Curve Fitting based Approach

Curve fitting provides means of finding a curve which matches a series of data points. It supports in finding a relationship between one dependent variable and several independent variables. The calibration problem in this research is also of same type, where the relationship between the predicted signal strength and the actual signal strength is approximated. Hence the curve fitting method is applicable for the problem being dealt with.

Curve fitting is of two types, namely Parametric fitting & Non parametric fitting. Parametric fitting is based on a priori knowledge of a specific model, which involves finding co-efficient of the model. In contrast, the non parametric fitting does not assume any model and fits smooth curves through the available data points. The author uses parametric fitting for calibration during this research.

Robust least squares fitting method provided in Matlab Curvefitting Toolbox is used with its two variants Least Absolute Residuals (LAR) & Bi-square weights [57]. The LAR scheme finds a curve that minimizes the absolute difference of the residuals (data – fit), rather than the squared differences. Therefore, extreme values have a lesser influence on the fit. On the other hand, Bi-square weight scheme minimizes a weighted sum of squares of residuals, where the weight given to each data point depends on how far the point is from the fitted line. For most cases, the bi-square weight scheme is preferred over LAR because it simultaneously seeks to find a curve that fits the bulk of the data using the usual least squares approach, and it minimizes the effect of outliers. [57].

Four models available in the Toolbox are used for fitting curves. They are:

1. Polynomial - Degree 2

$$Y = aX^2 + bX + c \qquad \text{.........................} \ (3.14)$$

2. Polynomial – Degree 3

$$Y = aX^3 + bX^2 + cX + d \qquad \text{.........................} \ (3.15)$$

3. Exponential -1

$$Y = a.\exp(bX) \qquad \text{.........................} \ (3.16)$$

4. Exponential – 2

$$Y = a.\exp(bX) + c.\exp(dX) \qquad \text{.........................} \ (3.17)$$

Figure 3.14 shows two different approaches for curve fitting. In each approach, curves are fitted for Polynomial Degree-2, Polynomial Degree-3, Exponential -1 and exponential -2. Then, the best fit curve for each cell is identified among those four curves using the Root Mean Square Error computed for the testing data set.

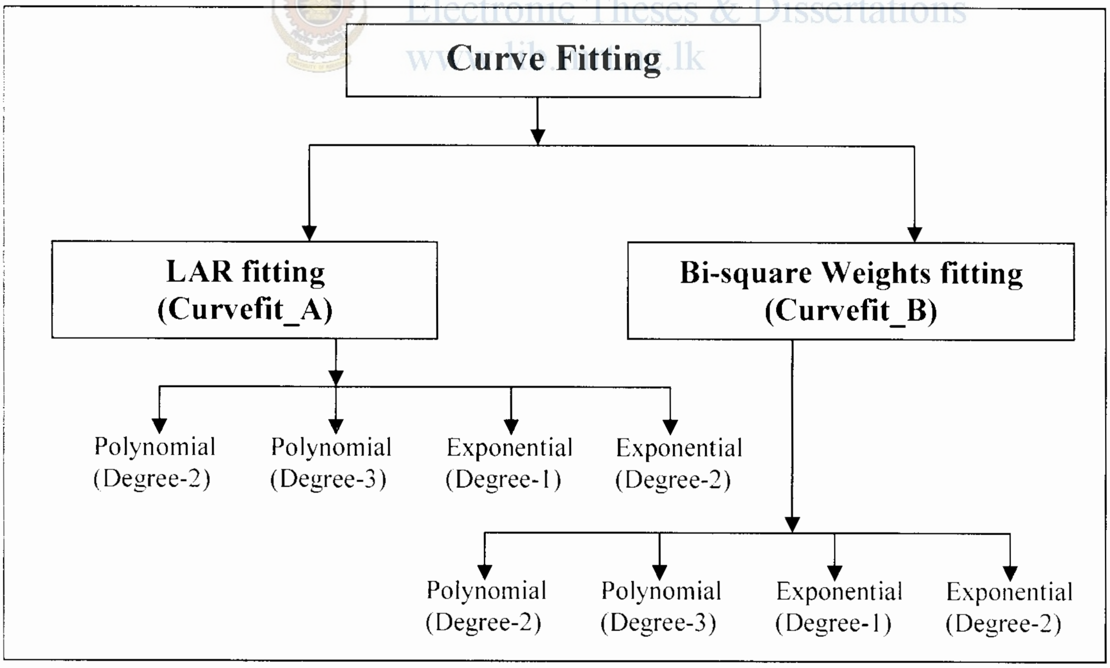


Figure 3.14: Curve fitting approaches

Chapter 4

Test Environment

Proving the performance of newly built positioning methodology in different environments, urban, suburban and rural, is a key goal of this research. This also includes comparing the performance of Fingerprinting method using a measured database with that using a predicted database. Hence, measurements should be taken extensively in all three environments in order to create the measured database, to calibrate the predictions as well as to form the test points.

As a result, three areas come under urban, suburban and rural environments were selected and the measurements were taken extensively. This chapter describes the measurements set up used in test drives and the nature of the selected environment comprehensively.

4.1 Measurement Setup

A mobile measurement unit and a GPS receiver (Garmin GPS II+), interfaced to a laptop are used as the measurement tool during this work. The mobile measurement unit is a hardware module built for the purpose of measuring signal strengths in GSM networks. It uses a GM862-PCS module for measuring GSM signals. The signals are measured through the BCCH channel in idle mode. The complete measurement setup is shown in Figure 4.1.

Figure 4.1: Complete measurement set up

A measurement taken by this setup consists of the GPS coordinates and the received signal strengths from the serving cell and up to five neighboring cells. The format of a single measurement is shown in Figure 4.2.

Session ID	Neighbor no	Cell ID	Lac	ARFCN	Stength	TA
1	0	A	7777	122	48	0
1	1	B	7777	119	53	
1	2	C	7777	102	60	

Session ID	Latitude	Longitude
1	0647.807	07954.079
2	0647.805	07954.082

Figure 4.2: Format of a measurement

Test drives are performed along roads of the selected area by a van equipped with the measurement tool. Collecting measurements to form the measured database is done by continuously moving along the roads in a speed less than 20km/h. Those measurements are also used in calibration purpose. Test points collection is done along the same roads in a different manner, by which the vehicle is stopped for a period of time enough to take a set of 10 measurements from the measurement set up.

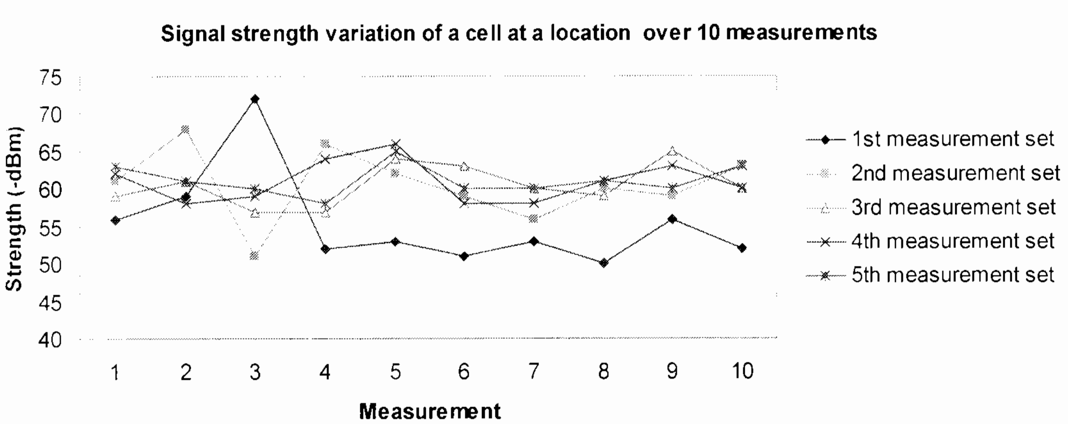


Figure 4.3: Signals strength variation of a cell at a location over ten measurements

As a result a test point consists of 10 measurements. In location estimation, the algorithm averages the signal strengths of the distinct cells in those 10 measurements before correlating with the database. This approach was selected to compensate the variation in signal strength at a given location over the time. When considering the 10 measurements at a test point, the signal strength from a particular cell varies considerably. The variation is also in a random fashion. This is illustrated in Figure 4.3. However, Figure 4.4 in turn shows that the variation in average signal strength taken over 10 measurements is not that significant. Hence, it was decided to take 10 measurements per location and average out in location estimation.

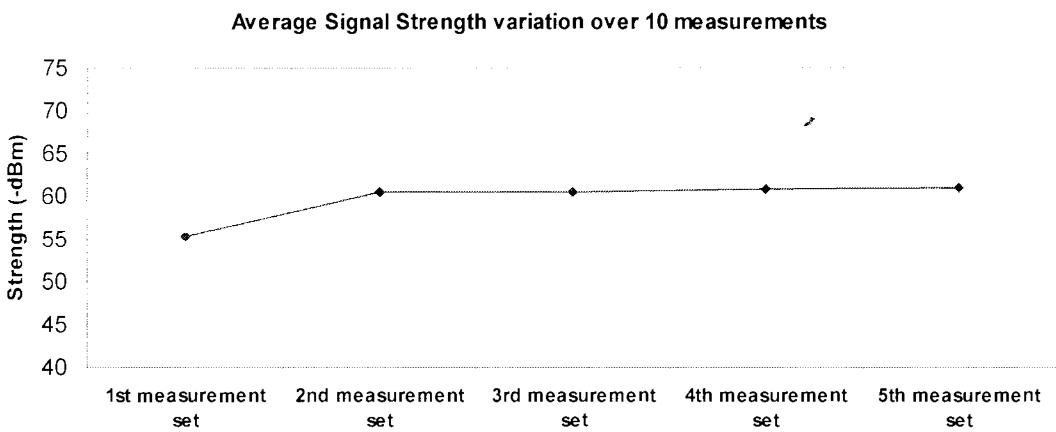


Figure 4.4: Average signal strength variation at a location

4.2 Urban area selection

The urban area is basically defined as highly populated with high building density with tall towers. In the cellular environment, it contains large number of near by cells which are mostly come under Micro Cell category. Propagation phenomenon like multi path fading and scattering are highly observable in this area.

In Sri Lanka, the Colombo city area falls under this category of environments. An area around 2.5 km^2, covering Bambalapitiya to Colpetty, is considered as the urban environment in this work. Two roads, namely, Galle Road and Duplication Road, can be identified as having different characteristics within the selected area. The portion of the Galle Road of selected area is bordered by tall buildings and there exist no bushes or trees along the border of the road. Hence, the signals are highly reflected and blocked and severe fading occurs along the road as illustrated in Figure 4.5. Hence, this road is considered as Bad urban scenario. In contrast to that, the duplication road is bordered by small buildings and there exist trees and bushes along the border of the road. The fading along the Duplication road is inferior to that along the Galle road, as illustrated in Figure 4.6. Therefore, duplication road can be considered as typical urban scenario.

A total of 70 cells are hearable within the selected urban environment.

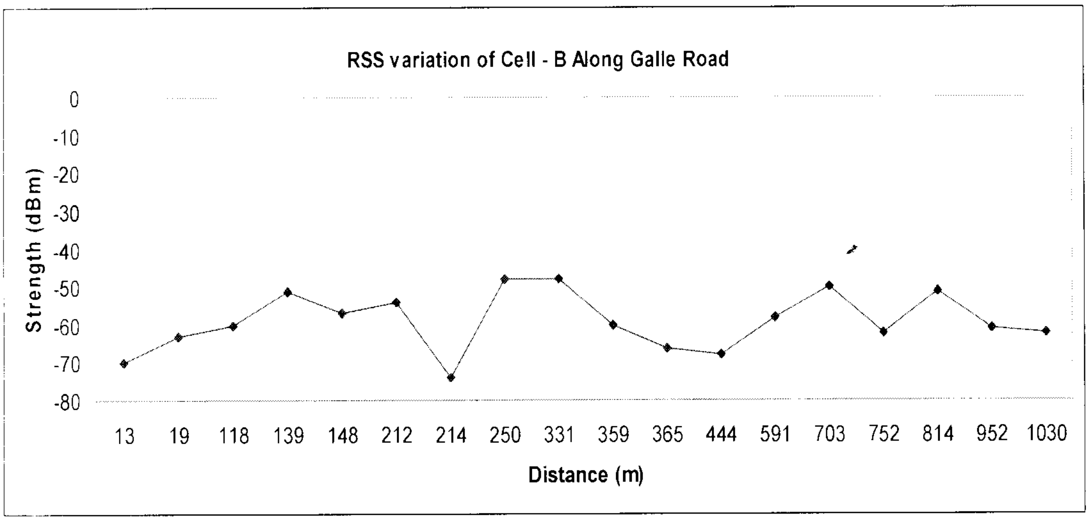


Figure 4.5: Received Signal strength variation along Galle road in urban environment

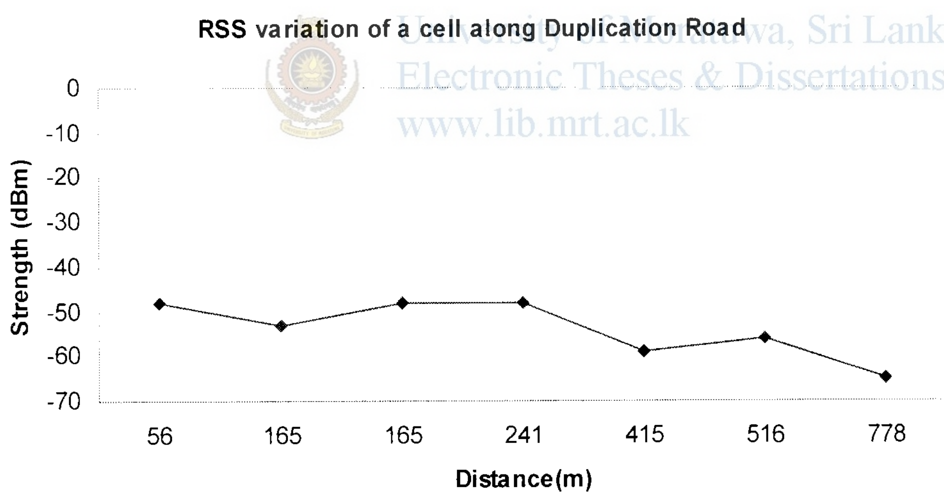
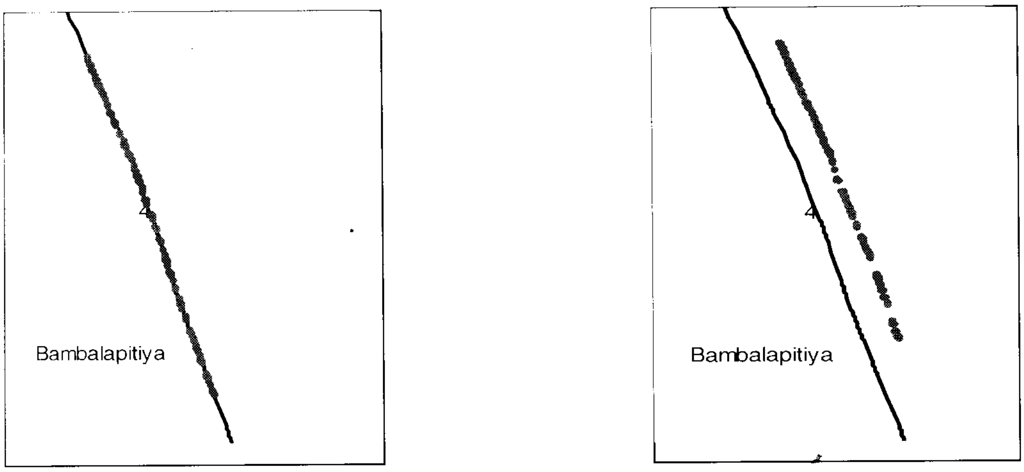


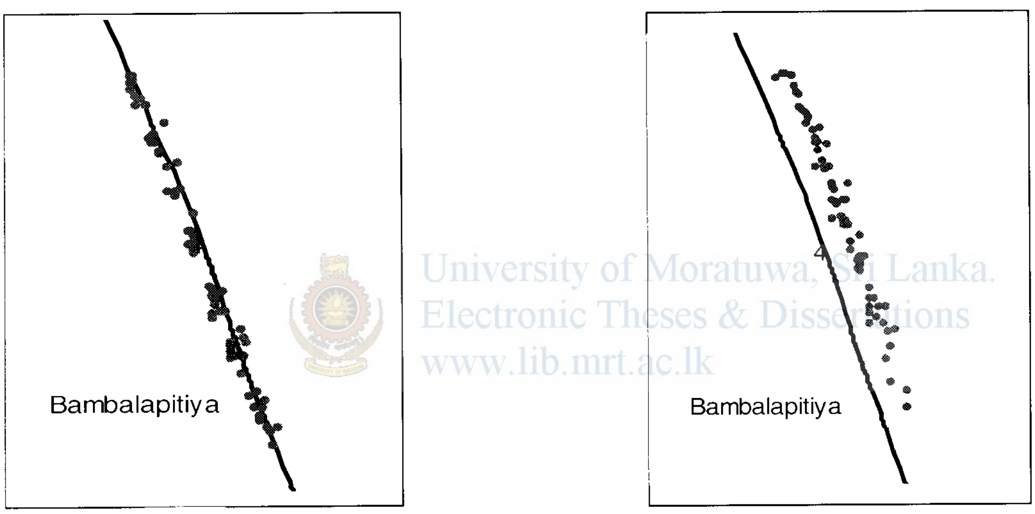
Figure 4.6: Received Signal strength variation along Duplication road in urban environment

Accordingly, measurements are taken along the duplication road and the Galle road as measured fingerprints and test points. Meanwhile, the predicted database is also created along both roads using the signal strength prediction of planning tool. Figure 4.7 shows the fingerprints formed along both roads using predictions while the measured fingerprints are shown in Figure 4.8.



(a) (b)

Figure 4.7: Predicted Fingerprints along roads in urban area
(a) Along Galle road (b) Along Duplication road



(a) (b)

Figure 4.8: Measured Fingerprints along the roads in urban
(a) Along Galle road (b) Along Duplication road

Table 4.1 summarizes the number of fingerprints and the test points obtained along each road.

Table 4.1: Summary of fingerprints and test points in urban environment

Road	**Measured Fingerprints**	**Predicted Fingerprints**	**Test Points**
Galle Road	311	66	50
Duplication Road	295	71	63

4.3 Suburban area Selection

The population and the building density are relatively low in suburban environment compared to the urban. The cells have larger coverage range and they are situated far apart than in urban environment. Multi-path fading and scattering are there with the Line of Site propagation up to some extent.

In Sri Lanka, the areas like, Moratuwa, Horana, Panadura, Maharagama, Homagama, Kiribathgoda, Kadawatha etc are come under this category. An area of about 6km^2, around the University of Moratuwa, from Katubedda junction to Piliyandala, is selected as the suburban area in this work. Since a clear distinction of the environment cannot be observed along different roads, all the roads in selected area are taken together in testing. The total number of hearable cells within the selected suburban area is 45.

Measurements are taken along the roads to form measured fingerprints and the test points while the predicted database is created along the same roads using the signal strength prediction of planning tool as illustrated in Figure 4.9 (a) and (b).

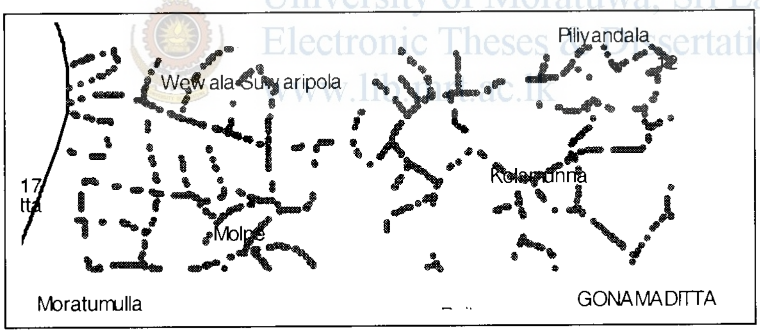


Figure 4.9 (a): Predicted Fingerprints in suburban

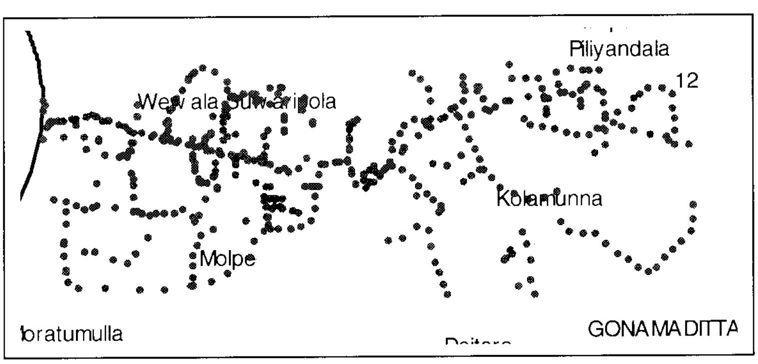


Figure 4.9 (b): Measured Fingerprints in suburban

Table 4.2 summarizes the number of fingerprints and the test points obtained along the roads in suburban.

Table 4.2: Summary of fingerprints and test points in suburban environment

Measured Fingerprints	**Predicted Fingerprints**	**Test Points**
518	3210	312

The signal strength variation of a particular cell within the selected area is shown in Figure 4.10.

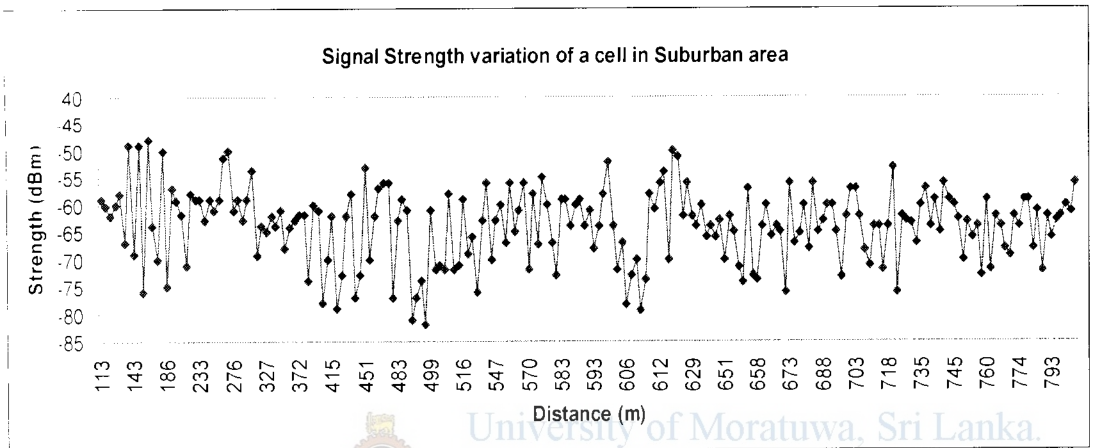


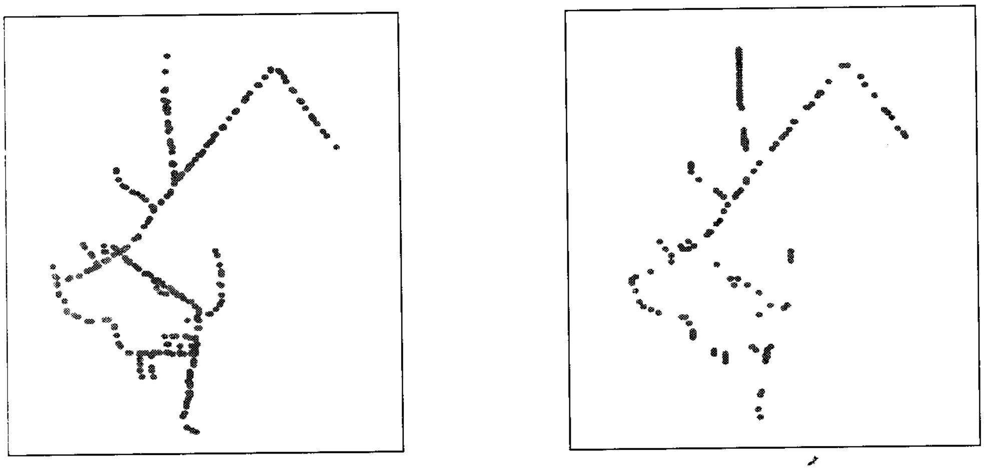
Figure 4.10: RSS variation of a cell in suburban area

4.4 Rural are Selection

Rural area is basically defined as less populated with low building density. In the cellular environment, it has a small number of base stations with larger coverage area, classified as macro cells.

In Sri Lanka, the areas like Anuradhapura, Ibbagamuwa, Melsiripura, Wariyapola etc are come under this category. Accordingly, an area of about 4km^2, around Ibbagamuwa is considered as the rural area in this research. All the roads in selected area are taken together as in suburban scenario. A total of 20 cells are hearable within the selected rural area.

Figure 4.11 (a) and (b) show the measured fingerprints and the predicted fingerprints along the roads in this area.



(a) (b)

Figure 4.11: Predicted and measured Fingerprints in suburban
(a) Predicted (b) Measured

Table 4.3 summarizes the number of fingerprints and the test points obtained along the roads in rural environment.

Table 4.3: Summary of fingerprints and test points in rural environment

Measured Fingerprints	Predicted Fingerprints	Test Points
281	170	154

Figure 4.12 shows the received signal strength variation of a cell in rural area.

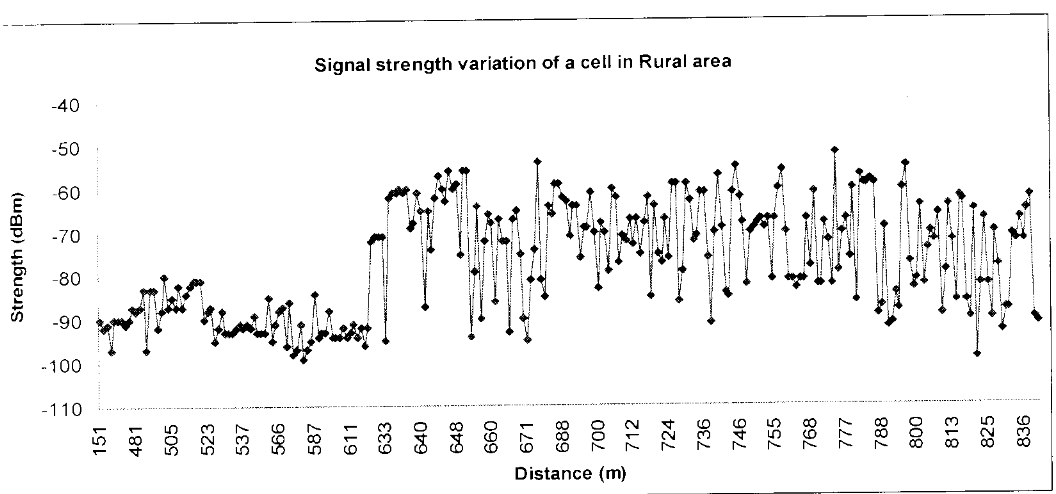


Figure 4.12: RSS variation of a cell in rural area

4.5 Analysis of RSS variation

Due to the propagation phenomena such as reflection, diffraction scattering occur in mobile environment, the received signal strength varies considerably in nearby locations as well as the same location at different times. This section analyses such deviations occur in different locations during day time.

In order to do this, signal strengths from all hearable cells are measured at a particular location continuously, hour-by-hour, from morning to evening of the day. The analysis of RSS variation of three locations within the University of Moratuwa is presented in this section.

4.5.1 Location-1- ENTC Balcony

Figure 4.13 illustrates the variation of average received signal strength of different hours of the day-1 at a location in ENTC Balcony. Even though the serving cell was appeared to be same over different hours, there is a considerable variation of the signal strength of serving cell. Signal strength has increased considerably within the hours 2-3 and 3-4.

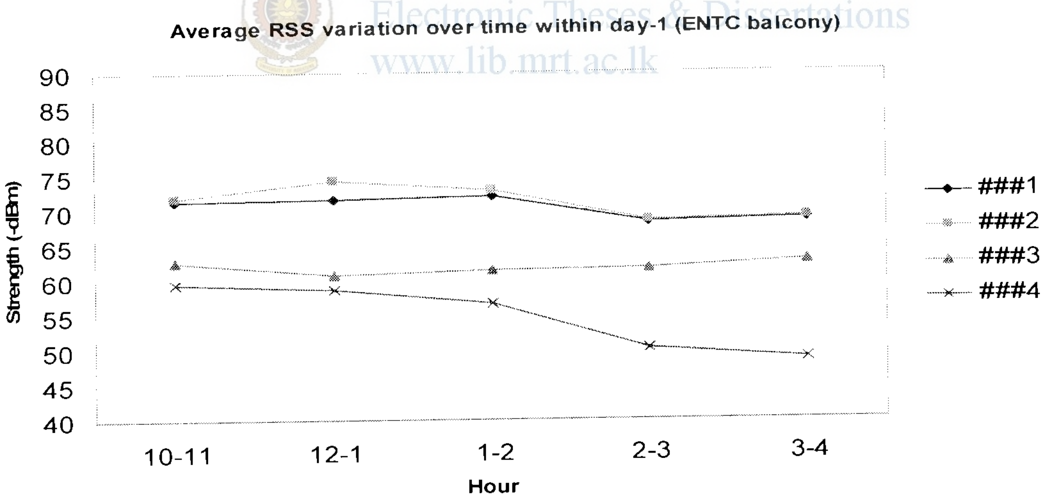


Figure 4.13: Average RSS variation in different hours of day-1 at ENTC Balcony
Cell IDs have been changed for the purpose of reporting

The signal strength variation at the same location in the next day is completely different from that in day-1 as demonstrate in Figure 4.14. A considerable decrease in signal strengths of all hearable cells can be seen after 12 noon. This could be due to a change done in transmission parameters by the operator.

Nevertheless, the relative positions of the RSS of neighboring cells with respect to that of serving cell are seem to be constant.

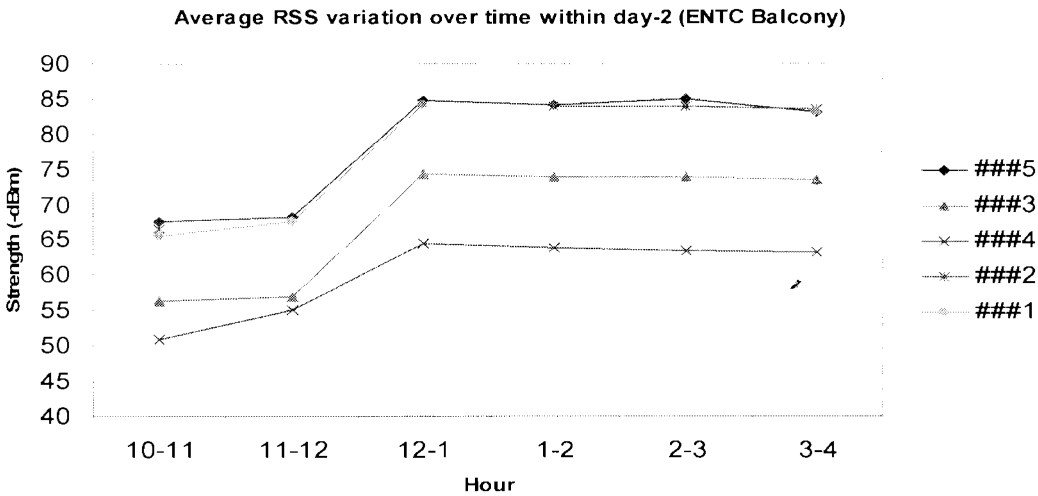


Figure 4.14: Average RSS variation in different hours of day-2 at ENTC Balcony
Cell IDs have been changed for the purpose of reporting

4.5.2 Location-2 – University Front

At the second location, the average received signal strength of most of the cells is more over less a constant over the different hours of the day. In addition there exist a considerable difference in signal strengths of serving cell and other cells and also the relative positions of RSS of neighboring cells with respect to that of serving cell are some what similar.

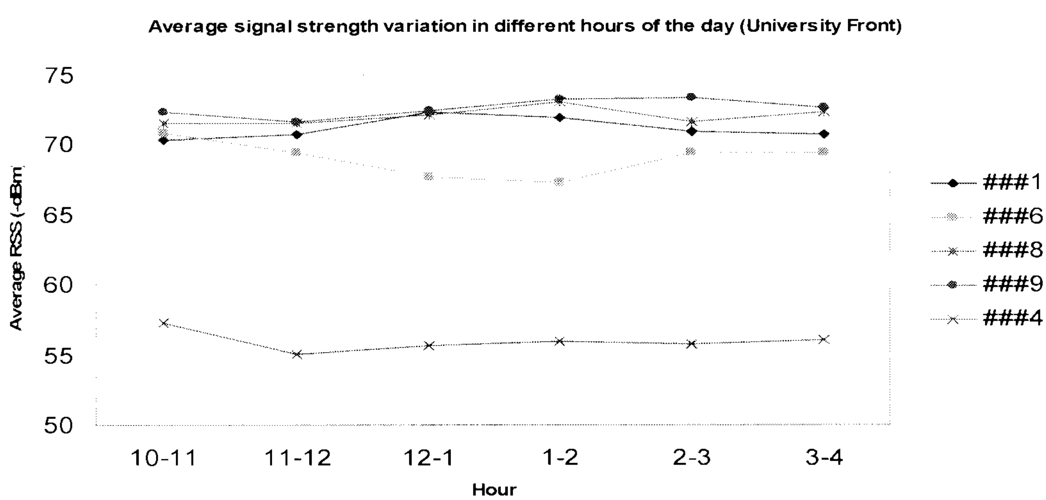


Figure 4.15: Average RSS variation in different hours of the day at University front
Cell IDs have been changed for the purpose of reporting

4.5.3 Location-3- Near IT Office

Figure 4.16 shows the average RSS in different hours of the day at a location near IT office. A considerable variation in RSS of serving cell and one neighboring cell can be seen after 12 noon. However, the relative signal strength is almost the same in most of the time.

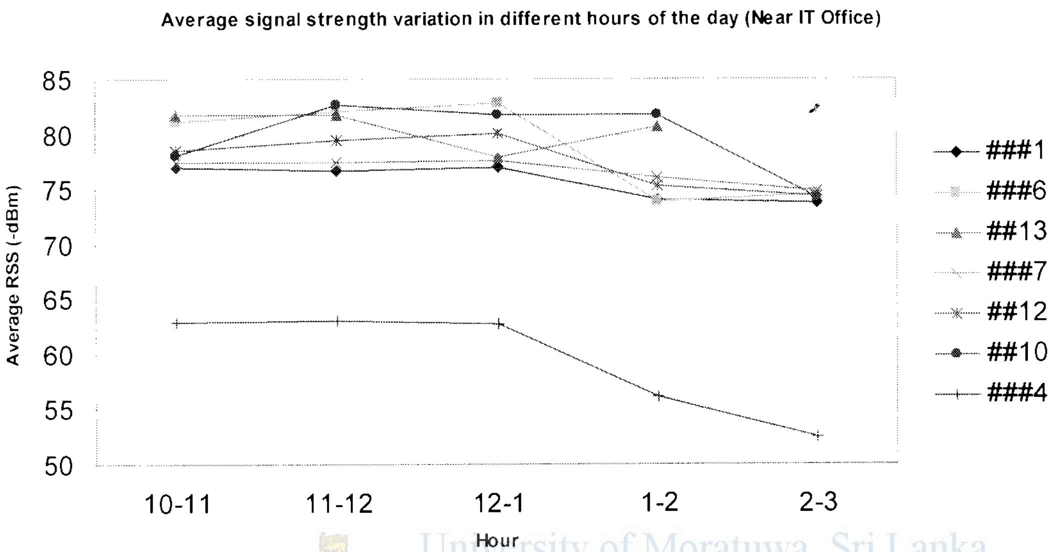


Figure 4.16: Average RSS variation in different hours of the day-1 near IT office
Cell IDs have been changed for the purpose of reporting

4.5.4 Impact on DCM Algorithm

The analysis shown in sub Sections 4.5.1 to 4.5.4 demonstrates the variation in received signal strength at a location with respect to time. Furthermore, it is worthwhile to analyze the effect of this RSS variation on the performance of DCM.

Accordingly, the author has performed a positioning test for the measurements taken at ENTC-Balcony. In this test, all the measurements taken within the day are divided in to groups of 10 consecutive measurements, such that each group resembles one test point. This resulted in 118 test measurements at the same location. The GPS coordinates of the test location is measured to compare the accuracies. The algorithm used for location estimation is Approach-A with Cost Function-2 and measured database for suburban.

Figure 4.17 shows the positioning error graph plotted for each test measurement.

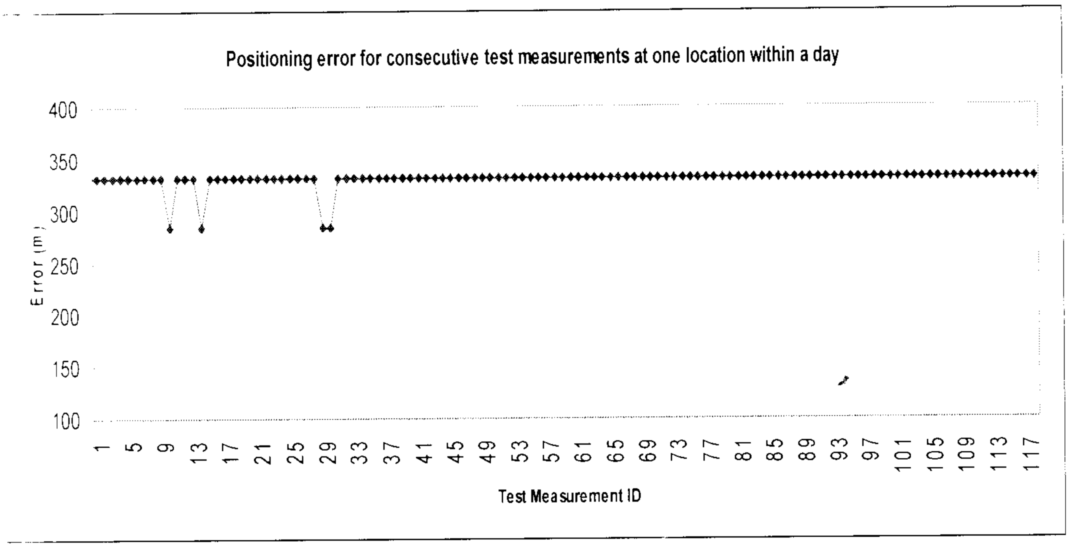


Figure 4.17: Error for consecutive test measurements at one location within a day

The location estimate given by DCM algorithm is almost the same for all test measurement at a location, while there were four cases out of 118 where a different estimate was given. Hence, it can be concluded that the impact of RSS variation with respect to time on the DCM algorithm is negligible.

Chapter 5

Results Analysis

The results of the methodology described in Chapter 3 are presented in this chapter. Section 5.1 discusses the results of the deviation analysis between predictions and measurements while Section 5.2 to Section 5.6 discuss the results using predicted database, results using measured database, performance comparison using predicted and measured databases, performance of different calibration techniques and overall results analysis, respectively. The organization of the presentation of results in this chapter is shown in Figure 5.1.

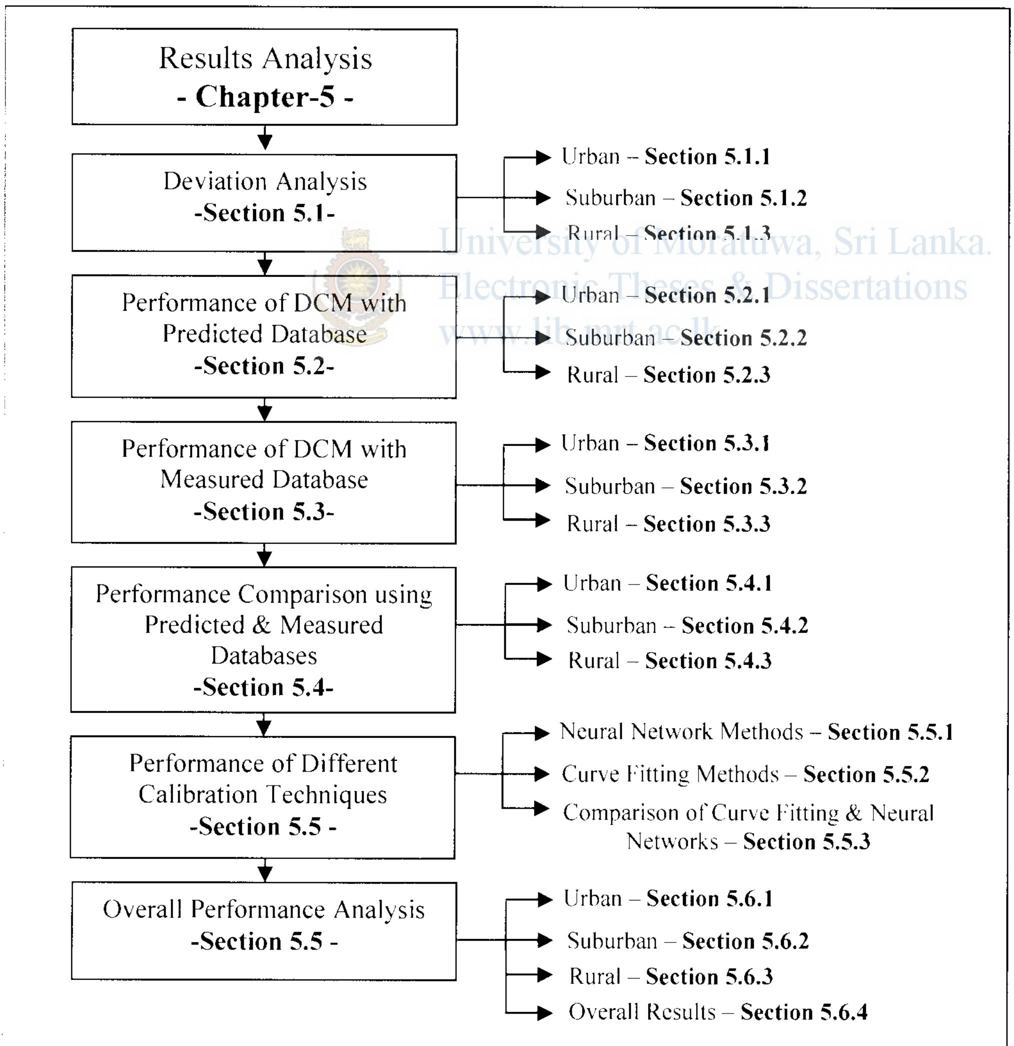


Figure 5.1: Organization of the Presentation of Results

Root Mean Square Error is used as the performance measure in deviation analysis whereas the cumulative distribution function of positioning error is used in performance analysis of database correlation method with different positioning algorithms.

5.1 Deviation Analysis

Deviation analysis was done using two approaches, namely cell-wise analysis and fingerprint-wise analysis, as described in Section 3.2. Those results are discussed in this section per each environment.

5.1.1 Urban Environment

A Galle Road

Cell-wise Analysis

Table 5.1 shows the Root Mean Square Error computed in dB and dBm per cell along Galle Road in urban environment.

Accordingly, the RMSE lies in the range of 5dB – 45 dB, while that in dBm is comparable to measured values. The average deviation is 20.18 dB. Hence, the deviation between planning tool predictions and the actual measurements along Galle Road is considerable.

Table 5.1: Cell-wise analysis – Galle Road
Cell IDs have been changed for the purpose of reporting

Cell ID	RMSE-(dB)	RMSE-(dBm)	Cell ID	RMSE-(dB)	RMSE-(dBm)
***1	19.23	-50.76	***7	15.67	-62.02
***2	20.28	-50.01	***8	10.51	-48.94
***3	10.33	-51.80	***9	13.50	-50.36
***4	32.24	-52.52	**10	15.47	-51.95
***5	10.44	-50.37	**11	14.16	-58.31
***6	18.29	-51.89	**12	11.24	-55.40

Actual signal strengths and predicted signal strengths of a cell, along Galle Road, are plotted in the same graph with respect to the distance from the transmitter, in Figure 5.2. This also proves the existence of a considerable deviation between predictions and actual measurements along Galle Road.

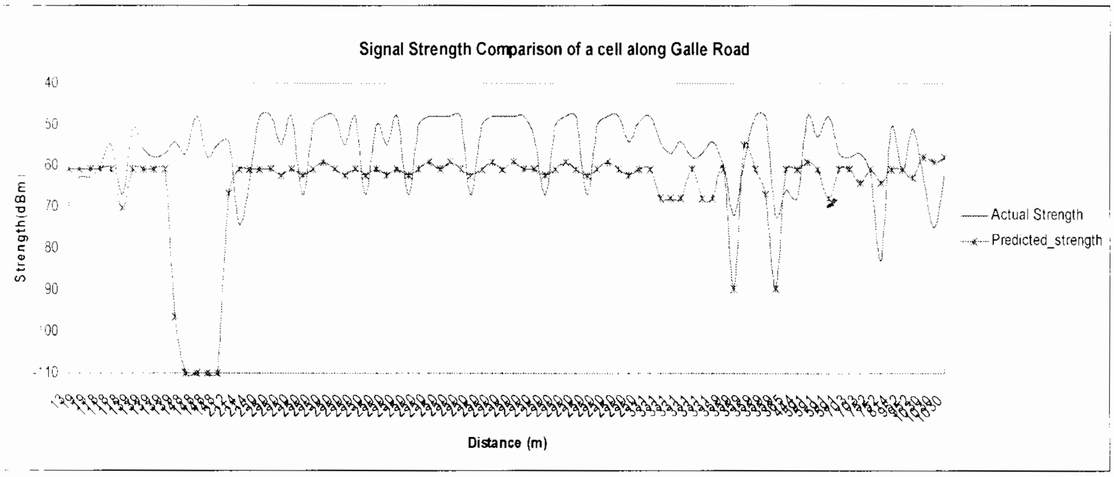


Figure 5.2: Signal Strength Comparison of a cell along Galle Road

Fingerprint-wise analysis

Figure 5.3 illustrates the RMSE per fingerprint, computed by Equation (3.2), along Galle Road while Figure 5.4 shows the RMSE histogram. Here, the deviation lies in the range of 0dB – 48dB with an average of 22dB. This also proves the higher deviation in predictions along Galle Road, which is selected to be the Bad Urban scenario.

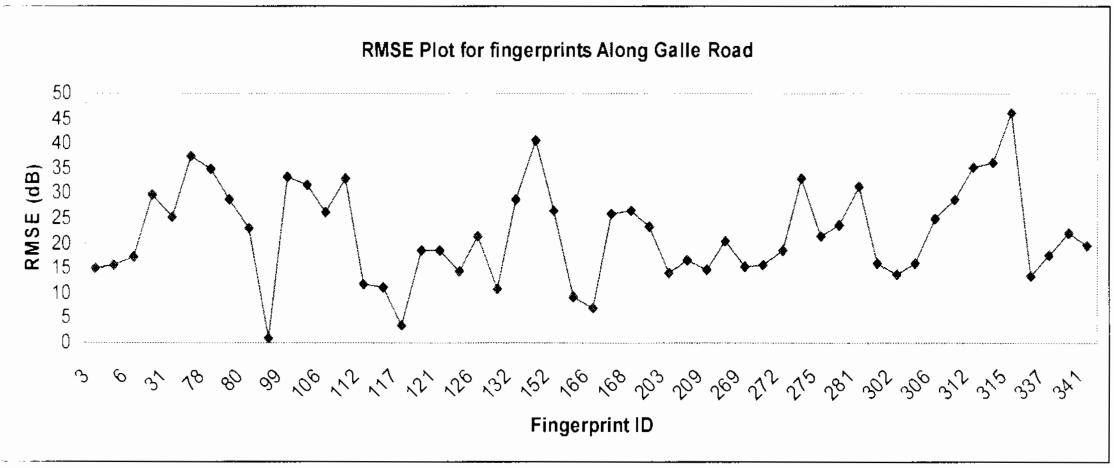


Figure 5.3: RMSE plot for Fingerprints along Galle Road

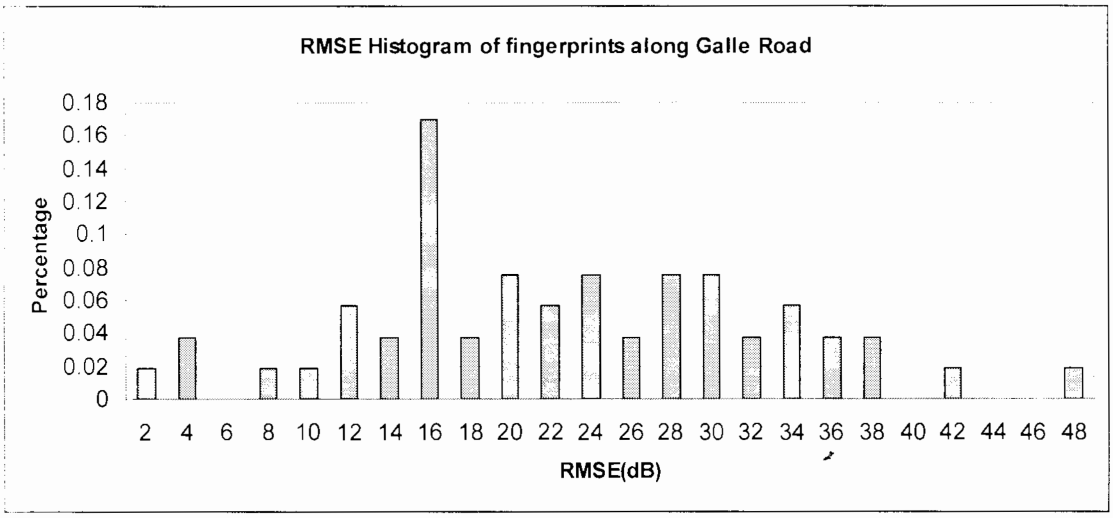


Figure 5.4: RMSE Histogram of Fingerprints along Galle Road

B Duplication Road

Cell-wise Analysis

According to Table 5.2, which shows the Root Mean Square Error for some cells, the deviation between the predicted and actual measurements along Duplication road lies in the range of 5dB-30dB, which is lesser compared to that along Galle road. The average deviation is 16 dB. Hence, the deviation of predictions from actual measurements along Duplication road is moderate.

Table 5.2: Cell-wise Analysis – Duplication Road
Cell IDs have been changed for the purpose of reporting

Cell ID	RMSE-(dB)	RMSE-(dBm)	Cell ID	RMSE-(dB)	RMSE-(dBm)
###1	8.40	-65.57	###7	6.19	-59.27
###2	14.80	-56.53	###8	11.34	-61.02
###4	11.86	-61.01	###9	13.22	-50.49
###5	36.69	-53.59	##10	12.80	-50.46
###6	5.16	-54.82	##11	12.10	-53.68

Fingerprint-wise analysis

Figure 5.5 shows a plot of RMSE of fingerprints along Duplication Road. The RMSE ranges from 0dB to 35dB with an average value of 14.7dB. This deviation is better compared to that along Duplication road.

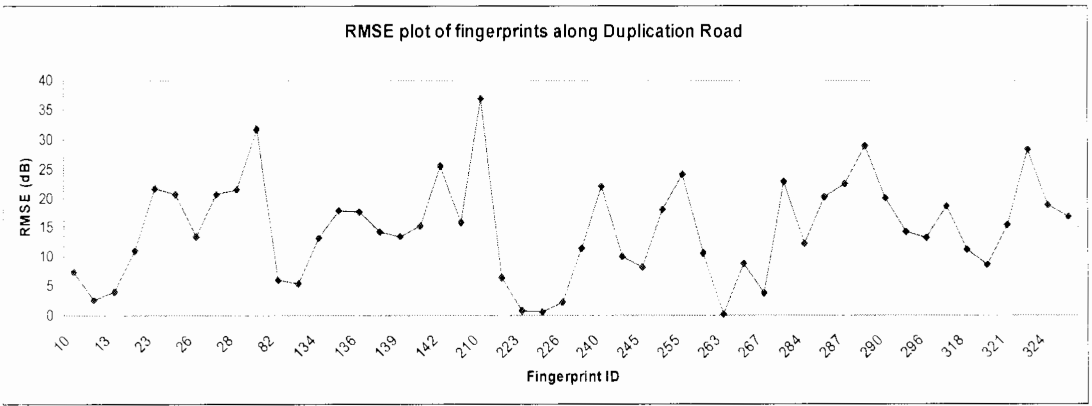


Figure 5.5: RMSE plot of fingerprints along Duplication Road

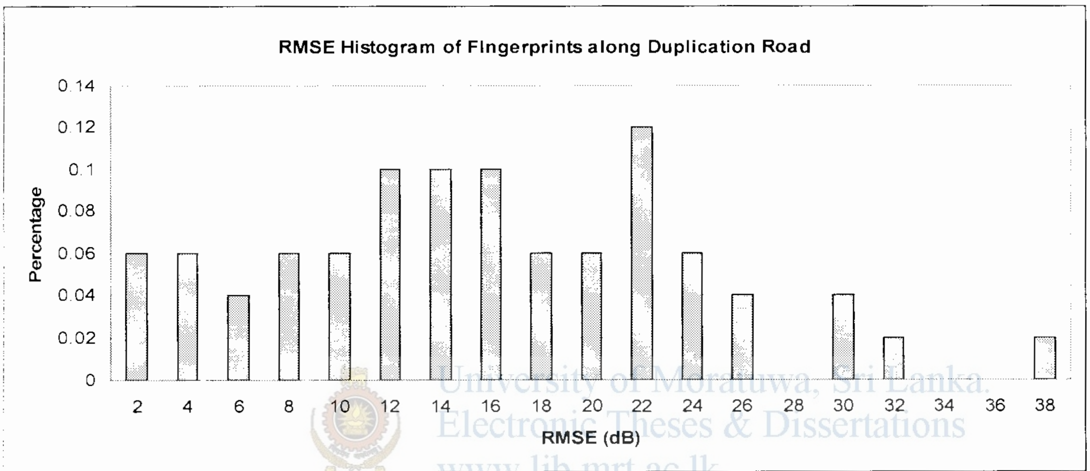


Figure 5.6: RMSE Histogram of fingerprints along Duplication Road

Furthermore, the histogram shown in Figure 5.6 illustrates that the RMSE for more than 80% of the fingerprints is below 25dB.

5.1.2 Suburban Environment

Cell-wise analysis

Results of the cell-wise analysis along roads in suburban are given in Table 5.3.

Apparently, the deviation lies in the range of 5dB – 20dB with an average of 10dB. The deviation computed in dBm is also lower than that in urban environment. Hence, it is evident that the planning tool predictions are closer to actual measurements in suburban environment than in urban.

Table 5.3: Cell-wise analysis – Suburban
Cell IDs have been changed for the purpose of reporting

Cell_ID	RMSE-(dB)	RMSE-(dBm)	Cell_ID	RMSE-(dB)	RMSE-(dBm)
$$$2	14.36	-73.70	**$$$3**	8.06	-63.21
$$$7	6.17	-69.41	**$$$1**	10.75	-57.86
$$$9	7.64	-75.01	**$$$6**	11.34	-72.72
$$$8	15.35	-80.17	**$$$5**	5.94	-76.54

Figure 5.7 shows the actual and predicted signal strength variation of a cell in suburban.

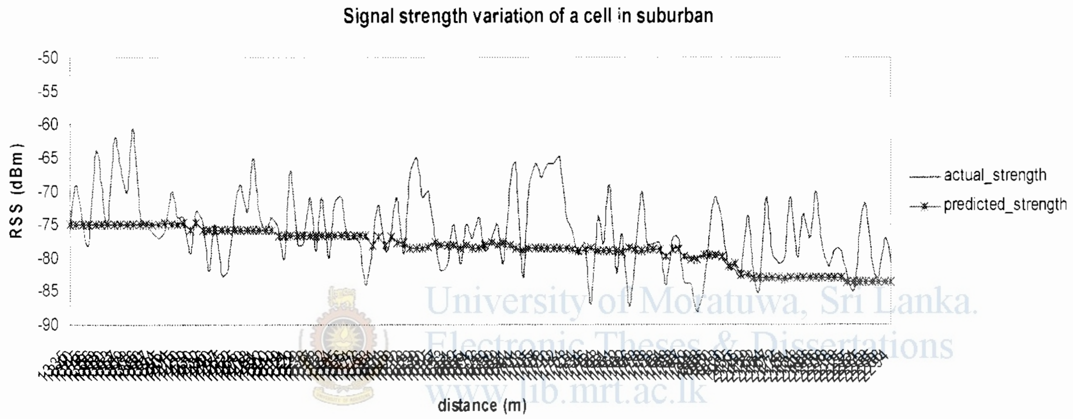


Figure 5.7: Signal strength variation of a cell in suburban

Fingerprint-wise analysis

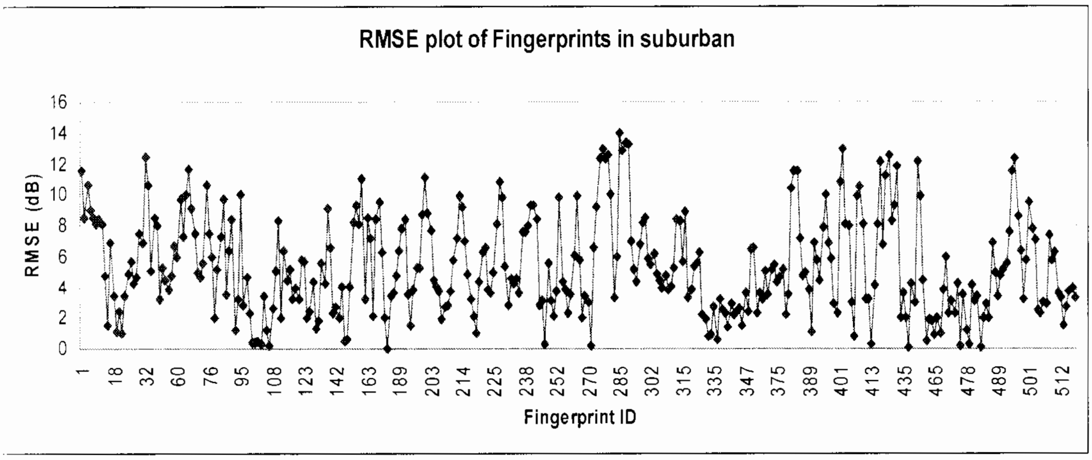


Figure 5.8: RMSE plot of Fingerprints in suburban

From Figure 5.8, it appears that the RMSE of fingerprints in suburban area ranges from 0dB to 15dB, which is lesser than that in urban area. The average value of that is 5dB, which is quite good. This is also proved by the histogram shown in Figure 5.9.

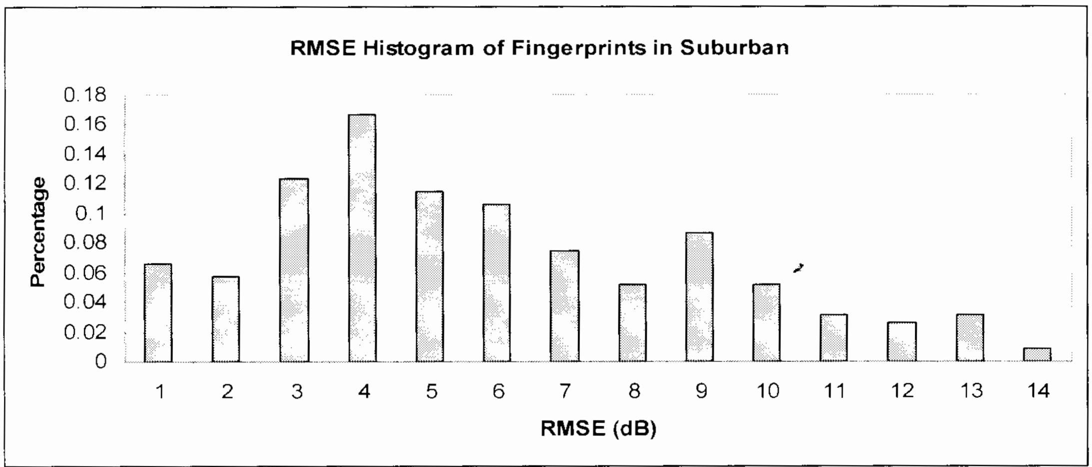


Figure 5.9: RMSE histogram of Fingerprints in suburban

5.1.3 Rural Environment

Cell-wise analysis

The results of cell-wise analysis shown in Table 5.4 give evidence to the fact that the deviation between measured and predicted strengths is comparatively small in rural environment. While the deviation in dB lies in the range 3dB-15dB with an average of 7.8dB, that in dBm is small compared to measured strengths.

Table 5.4: Cell-wise Analysis – Rural
Cell IDs have been changed for the purpose of reporting

Cell ID	RMSE-(dB)	RMSE-(dBm)	Cell ID	RMSE-(dB)	RMSE-(dBm)
&&&3	9.29	-58.40	**&&&5**	13.82	-86.59
&&&2	8.04	-60.11	**&&&6**	8.24	-72.14
&&&7	8.14	-55.61	**&&&9**	5.89	-89.45
&&&4	8.51	-55.58	**&&&1**	6.49	-92.25

Figure 5.10 shows the signal strength variation of a cell in rural environment, with respect to the distance from the transmitter. Accordingly, the deviation is even lower in rural environment, compared to urban and suburban environments.

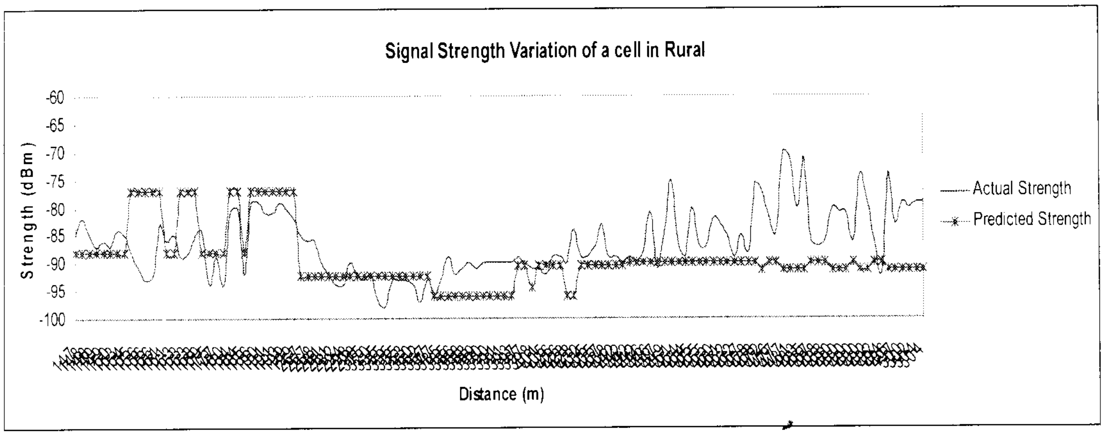


Figure 5.10: Signal strength variation of a cell in Rural

Fingerprint-wise analysis

The RMSE plot shown in Figure 5.11 and the histogram plot in Figure 5.12 demonstrate the lower deviation between measured and predicted fingerprints in rural environment.

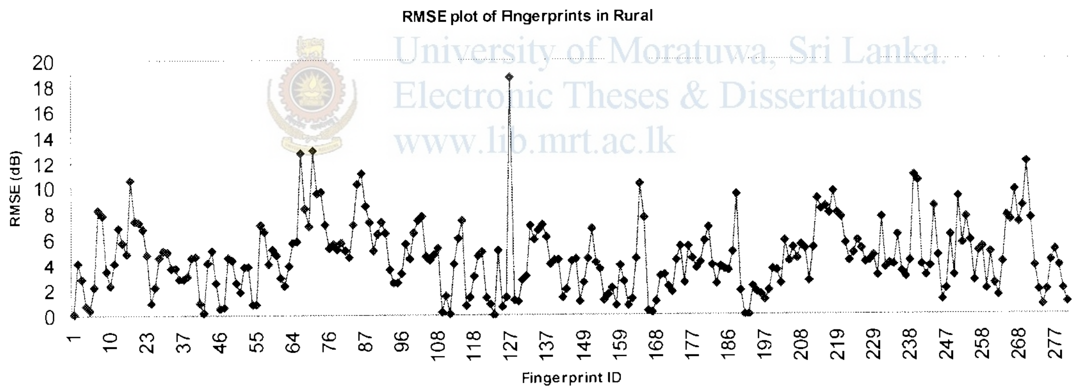


Figure 5.11: RMSE plot of Fingerprints in rural

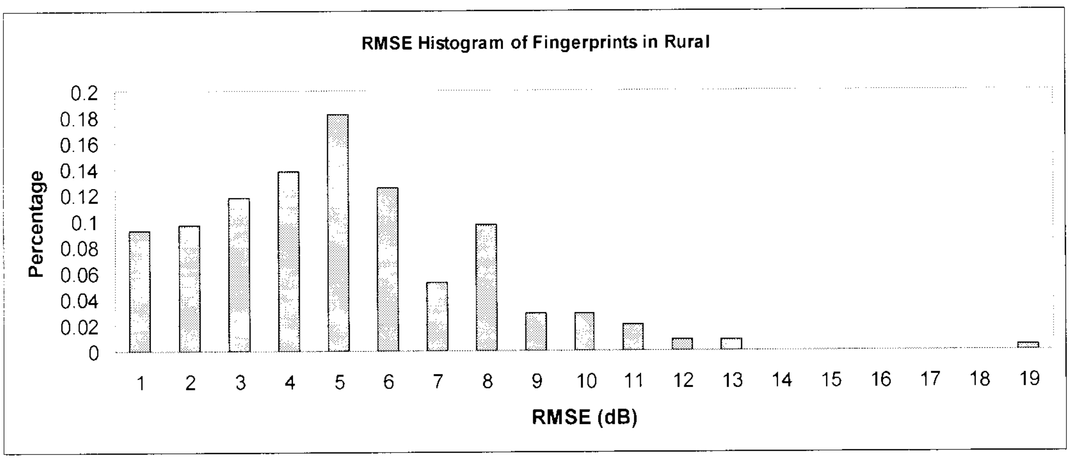


Figure 5.12: RMSE histogram of Fingerprints in rural

5.2 Performance of DCM with Predicted Database

One of the major objectives of the research is to analyze the performance of database correlation method with predicted database in all three environments. This section is devoted for the demonstration of the results of that work.

5.2.1 Urban

A. Galle Road

Figure 5.12 shows the error CDF curves of database correlation method with positioning approach-A, which uses the serve cell for fingerprint filtering as described in Section 3.3. Five curves correspond to five different Cost Functions introduced in the same section.

It seems that, the approach –A with novel Cost Function, Cost Function-4, performs well with predicted database along Galle Road. This demonstrates the potential of the novel Cost Function for higher accuracies over others. However, the positioning error is less than 330m in 80% of the estimates, which is not an acceptable result for urban scenario.

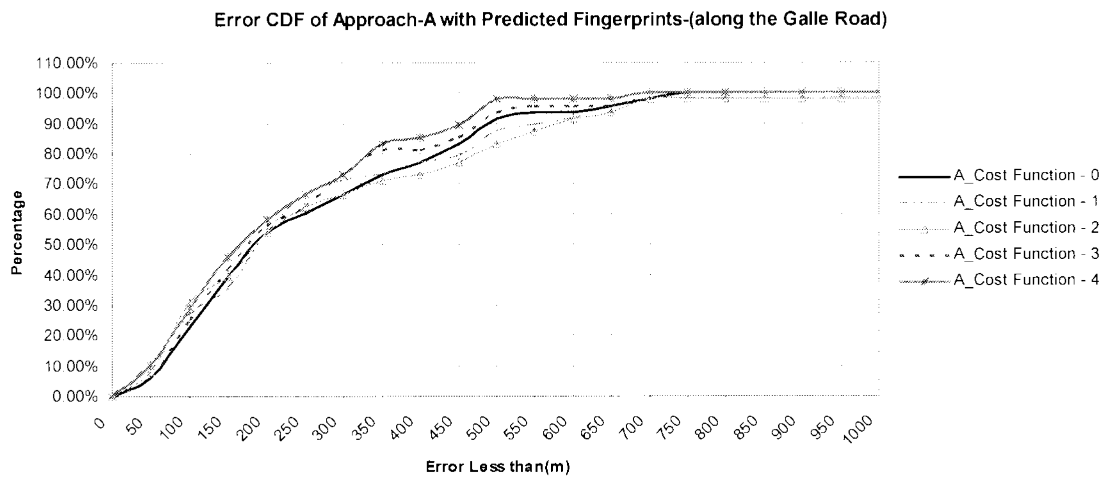


Figure 5.13: Error CDF of Approach-A with Predicted Fingerprints- Galle Road

The error performance of positioning approach-B, which uses the novel filtering method described in Section 3.3, for a predicted database along Galle road is illustrated in Figure 5.14 for different Cost Functions. It appears that, the approach-B with K=8 and Cost Function-4 gives better performance with a positioning error less than 245 m in 80% of the estimates.

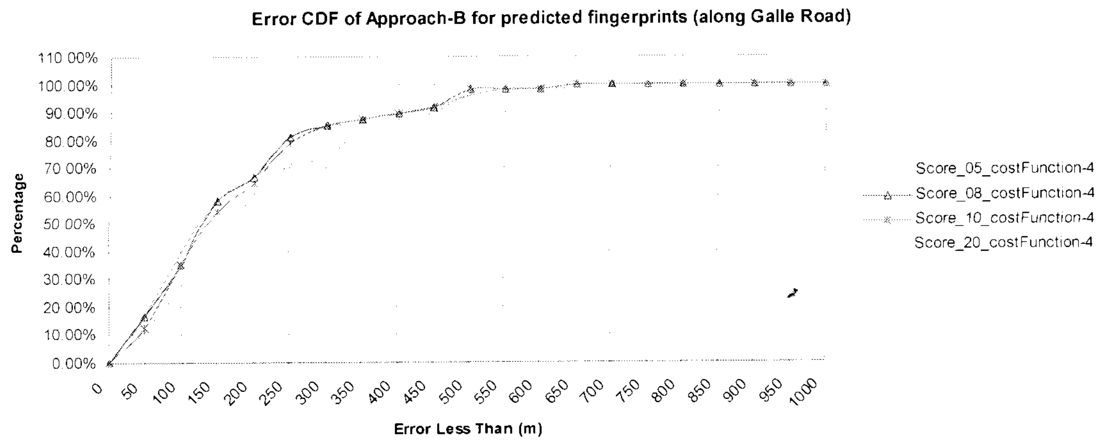


Figure 5.14: Error CDF of Approach-B with Predicted Fingerprints- Galle Road

Finally, Figure 5.15 demonstrates a comparison of the best results from positioning approach-A and approach-B with a predicted database along Galle road. This also compares those two approaches with the basic Cell_ID method for positioning.

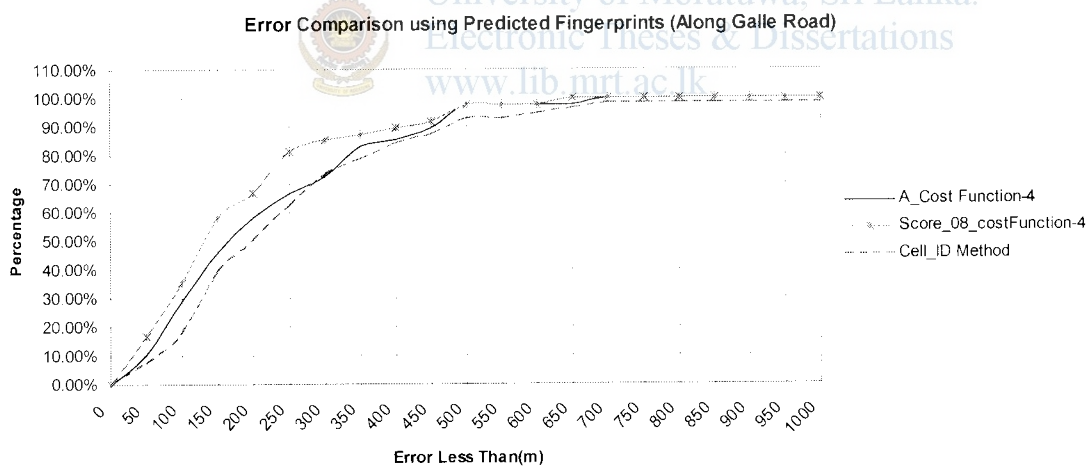


Figure 5.15: Error comparison using predicted fingerprints- Galle Road

It is clear that, the novel filtering method with K=8 and Cost Function-4 has the better performance when using a predicted database in fingerprinting method. The positioning error is less than 245m in 80% of the estimates while that is less than 400m in 90% of the time.

Table 5.5 summarizes those results comparing with that of basic Cell_ID method. The performance of DCM with predicted database is far better than that of Cell_ID method along Galle road in urban environment.

Table 5.5: Results summary using predicted database

	With Predicted Fingerprints	Cell_ID Method
	Score_8-Cost Function-4	
80% (m)	245	370
90% (m)	400	475
Maximum (m)	616	1020
Minimum (m)	31	27
Average (m)	173	245
STD (m)	138	185
Median (m)	130	200

From here onwards, the results of novel filtering approach with K=8 and Cost Function-4 is referred to as the results with predicted database along Galle road.

B. Duplication Road

The performance of predicted database along Duplication road in urban environment is discussed in this section.

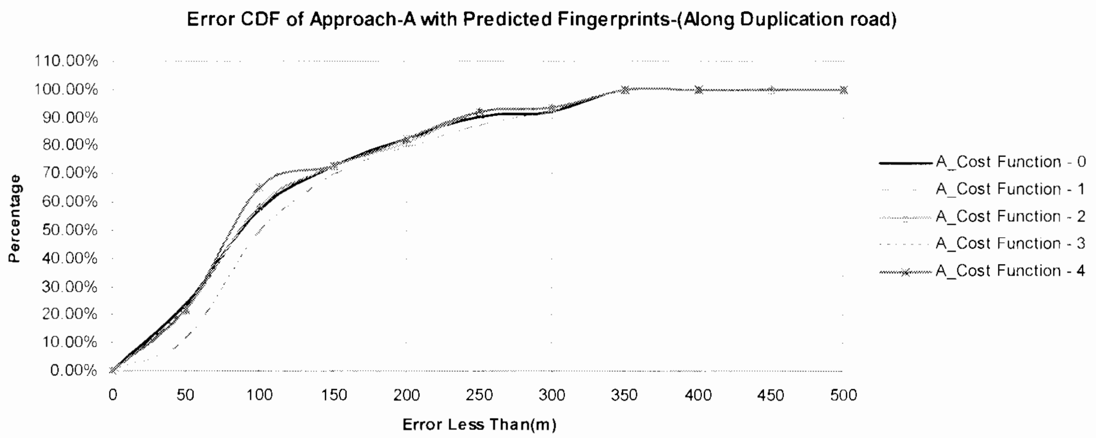


Figure 5.16: Error CDF of Approach-A with Predicted Fingerprints- Duplication Road

According to Figure 5.16, all the Cost Functions, except Cost Function-1, have a comparable performance in approach-A. Among them, Cost Function-4 can be selected to be the best with all error statistics, mean, median and standard deviation. The positioning error with Cost Function-4 is less than 185m in 80% of the estimates. This is an acceptable result for urban scenario.

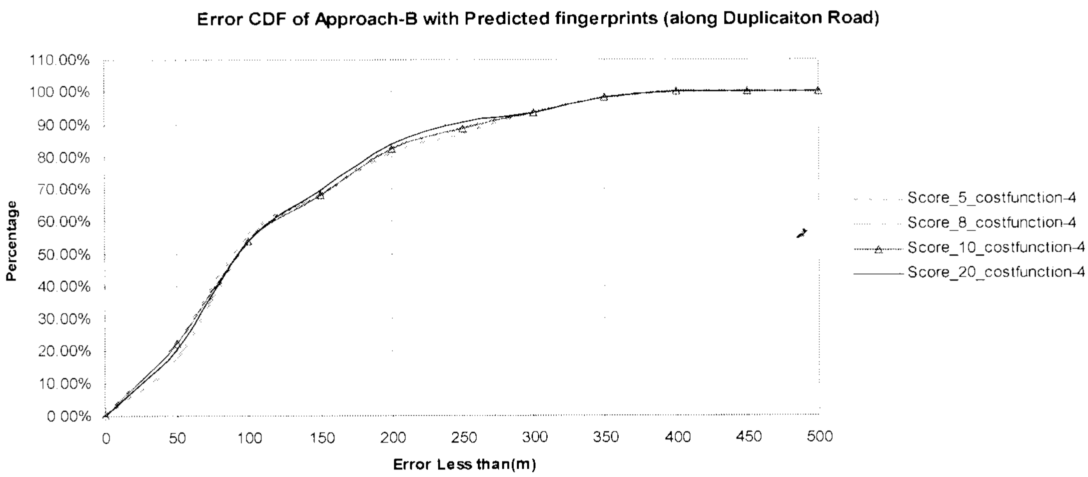


Figure 5.17: Error CDF of Approach-B with Predicted Fingerprints- Duplication Road

Furthermore, the performance of positioning approach-B with different K values does not show a clear distinction from each other. Among them, approach-B with K=20 and Cost Function-4 seems to be better.

From the comparison in Figure 5.18, approach-A with Cost Function-4 can be selected to be the best with predicted fingerprints along the duplication road giving a positioning error of 185m in 80% of the estimates and that of 235m in 90% of the estimates. This result is far better than the results of Cell_ID method for positioning.

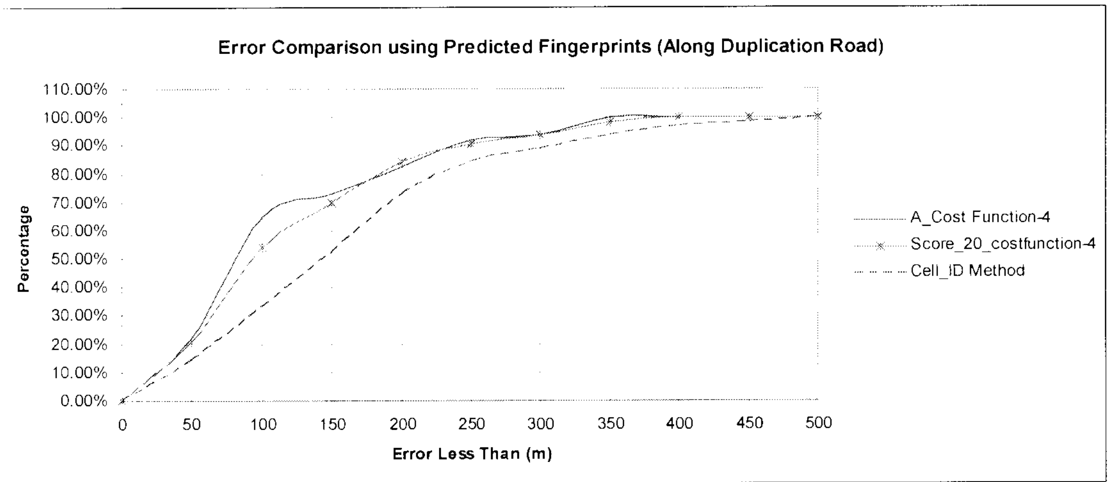


Figure 5.18: Error comparison using Predicted Fingerprints- Duplication Road

Table 5.6 gives a summary of the best results along Duplication road using a predicted database.

Table 5.6: Results summary with predicted fingerprints – Duplication Road

	With Predicted Fingerprints	
	A_Cost Function-4	**Cell_ID Method**
80% (m)	185	225
90% (m)	235	320
Maximum (m)	343	463
Minimum (m)	7	11
Average (m)	114	158
STD (m)	83	105
Median (m)	90	139

These results of approach-A with Cost Function-4 using a predicted database is referred to as results with predicted database along Duplication road in future sections.

5.2.2 Suburban

This section discusses the results of approach-A and approach-B for positioning using a predicted database along the roads in suburban environment.

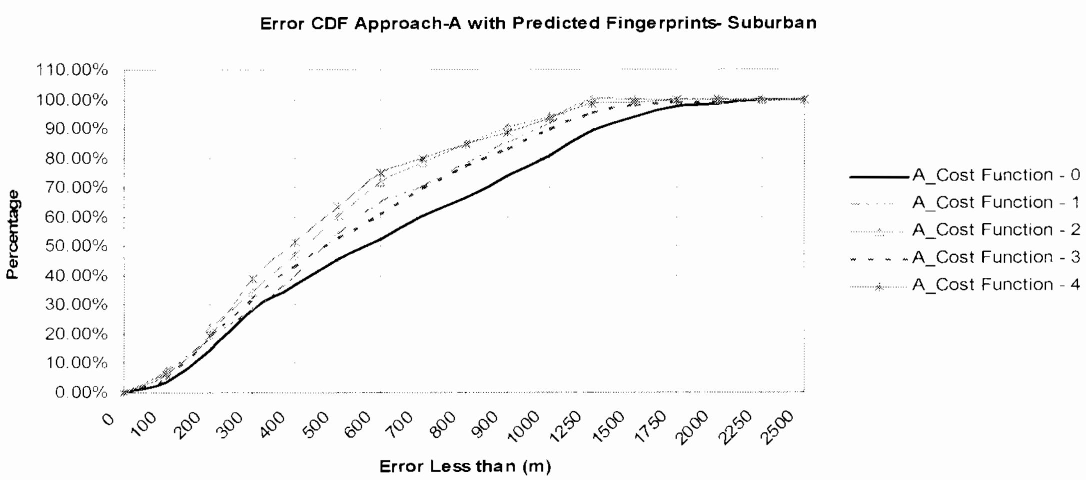


Figure 5.19: Error CDF of approach-A with predicted fingerprints - Suburban

It is clear from Figure 5.19 that the positioning error is less when using novel Cost Function, Cost Function-4, with approach- A in suburban.

Furthermore, when using approach-B with predicted fingerprints in suburban environment, the performance is better with K=8 and Cost Function-0. This is demonstrated in Figure 5.20.

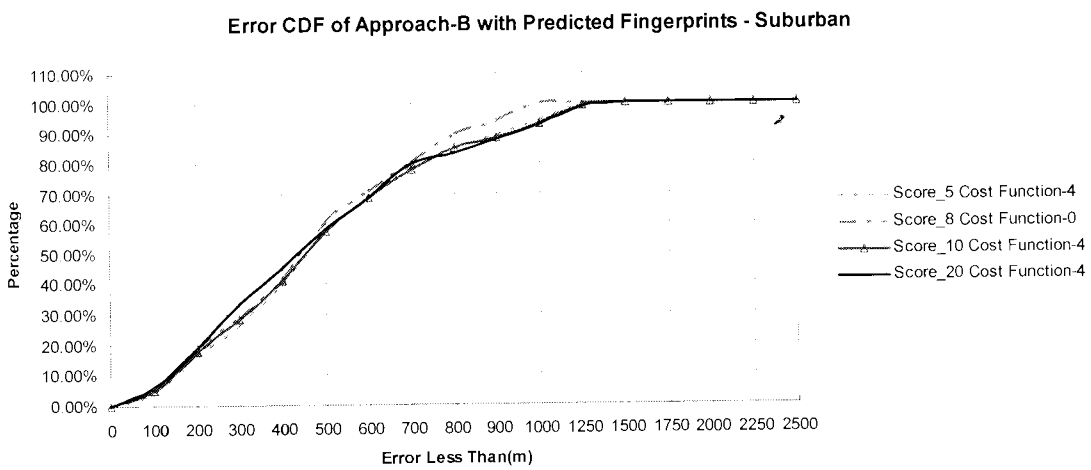


Figure 5.20: Error CDF of approach-B with predicted fingerprints - Suburban

Figure 5.21 shows a comparison between approach-A and approach-B with predicted fingerprints in suburban.

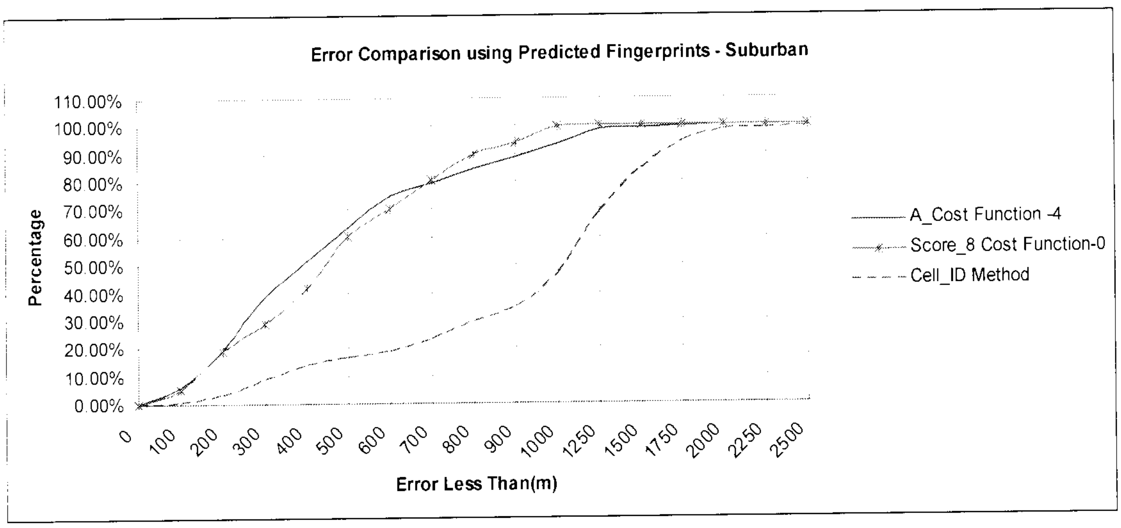


Figure 5.21: Error comparison using predicted fingerprints - Suburban

Apparently, approach-B with K=8 and Cost Function-0 has a better performance with an error less than 700m in 80% of the estimates while that is less than 800m in 90% of the estimates.

Table 5.7: Results summary with predicted fingerprints - Suburban

	With Predicted Fingerprints	
	Score_8_Cost Function-0	**Cell_ID Method**
80% (m)	700	1400
90% (m)	800	1675
Maximum (m)	1293	2699
Minimum (m)	24	31
Average (m)	482	1037
STD (m)	283	485
Median (m)	436	1030

Table 5.7 summarizes the error statistics of best approach using predicted database in suburban in comparison with those of Cell_ID method for positioning. The results with a predicted database for fingerprinting are far better than that of Cell_ID method for positioning in suburban environment.

The best results obtained with a predicted database using novel filtering method with K=8 and Cost Function-0 are referred to as the results of suburban environment with a predicted database in future sections.

5.2.3 Rural

The outcomes of same approach-A and approach-B for positioning in rural environment with a predicted database are described in this section.

The performance of approach –A is comparable for all Cost Functions, except Cost Function-1. Among them, Cost Function-4 can be selected as the best since it performs slightly better in higher percentages as can be seen by the Figure 5.22.

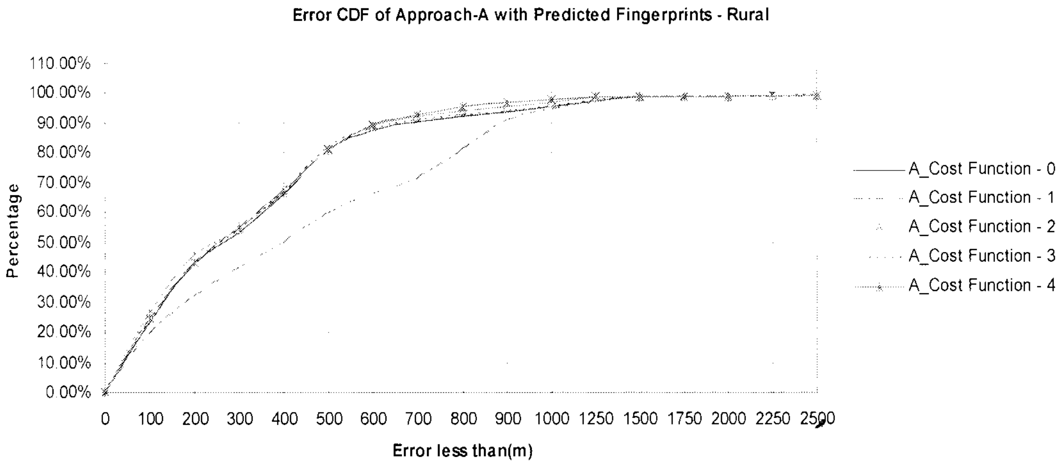


Figure 5.22: Error CDF of approach-A with predicted fingerprints - Rural

Figure 5.23 shows the positioning error CDF for approach-B with different K values using a predicted database. There also, the performance is comparable for K=8 and K=10.

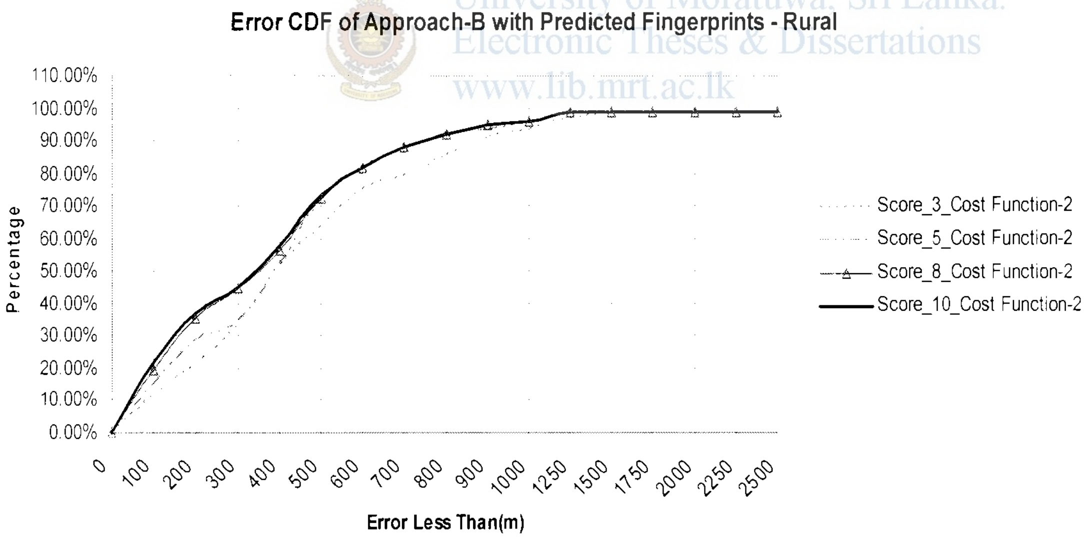


Figure 5.23: Error CDF of approach-B with predicted fingerprints - Rural

The comparison of two approaches shown in Figure 5.24 illustrates that, approach-A with Cost Function-4 has the highest performance with a positioning error less than 495m in 80% of the time while that is less than 600m in 90% of the time. This performance is remarkable for a rural environment.

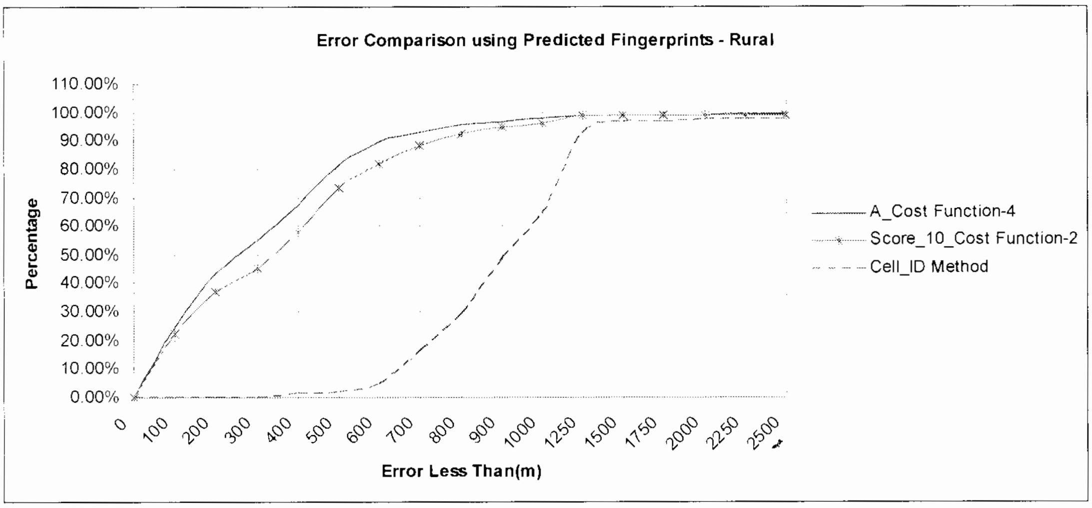


Figure 5.24: Error comparison using predicted fingerprints - Rural

The error statistics for the best approach using DCM with predicted database are shown in Table 5.8 compared with those of Cell_ID method for the same environment.

Table 5.8: Results summary with predicted fingerprints - suburban

	With Predicted Fingerprints	
	A_Cost Function-4	**Cell_ID Method**
80% (m)	495	1125
90% (m)	600	1200
Maximum (m)	3842	4949
Minimum (m)	3	398
Average (m)	331	1003
STD (m)	393	606
Median (m)	274	907

5.3 Performance of DCM with Measured Database

This section figures out the performance of fingerprinting method using a measured database in all three environments consider in this research.

5.3.1 Urban

A. Galle Road

Figure 5.25 illustrates the positioning error CDF of approach-A using a measured database along Galle road. It can be seen that all the Cost Functions have a similar performance while Cost Function-4 giving the best.

The performance of approach-B with different K values for measured data is shown in Figure 5.26. There, the performance of K=3 and K=5 are comparable with K=5 giving a slightly best values.

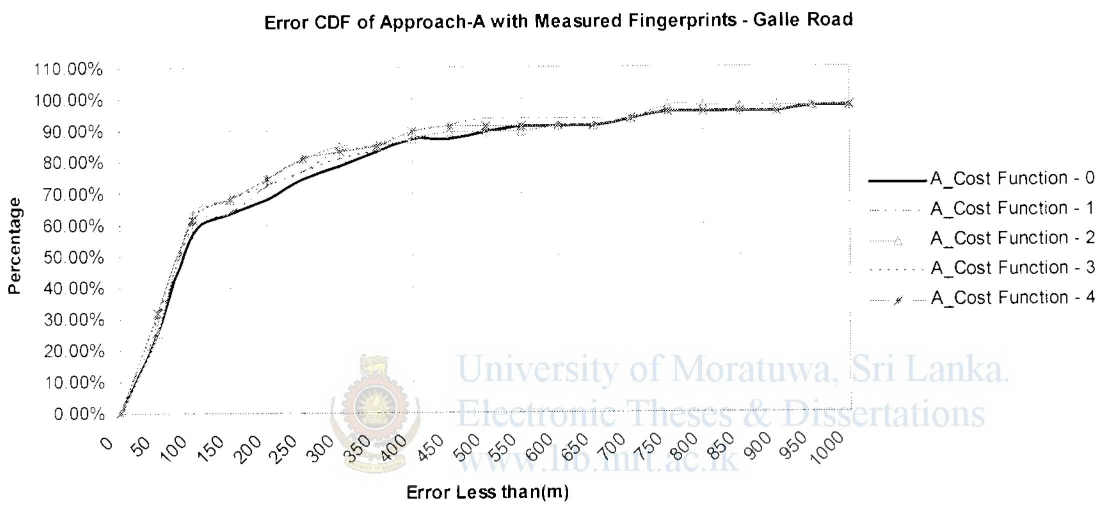


Figure 5.25: Error CDF of approach-A with measured fingerprints – Galle road

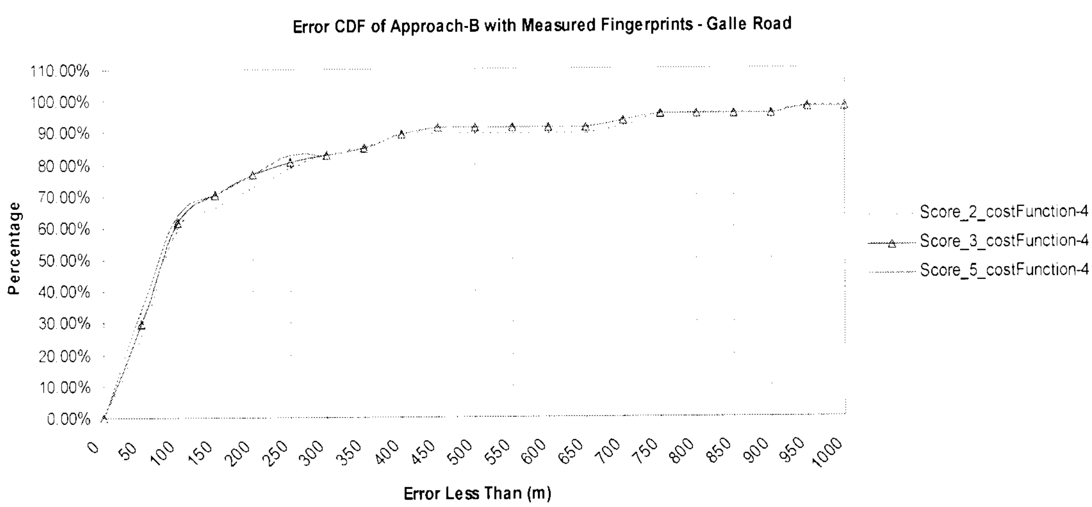


Figure 5.26: Error CDF of approach-B with measured fingerprints – Galle road

The performance comparison of approach-A and approach-B demonstrates that both approaches have a similar performance along Galle Road for measured fingerprints. Among them, approach-B with K=5 and Cost Function-4 has a slightly higher performance giving a positioning error of 225m in 80% of the estimates and that of 425m in 90% of the estimates.

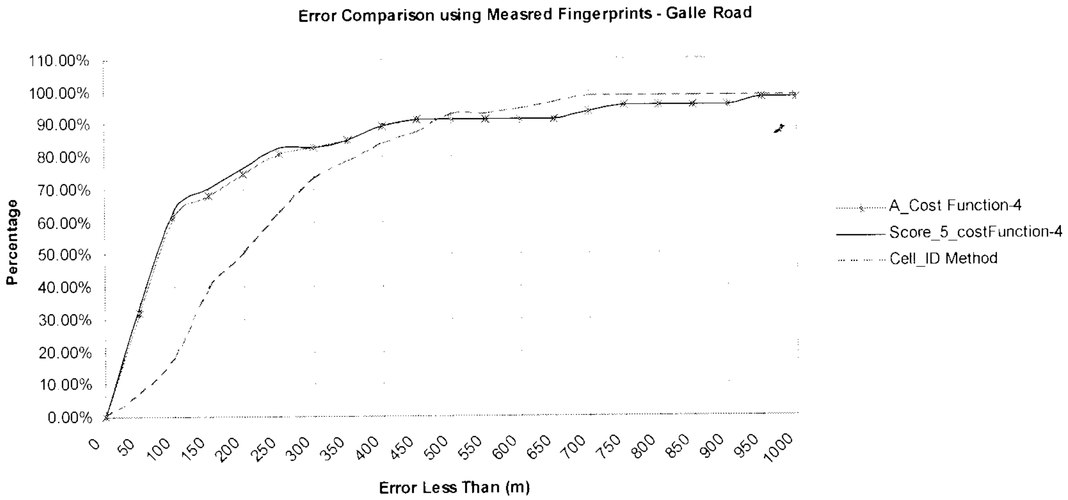


Figure 5.27: Error comparison using measured fingerprints – Galle Road

A summary of the error statistics of the best approach using measured fingerprints along Galle road is given in Table 5.9 in comparison with the Cell_ID method for positioning.

Table 5.9: Results summary with measured fingerprints – Galle road

	With Measured Fingerprints	
	Score_5-Cost Function-4	**Cell_ID Method**
90% (m)	425	475
80% (m)	225	370
Maximum (m)	2070	1020
Minimum (m)	13	27
Average (m)	188	245
STD (m)	341	185
Median (m)	67	200

B. Duplication Road

The error performance of positioning approach-A using measured fingerprints along Duplication road is shown in Figure 5.28. It appears that, Cost Function-3 has a better performance over other in approach-A giving a positioning error less than 118m in 80% of the estimates.

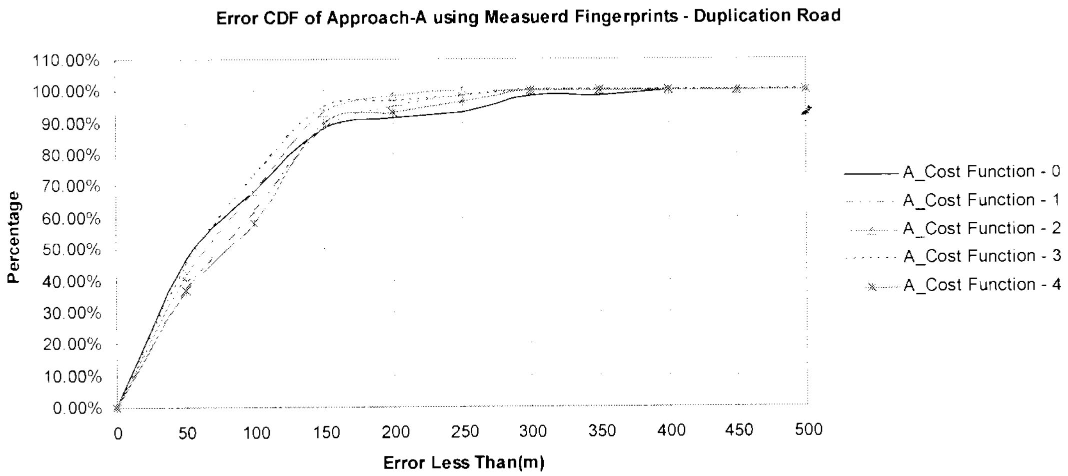


Figure 5.28: Error CDF of approach-A with measured fingerprints – Duplication road

Positioning approach-B for different K values has a similar performance as shown in Figure 5.29 and K=5 can be selected as the best among them.

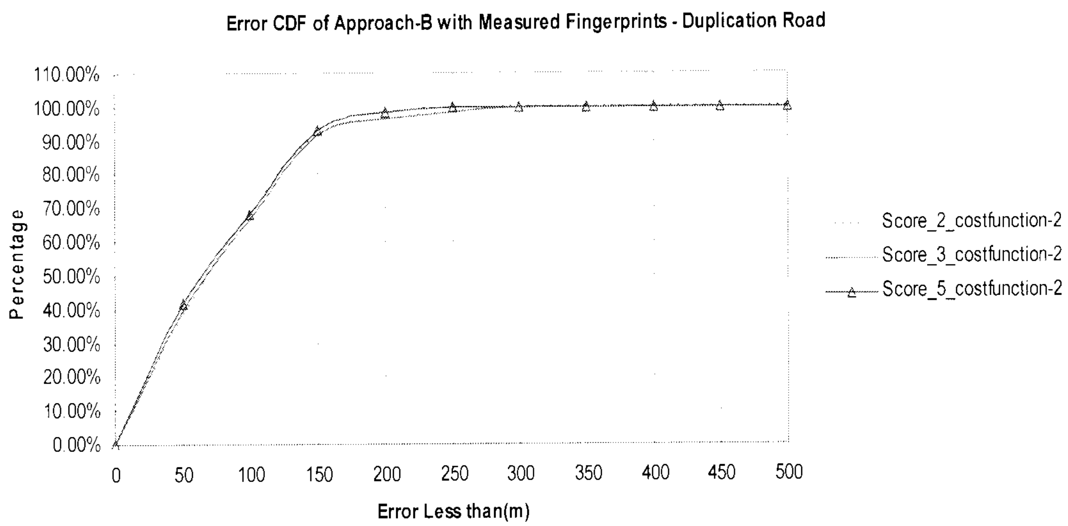


Figure 5.29: Error CDF of approach-B with measured fingerprints – Duplication road

Figure 5.30 illustrates a comparison of positioning error of two approaches together with that of Cell_ID method. It appears that, approach-A with Cost Function-3 performs well with a positioning error less than 118m in 80% of the estimates and 135m in 90% of the estimates. These results using a measured database for DCM is far better than those of basic Cell_ID method.

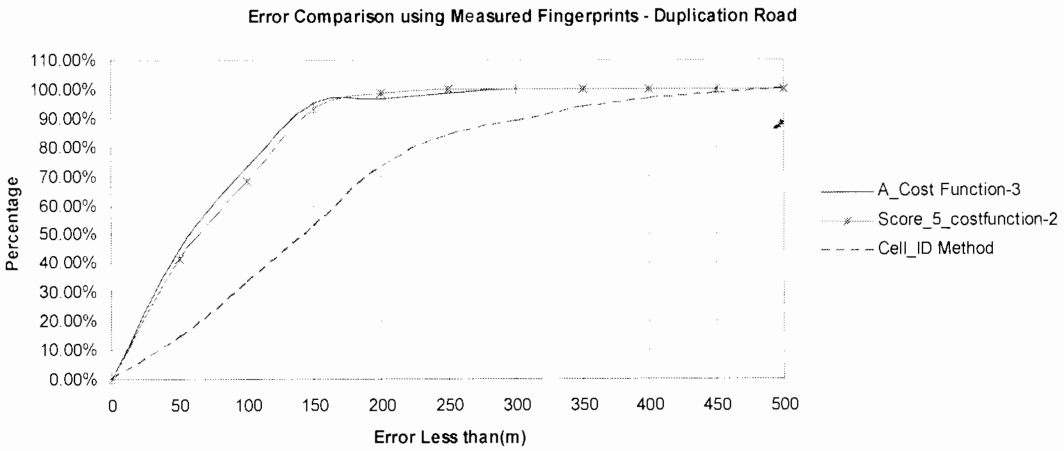


Figure 5.30: Error comparison using measured fingerprints – Duplication road

Performance comparison of DCM with measured database and Cell_ID method along Duplication road is shown in Table 5.10.

Table 5.10: Results summary with measured fingerprints – Duplication road

	With Measured Fingerprints	
	A_Cost Function-3	**Cell_ID Method**
80% (m)	118	225
90% (m)	135	320
Maximum (m)	256	463
Minimum (m)	4	11
Average (m)	72	158
STD (m)	54	105
Median (m)	56	139

Approach-A with Cost Function-3, which gave the best results with a measured database along duplication road, is referred to as the results of DCM with measured database along Duplication road in future sections.

5.3.2 Suburban

According to Figure 5.31, which shows the error CDF of approach-A using a measured database along roads in suburban environment, Cost Function-1 and Cost Function-2 has a comparable performance while Cost Function-4 has a decreasing performance towards higher percentages. Among them, Cost Function-2 can be selected to be the best, when considering other statistics as mean, median and standard deviation.

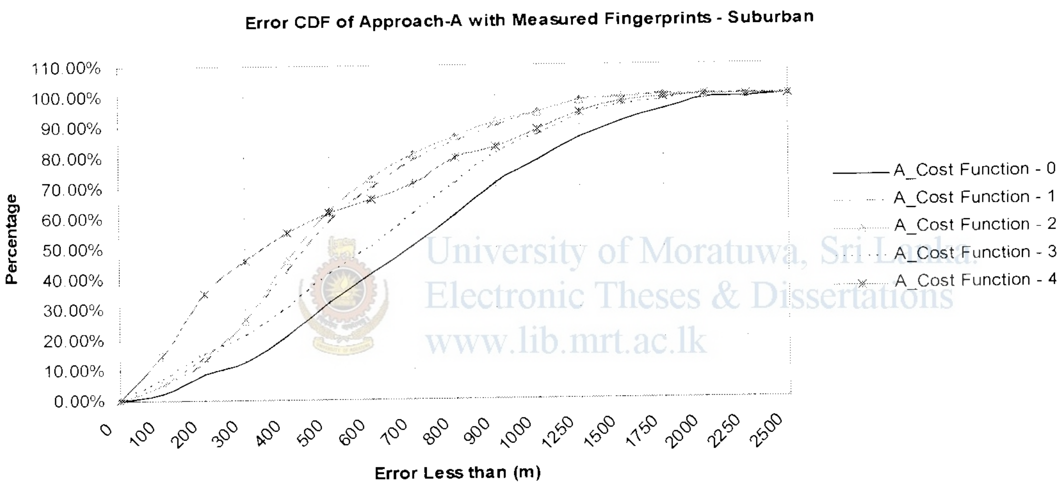


Figure 5.31: Error CDF of approach-A with measured fingerprints - Suburban

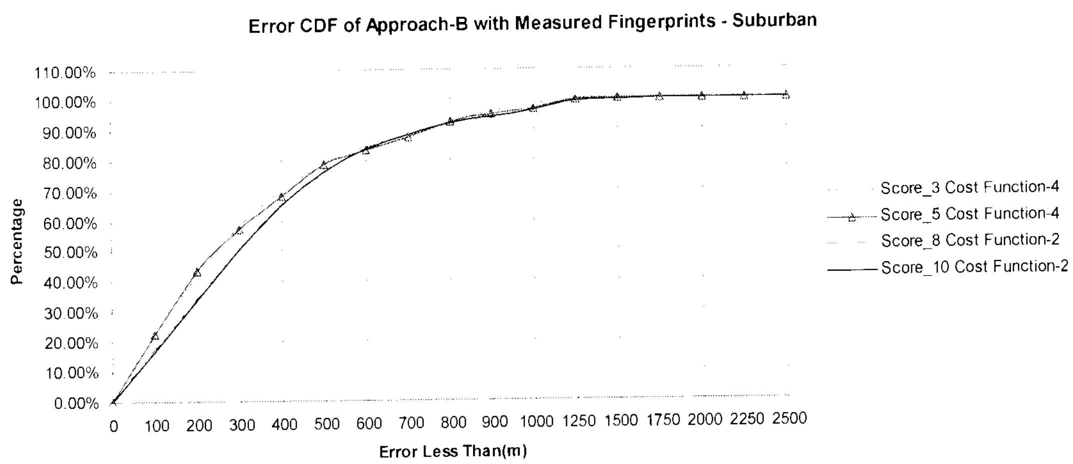


Figure 5.32: Error CDF of approach-B with measured fingerprints - Suburban

Approach-B with different K values also has comparable performances and among all, K=3 with Cost Function-4 can be selected to be the best.

Figure 5.33 demonstrates a comparison between the best methods in approach-A and approach-B. Clearly, approach-B with K=3 and Cost Function-4 gives a higher performance with a positioning error less than 525m in 80% of the estimates and 750m in 90% of the estimates. This is a poor performance for suburban environment.

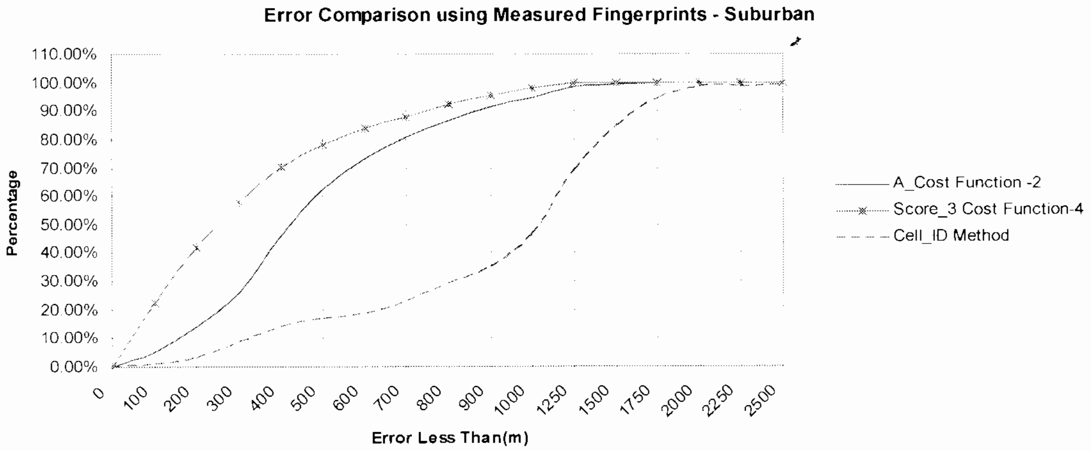


Figure 5.33: Error comparison using measured fingerprints - Suburban

Table 5.11 summarizes the error statistics of best methods in suburban in comparison with that of Cell_ID method.

Table 5.11: Results summary with measured fingerprints - Suburban

	With Measured Fingerprints	
	Score_3-Cost Function-4	**Cell_ID Method**
80% (m)	525	1400
90% (m)	750	1675
Maximum (m)	1218	2699
Minimum (m)	5	31
Average (m)	325	1037
STD (m)	266	485
Median (m)	261	1030

5.3.3 Rural

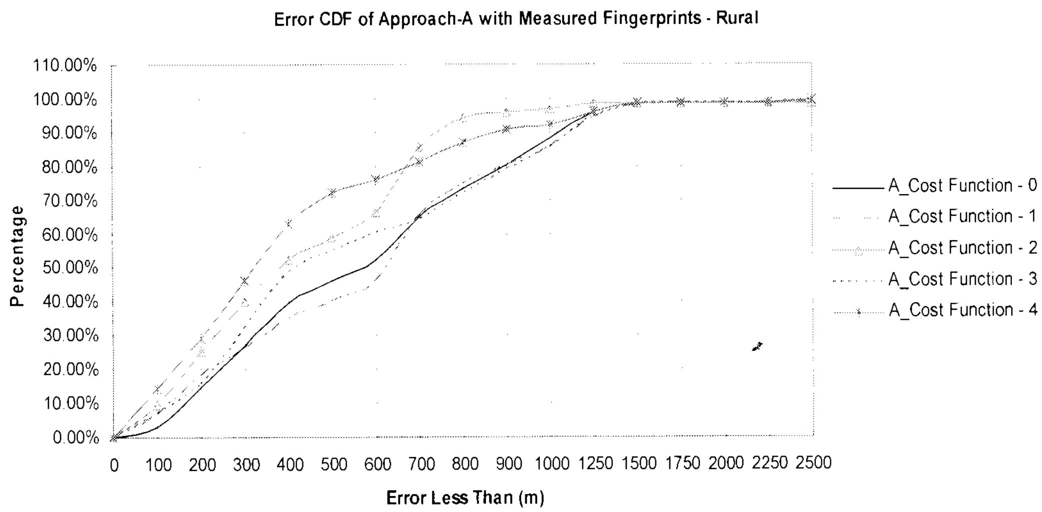


Figure 5.34: Error CDF of approach-A with measured fingerprints - Rural

It can be seen from Figure 5.34 that the performance of DCM with approach-A using a measured databse is competitive with Cost Function-2 and Cost Function-4. Consequently, Cost Function-2 can be taken as the best as its performance increases rapidly at higher percentages while the performance of Cost Function-4 decreases.

The performance demonstration in Figure 5.35 says that, approach-B with different K values has comparable performance for all K values and among them, K=2 with Cost Function-2 can be selected to be the best.

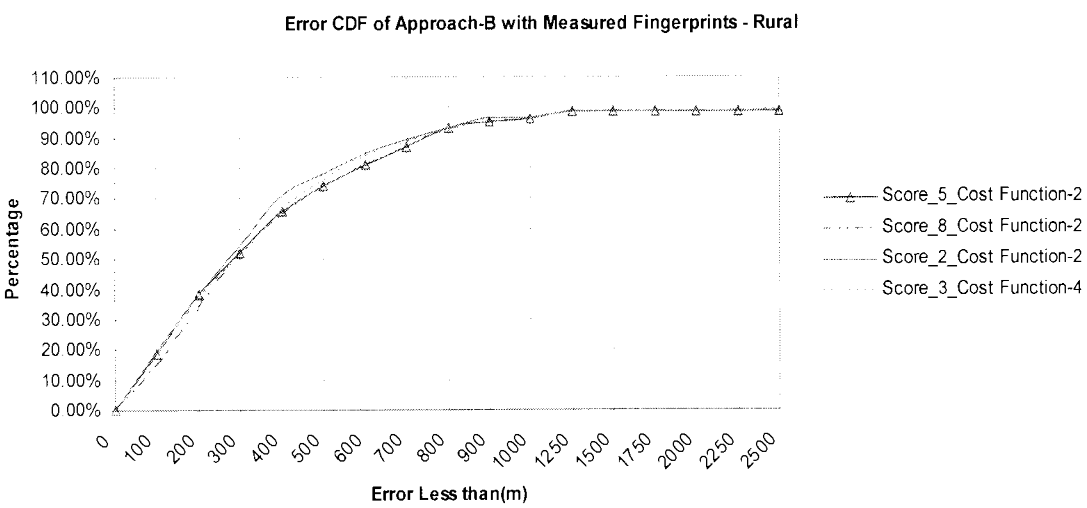


Figure 5.35: Error CDF of approach-B with measured fingerprints - Rural

According to the comparison of approach-A and approach-B in Figure 5.36, approach-B with K=2 and Cost Function-2 is best for rural environment with measured database.

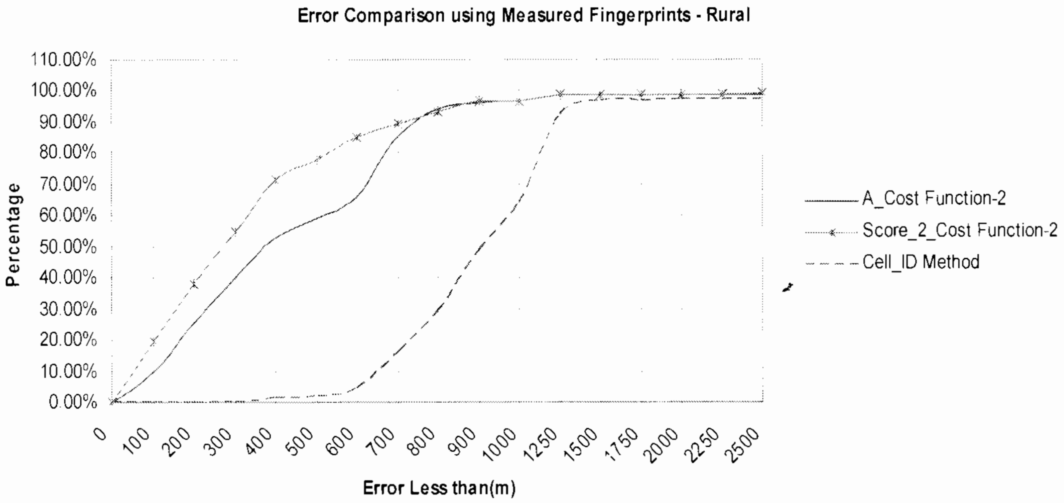


Figure 5.36: Error comparison using measured fingerprints - Rural

Table 5.12 summarizes the accuracy statistics of positioning in rural environment using a measured database in comparison with those of Cell_ID method.

Table 5.12: Results summary with measure fingerprints - Rural

	With Measured Fingerprints	
	Score_2-Cost Function-2	**Cell_ID Method**
80% (m)	540	1125
90% (m)	700	1200
Maximum (m)	3424	4949
Minimum (m)	3	398
Average (m)	351	1003
STD (m)	384	606
Median (m)	260	907

Performance Comparison using Predicted and Measured Databases

s section is devoted for the performance comparison of Database Correlation thod using measured database and a predicted database in three different ronments, urban, suburban and rural. Furthermore, the performance is compared h that of basic Cell_ID method for positioning.

.1 Urban

alle Road

sitioning error comparison, using measured and predicted fingerprints, along Galle ad is shown in Figure 5.37. It appears that, in lower percentages, the performance is tter with measured fingerprints while that is better with predicted fingerprints in rcentages above 90%. Hence, it can be stated that the DCM with predicted gerprints has a potential for better accuracies along Galle road.

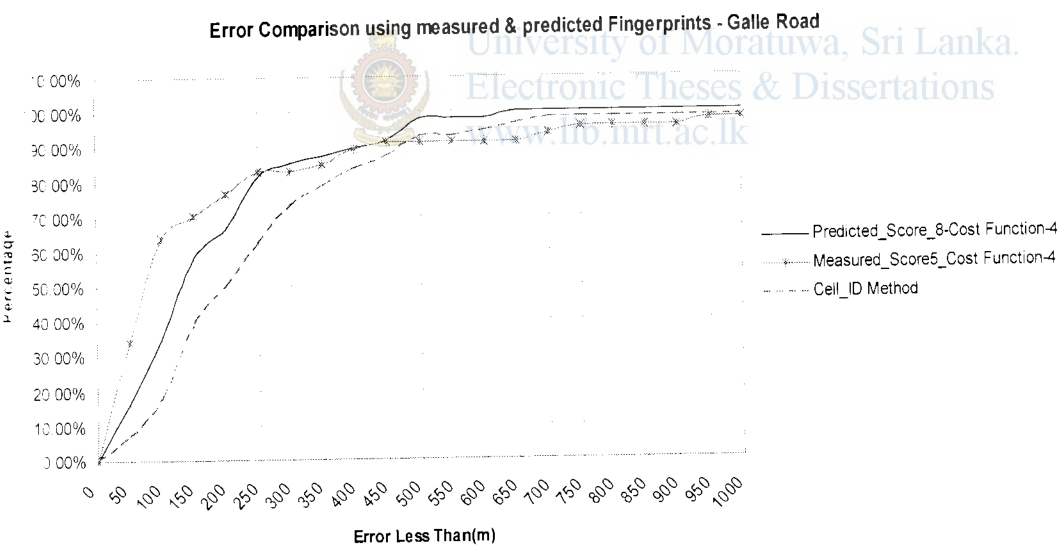


Figure 5.37: Error comparison using measured and predicted databases – Galle road

omparison of error statistics, such as maximum, minimum, average and median, for easured and predicted databases is shown in Table 5.13.

Table 5.13: Performance comparison using measured and predicted fingerprints – Galle road

	With Measured Fingerprints	With Predicted Fingerprints	Cell_ID Method
	Score_5-Cost Function-4	Score_8-Cost Function-4	
90% (m)	425	400	475
80% (m)	225	245	370
Maximum (m)	2070	616	1020
Minimum (m)	13	31	27
Average (m)	188	173	245
STD (m)	341	138	185
Median (m)	67	130	200

B. Duplication Road

The performance is far better with a measured database along Duplication road as it appears in Figure 5.38. Further, the performance of Cell_ID method is inferior to both of other methods.

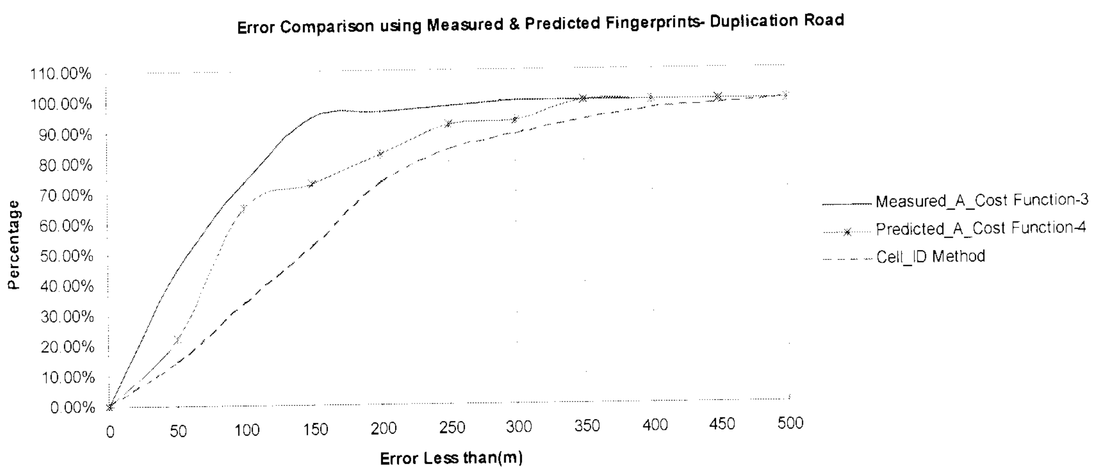


Figure 5.38: Error comparison using measured and predicted fingerprints – Duplication road

Table 5.14 gives a comparison of positioning error statistics of DCM with measured and predicted databases.

Table 5.14: Performance comparison using measured and predicted fingerprints – Duplication road

	With Measured Fingerprints A_Cost Function-3	With Predicted Fingerprints A_Cost Function-4	Cell_ID Method
80% (m)	118	185	225
90% (m)	135	235	320
Maximum (m)	256	343	463
Minimum (m)	4	7	11
Average (m)	72	114	158
STD (m)	54	83	105
Median (m)	56	90	139

5.4.2 Suburban

Comparison shown in Figure 5.39 demonstrates that the performance of DCM with a measured database is superior to that with a predicted database in suburban. However, both perform comparatively at higher percentages. The performance of Cell_ID method is poorer than other two methods.

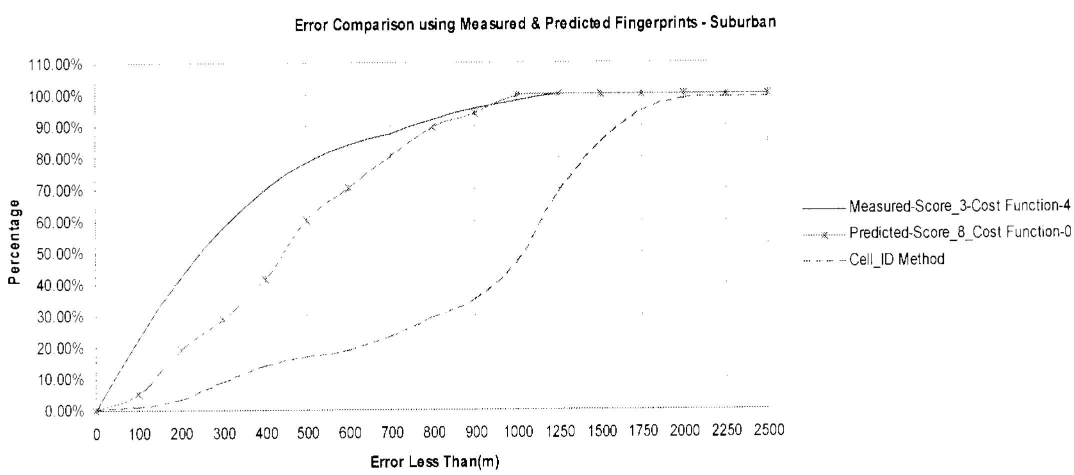


Figure 5.39: Error comparison using measured and predicted fingerprints - suburban

Table 5.15 gives a summary of comparison shown in Figure 5.39.

Table 5.15: Performance comparison using measured and predicted fingerprints - suburban

	With Measured Fingerprints	With Predicted Fingerprints	Cell_ID Method
	Score_3-Cost Function-4	Score_8_Cost Function-0	
80% (m)	525	700	1400
90% (m)	750	800	1675
Maximum (m)	1218	1293	2699
Minimum (m)	5	24	31
Average (m)	325	482	1037
STD (m)	266	283	485
Median (m)	261	436	1030

5.4.3 Rural

Rural environment exhibits a remarkable performance with a predicted database which is almost comparable to the performance with measured database.

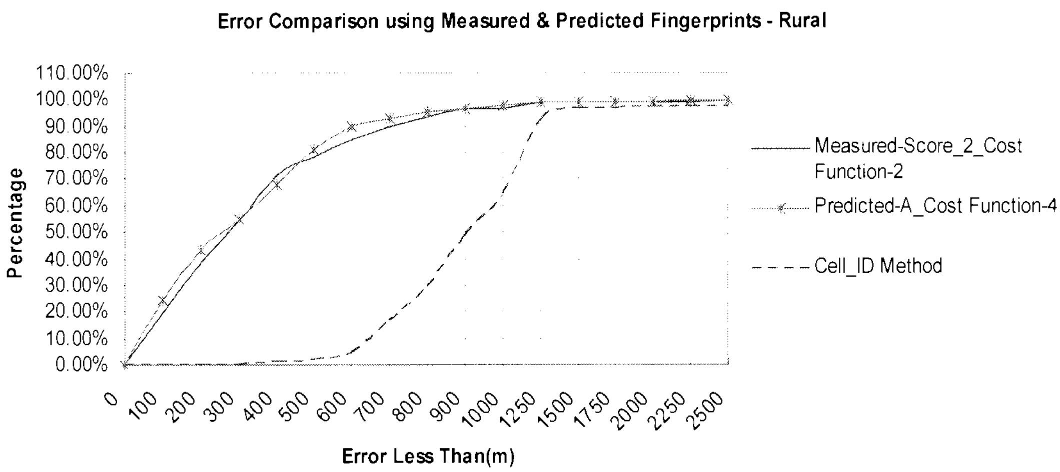


Figure 5.40: Error comparison using measured and predicted fingerprints - Rural

When considering the 80^{th} percentile and 90^{th} percentile the performance of predicted database is superior to that with measured database. This is due to the lower deviation between predictions and measurements in rural environment as pointed out in Section 5.1. In addition, the performance of DCM with measured and predicted databases is far better than that of Cell_ID method.

Table 5.16 summarizes the performance shown in Figure 5.39 comparing with Cell_ID method.

Table 5.16: Performance comparison using predicted and measured fingerprints - Rural

	With Measured Fingerprints	**With Predicted Fingerprints**	**Cell_ID Method**
	Score_2-Cost Function-2	**A_Cost Function-4**	
80% (m)	540	495	1125
90% (m)	700	600	1200
Maximum (m)	3424	3842	4949
Minimum (m)	3	3	398
Average (m)	351	331	1003
STD (m)	384	393	606
Median (m)	260	274	907

5.5 Performance of different Calibration Techniques

According to the deviation analysis in Section 5.1, there exist a considerable deviation between measured and predicted signal strengths in urban area while the deviation is moderate in sub urban and small in rural. Hence, calibration techniques were applied for minimizing the deviations such that the performance of database correlation method is enhanced.

Accordingly, the performance after calibration with different techniques is analyzed in this section in order to come up with a best technique for calibration.

5.5.1 Neural Network Techniques

The performance of database correlation method after calibrating the predictions using different neural networks is analyzed for all three environments.

Urban - Galle Road

Five different neural networks were tested by training with different algorithms, as described in Section 3.4, with the data along Galle road. It appears that the neural network trained to output the error in signal strength loss has a potential for better performance in calibration (Figure 5.41). The training algorithm used to train this neural network for cells is BFGS algorithm.

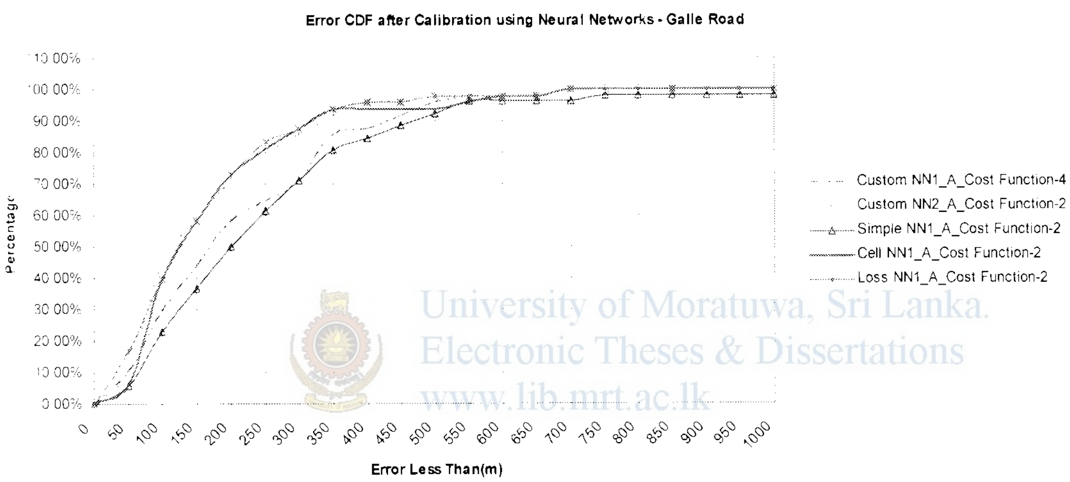


Figure 5.41: Positioning error CDF after calibration using different neural networks – Galle road

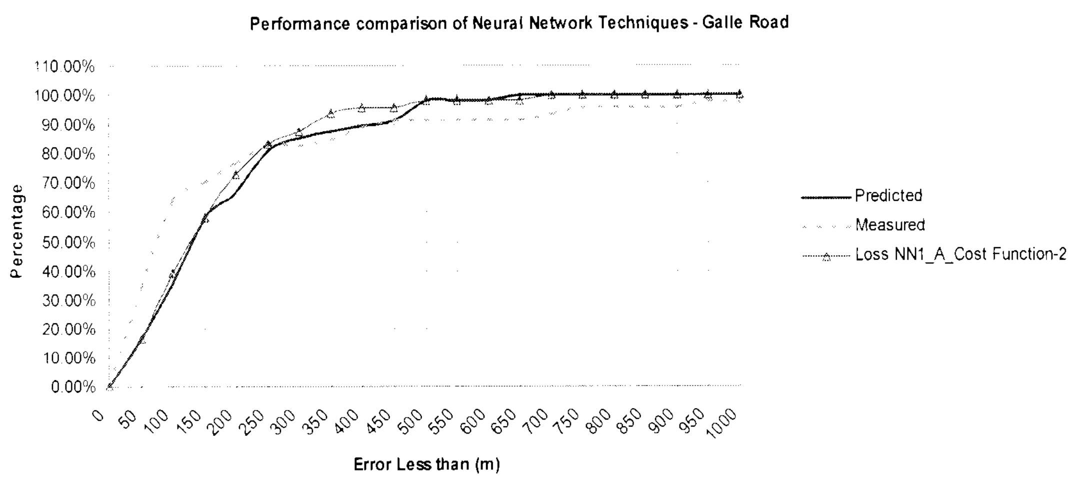


Figure 5.42: Performance comparison of neural network techniques –Galle road

Figure 5.42 shows a comparison of the best performance obtained after calibration using neural networks, with the performance using measured and predicted databases.

Apparently, the neural network calibration has improved the performance along Galle road, but it is inferior to the performance using measured data at lower percentages.

B. Urban – Duplication Road

Figure 5.43 shows a performance comparison of calibrations using neural network trained to output the error in signal strength loss with different training algorithms and training parameters. It seems that, LossNN1_2, which was trained by particle swarm optimization algorithm type-2, has given a better performance using positioning approach-A with Cost Function-4.

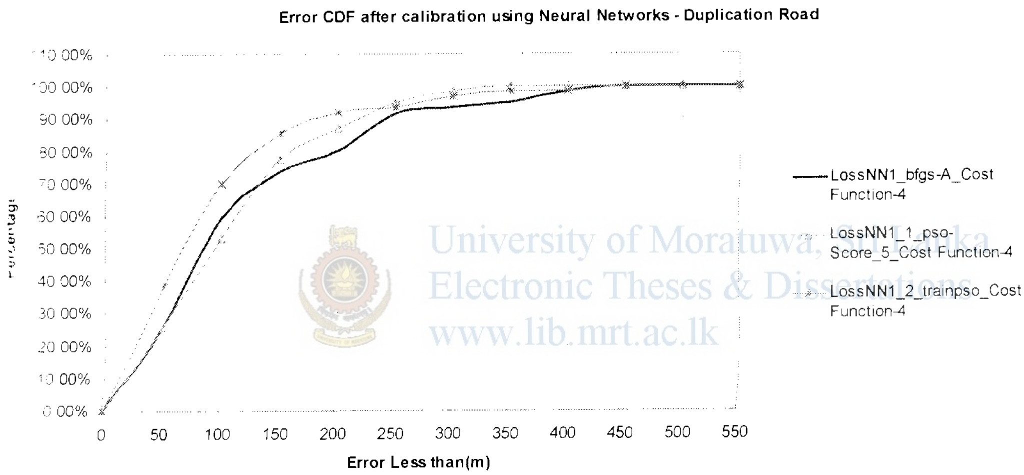


Figure 5.43: Positioning error CDF after calibration using different neural networks – Duplication road

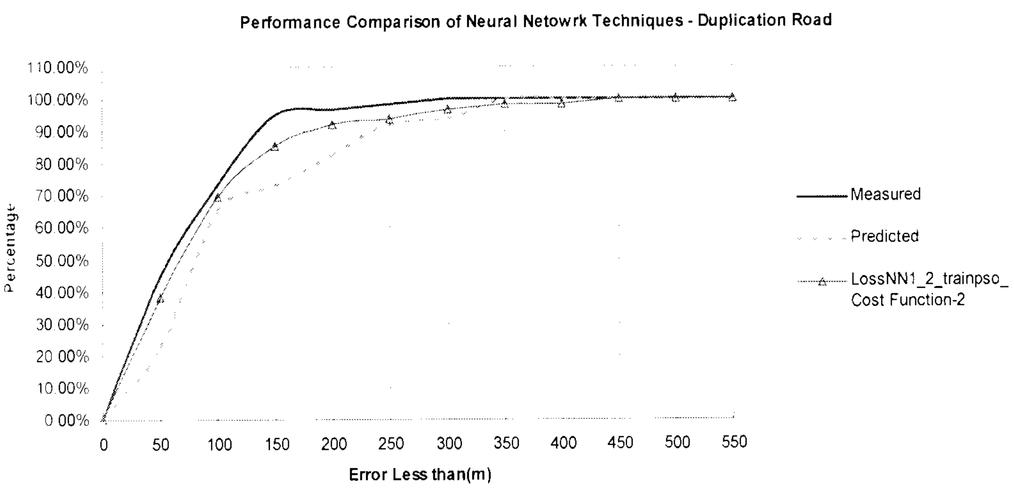


Figure 5.44: Performance comparison of neural network techniques – Duplication road

According to the comparison in Figure 5.44, the neural network calibration has improved the performance of DCM, however that is poorer than the performance with a measured database along Duplication road.

(*Suburban*

Among four different forms of LossNN1, the second form has shown superior in suburban and the positioning approach-A with Cost Function-2 is the one which matches that calibration. The training algorithm used for training of LossNN1_2 is particle swarm optimization common type.

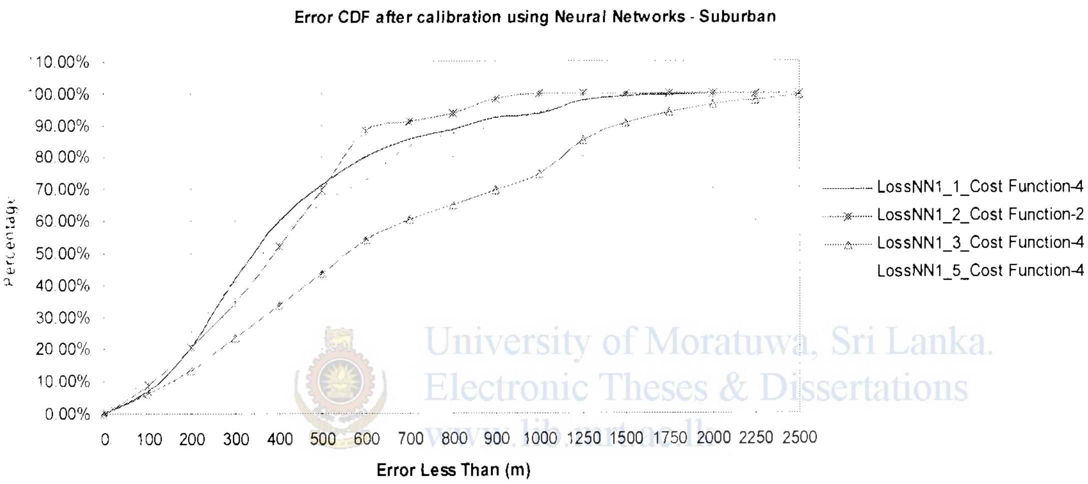


Figure 5.45: Positioning error CDF after calibration using different neural networks - Suburban

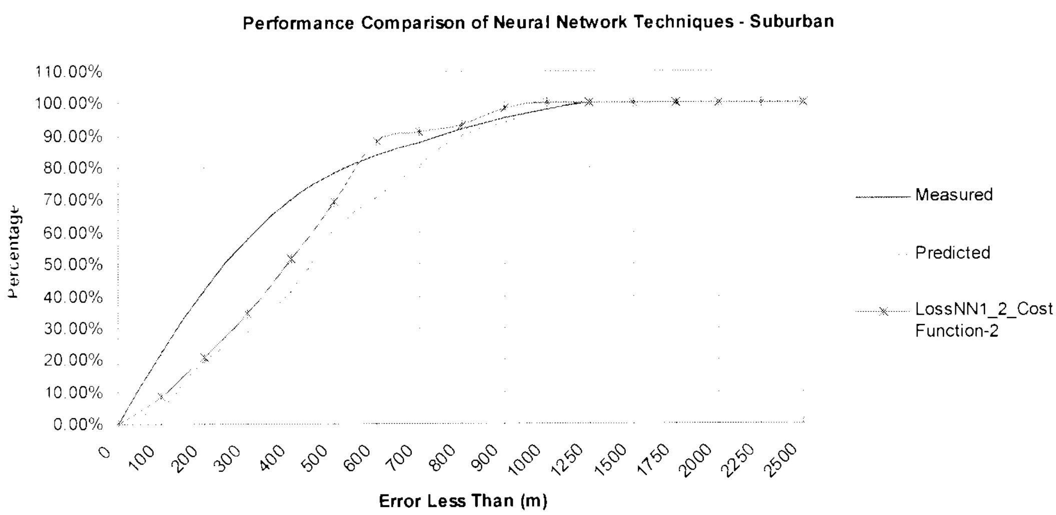


Figure 5.46: Performance comparison of neural network techniques - Suburban

Figure 5.46 demonstrates that the performance after calibration is better than before calibration as well as it is superior to the performance using a measured database in higher percentages.

D) Rural

Two forms of LossNN1 were tested for calibration in rural environment, in which the first form, LossNN1_1, trained using particle swarm optimization common type algorithm, has succeeded in calibration. The best performance in positioning error is 585m in 80% of the estimates, which is superior to the performance of suburban environment as well.

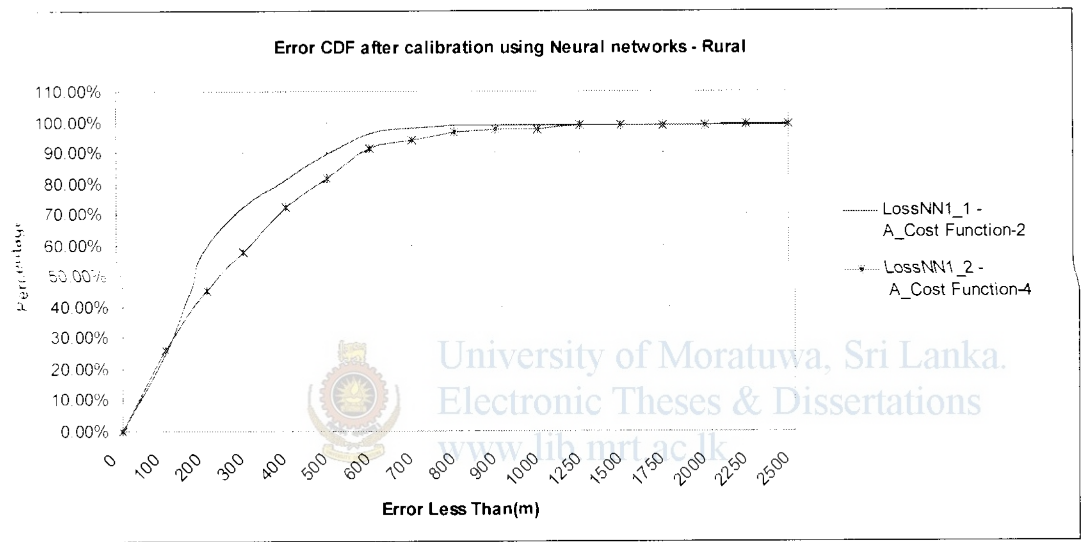


Figure 5.47: Positioning error CDF after calibration using different neural networks - Rural

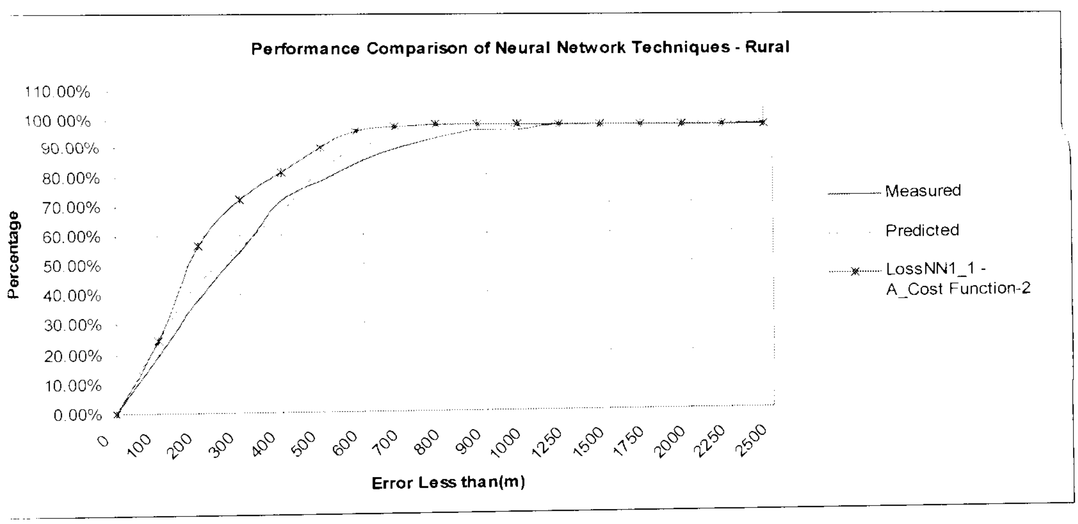


Figure 5.48: Performance comparison of neural network techniques - Rural

\ remarkable improvement can be seen in performance after calibration using neural ıetworks in rural environment. It is a cut above for the performance using both neasured and predicted data.

5.5.2 Curve Fitting Techniques

urve fitting is the second approach used in calibration of predicted data using a lesser number of measured data. Calibration process using curve fitting was carried out as described in Section 3.4 and the results of that work are demonstrated in this section.

i Urban – Galle Road

Figure 5.49 illustrates the error performance of positioning algorithms after calibrating the predicted data using curve fitting methods along Galle road. Clearly, the curvefitting_B, which uses Bi-square weights fitting method, has given better performance over curvefitting_A, which uses Least Absolute Residual fitting method.

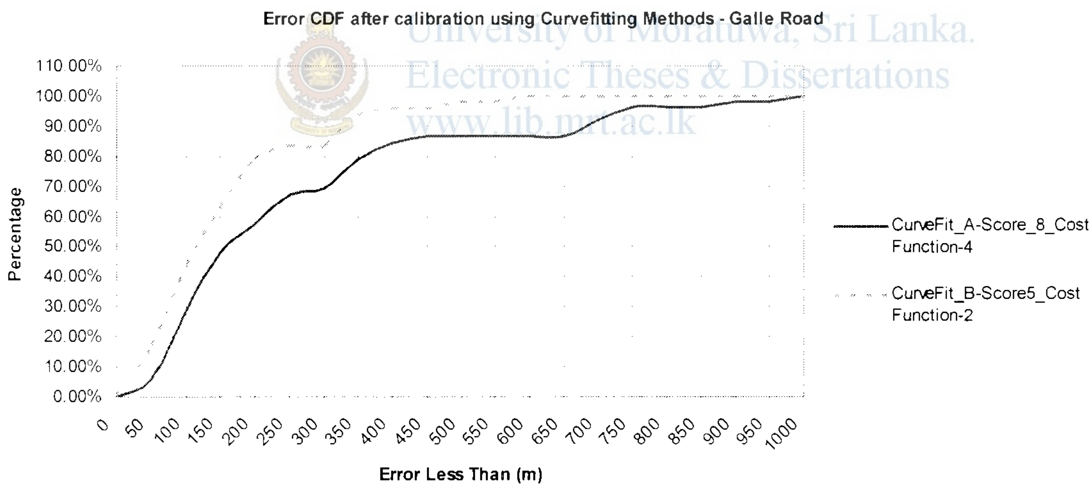


Figure 5.49: Positioning error CDF after calibration using curve fitting methods – Galle road

The performance comparison shown in Figure 5.50 illustrates that, positioning approach-B with K=5 and Cost Function-2 after calibration with curvefitting_B has a slightly improved performance over using the predicted data along Galle road.

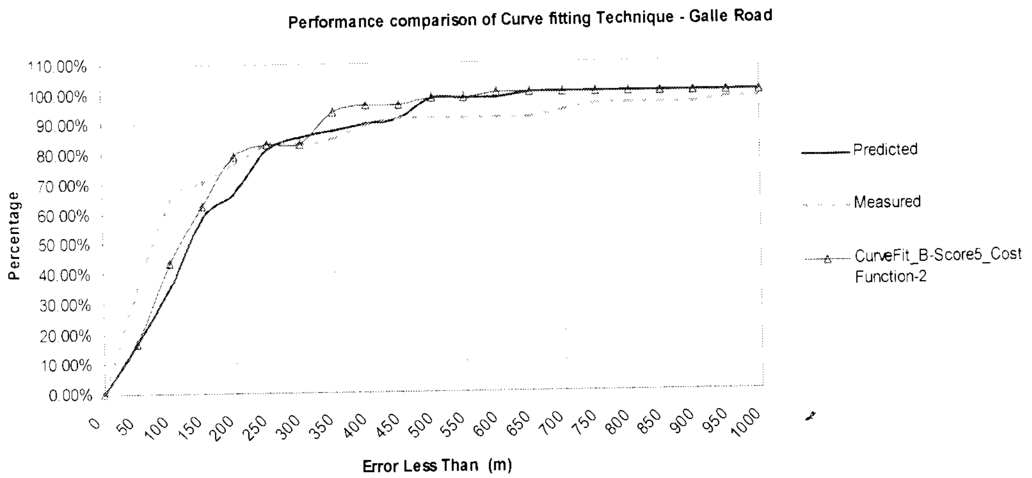


Figure 5.50: Performance comparison of curve fitting techniques – Galle Road

B Urban – Duplication Road

According to Figure 5.51, curvefitting_B performs well in calibration over curvefitting_A , proving the robustness of bi-square weights fitting method.

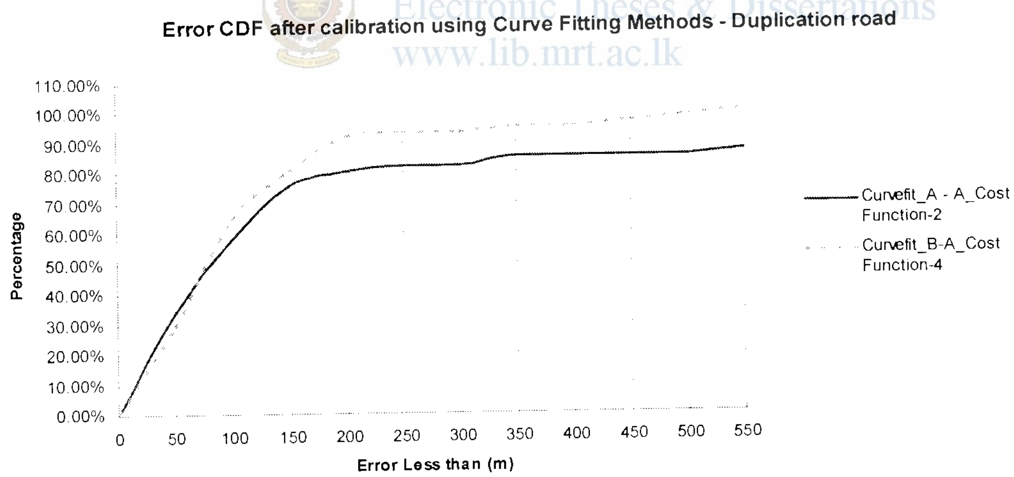


Figure 5.51: Positioning error CDF after calibration using curve fitting methods – Duplication road

The comparison in Figure 5.52 demonstrates that the performance after calibration with curve fitting is superior to that using predicted data while that is inferior to the performance using measured data.

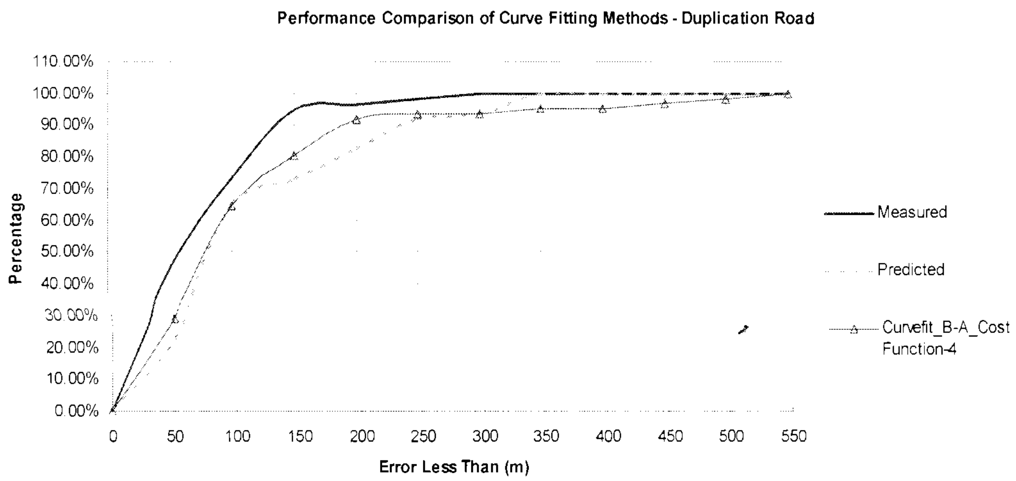


Figure 5.52: Performance comparison of curve fitting methods – Duplication road

C. Suburban

Figure 5.53 illustrates the performance of two curve fitting methods, in which, curvefitting_B has an improved performance in calibration along roads in suburban.

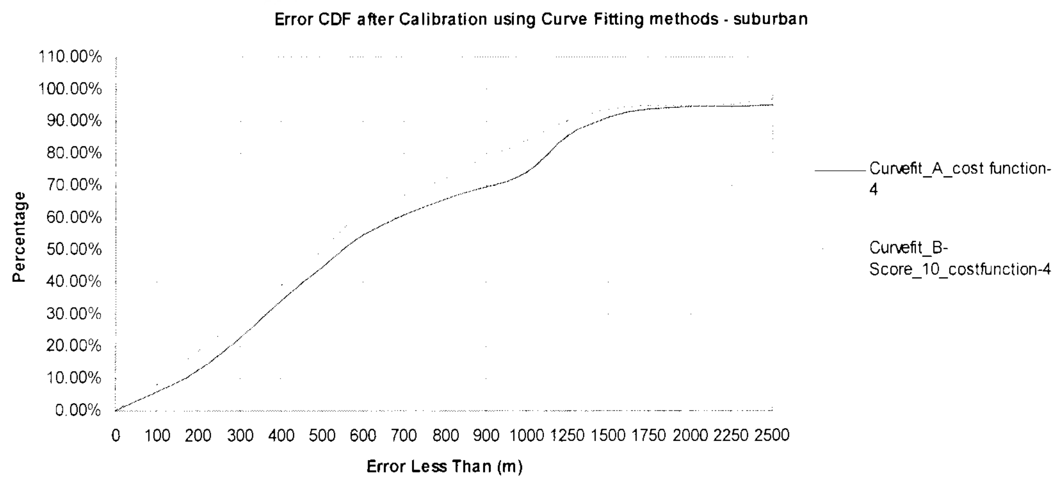


Figure 5.53: Positioning error CDF after calibration using curve fitting methods – Suburban

However, the performance of curvefitting_B is inferior to the performances using both measured and predicted databases. Hence, curve fitting would not be a solution for calibration of predictions in suburban environment.

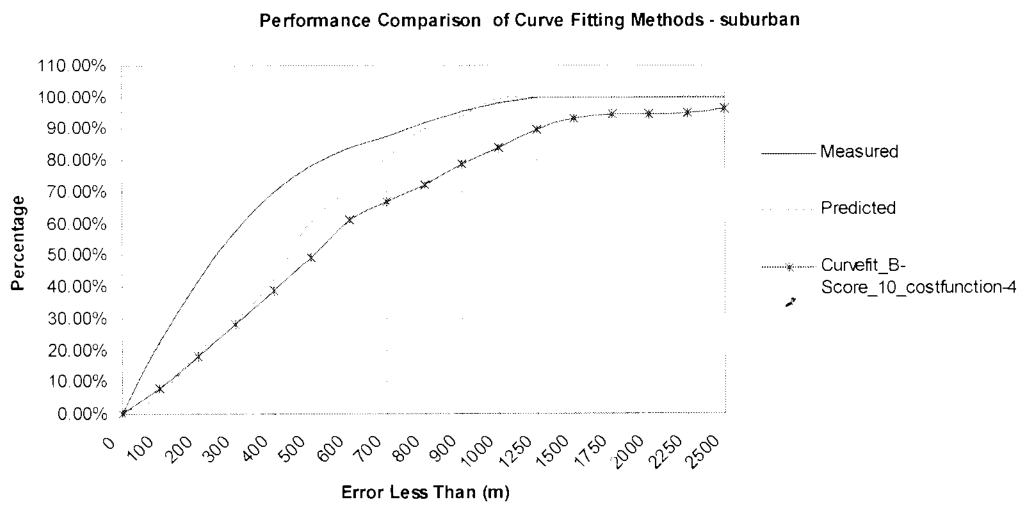


Figure 5.54: Performance comparison of curve fitting methods - Suburban

D. *Rural*

Apparently, the performance of both curve fitting methods for calibration is alike in rural environment. Further, the performances of them are comparable to those using measured and predicted databases too. These are illustrated in Figure 5.55 and 5.56 respectively.

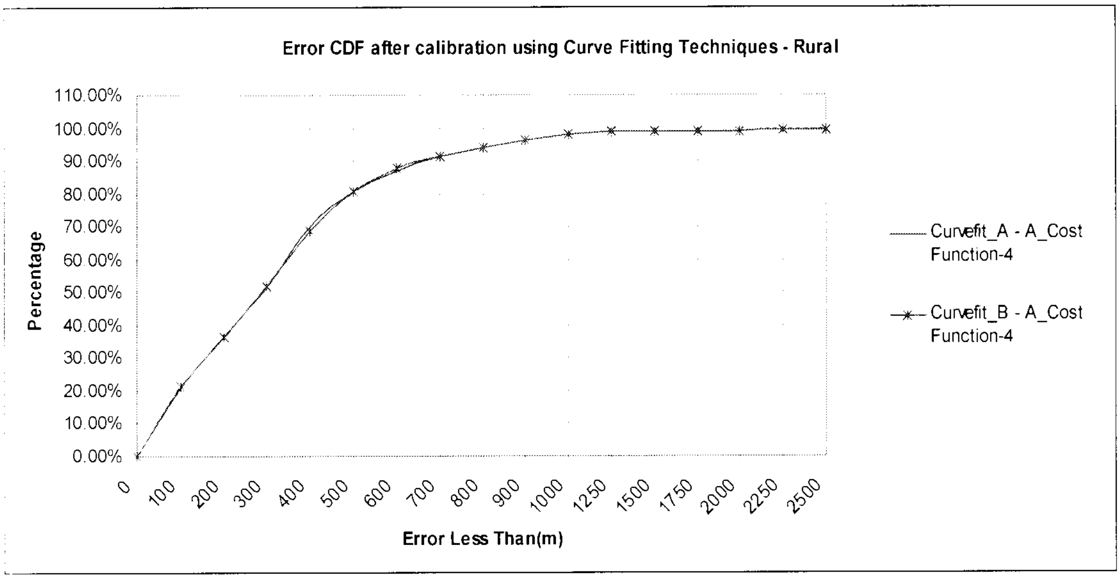


Figure 5.55: Positioning error CDF after calibration using curve fitting methods – Rural

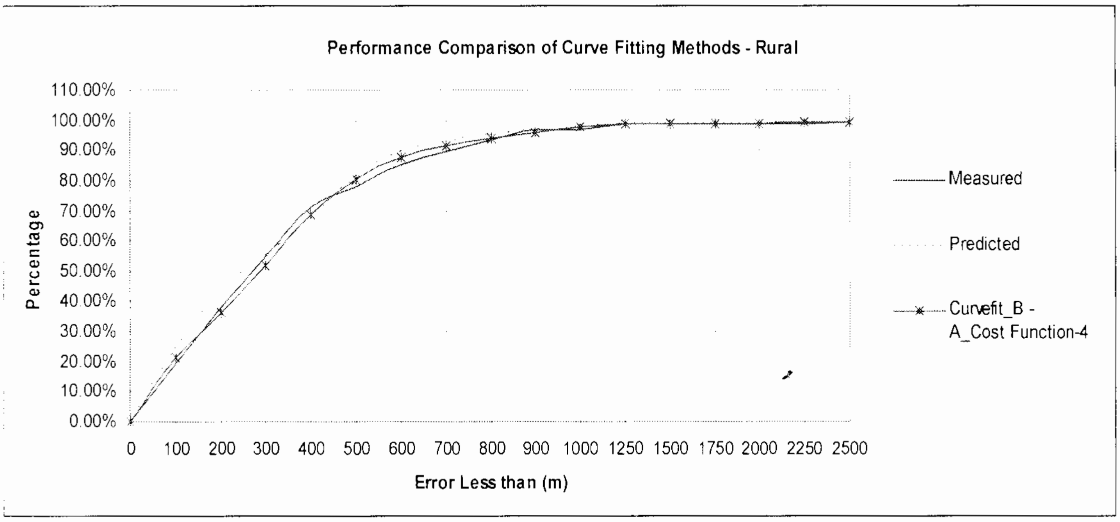


Figure 5.56: Performance comparison of curve fitting methods - Rural

5.5.3 Comparison of Curve Fitting & Neural Networks

This section compares the performance of DCM after calibration using neural networks and curve fitting methods in order to come up with a best calibration technique which minimizes the positioning error in each environment.

A. Urban – Galle Road

The performance after calibration using curve fitting and neural networks is comparable along Galle road. However, the error statistics shown in Table 5.17 demonstrates that curve fitting method is better than the neural network techniques for calibration.

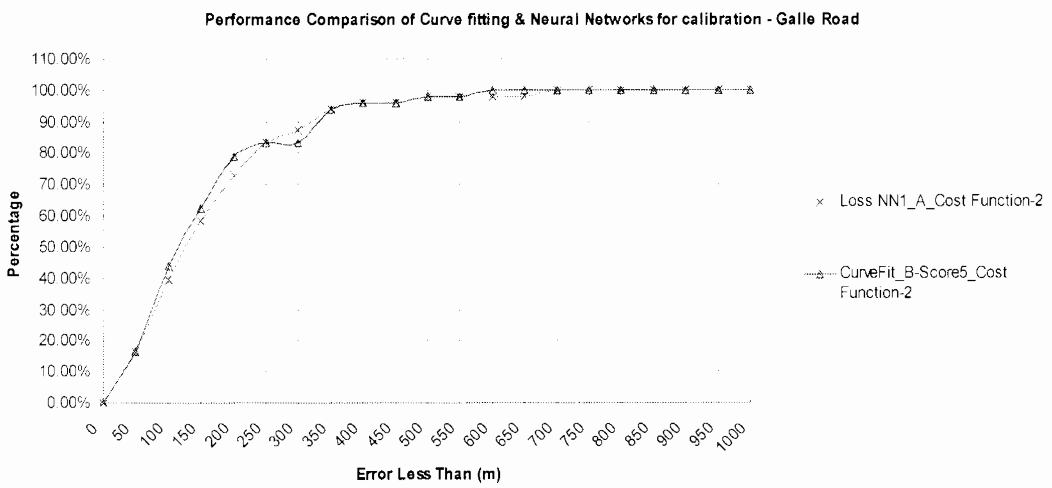


Figure 5.57: Performance comparison of curve fitting & neural networks for calibration – Galle road

Hence, it can be concluded that, curve fitting method with bi-square weight fitting is best in calibration along Galle road and the positioning approach-B with K=5 and Cost Function-2 is the best algorithm fits after calibration in this environment. Positioning error less than 200m in 80% of the estimates and less than 330m in 90% of the estimates is the highest performance obtained after calibration in bad urban scenario.

Table 5.17: Results summary of curve fitting & neural networks for calibration – Galle road

	Neural Networks for calibration	Curve Fitting for calibration
90% (m)	320	330
80% (m)	235	200
Maximum (m)	673	572
Minimum (m)	31	24
Average (m)	160	149
STD (m)	128	123
Median (m)	131	106

B Urban – Duplication Road

Unlike along Galle road, neural network techniques work best in calibration along Duplication road as shown in Figure 5.58.

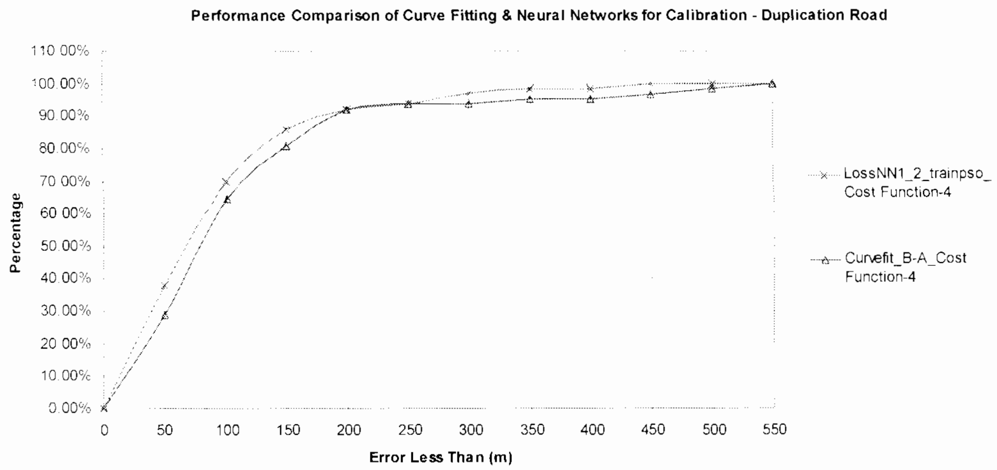


Figure 5.58: Performance comparison of curve fitting & neural networks for calibration – Duplication road

The positioning algorithm-A with Cost Function-4 has given best results after this calibration, with an error less than 125m in 80% of the estimates and less than 180m in 90% of the estimates. This is an acceptable result in urban environment for most of the information providing services.

Table 5.18: Results summary of curve fitting and neural networks for calibration -- Duplication road

	Neural Networks for calibration	Curve Fitting for calibration
90% (m)	180	190
80% (m)	125	150
Maximum (m)	433	546
Minimum (m)	9	16
Average (m)	89	107
STD (m)	83	104
Median (m)	65	78

C. *Suburban*

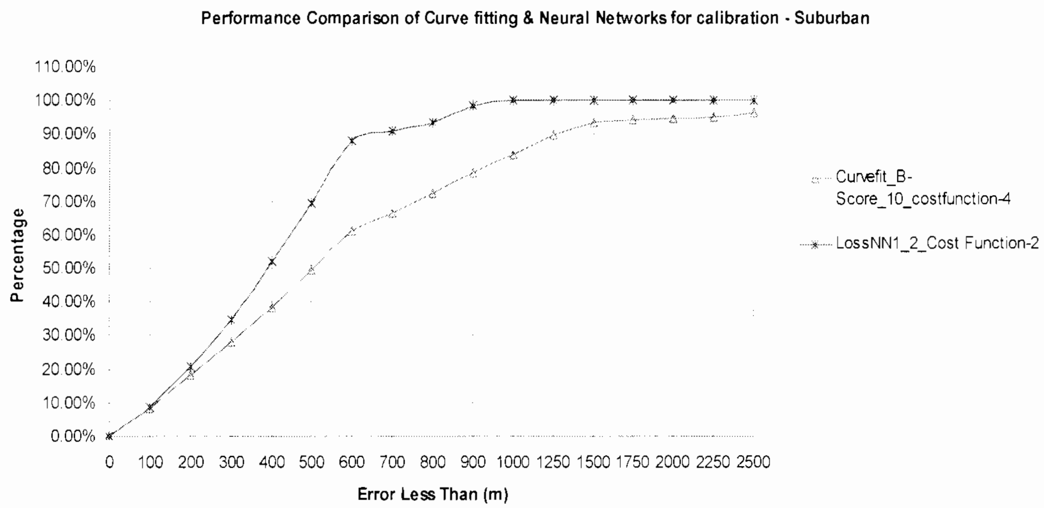


Figure 5.59: Performance comparison of curve fitting & neural networks for calibration – Suburban

As shown in Figure 5.59, neural network technique has the highest performance as a calibration technique in suburban environment. Neural network trained to output the error in signal strength loss is the best for calibration in suburban environment while positioning approach-A with Cost Function-2 is better in location estimation.

Table 5.19 summarizes the results after calibration. Positioning error less than 550m in 80% of the estimates is the better solution achieved in suburban environment.

Table 5.19: Results summary of curve fitting and neural networks for calibration - Suburban

	Neural Networks for Calibration	Curve Fitting for Calibration
80% (m)	550	925
90% (m)	625	1250
Maximum (m)	1363	3673
Minimum (m)	4	12
Average (m)	432	677
STD (m)	287	670
Median (m)	391	506

D. Rural

Similarly, neural network technique has the highest performance for calibration in rural environment as well.

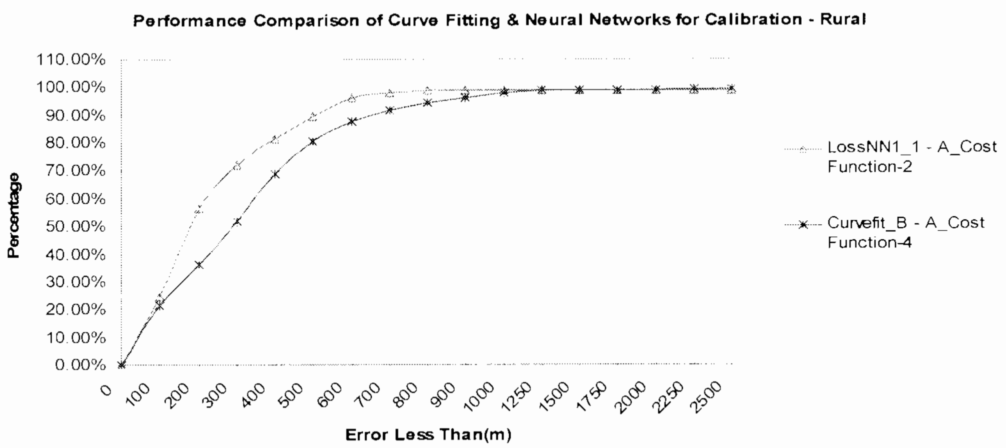


Figure 5.60: Performance comparison of curve fitting & neural networks for calibration – Rural

According to the error statistics shown in Table 5.20, positioning error is less than 385m in 80% of the estimates while that is less than 500m in 90% of the estimates in rural environment. This is far better than the performance in suburban environment and is remarkable.

Table 5.20: Results summary of curve fitting and neural networks for calibration - Rural

	Neural Networks for Calibration	Curve Fitting for Calibration
80% (m)	385	500
90% (m)	500	650
Maximum (m)	3502	3842
Minimum (m)	4	3
Average (m)	318	349
STD (m)	381	394
Median (m)	234	393

5.6 Overall Performance Analysis

Finally, the overall analysis of the results discussed so far is presented for urban, suburban and rural environments. The results of urban environment is discussed under two categories, bad-urban and urban correspond to Galle road and Duplication road respectively. Furthermore, the results of each environment are compared with the performance of basic Cell_ID method for positioning.

5.6.1 Urban

A. Galle Road

It appears that, the performance of database correlation method with a calibrated database is superior to that with a predicted database, while it is inferior to that with a measured database. Still, the performance after calibration is much better than the performance of Cell_ID method as can be seen in Figure 5.61.

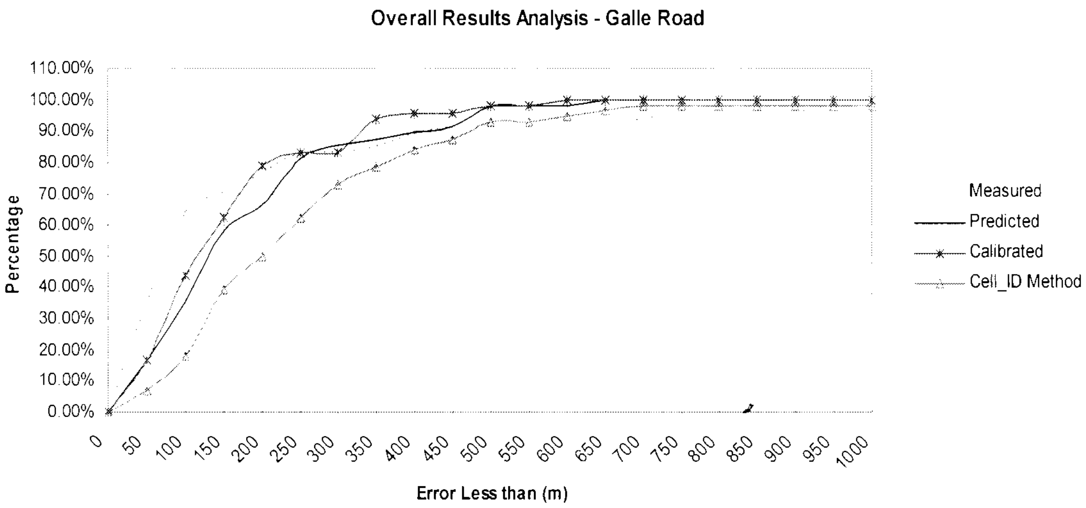


Figure 5.61: Overall results analysis – Galle road

Ultimately, the positioning error is less than 200m in 80% of the estimates whereas that is less than 330m in 90% of the time along Galle road. Accordingly, the accuracy has been improved by calibration in bad-urban environment up to a certain level.

Table 5.21: Overall results summary – Galle road

	Measured	**Predicted**	**Calibrated**	**Cell_ID Method**
90% (m)	425	400	**330**	475
80% (m)	225	245	**200**	370
Maximum (m)	2070	616	**572**	1020
Minimum (m)	13	31	**24**	27
Average (m)	188	173	**149**	245
STD (m)	341	138	**123**	185
Median (m)	67	130	**106**	200

B. Duplication Road

Figure 5.62 demonstrates the results analysis along Duplication road which was selected to be the normal urban environment. The performance of DCM has been improved clearly by calibration in this environment. Still, the performance after calibration is superior to that of Cell_ID method and the DCM with predicted database.

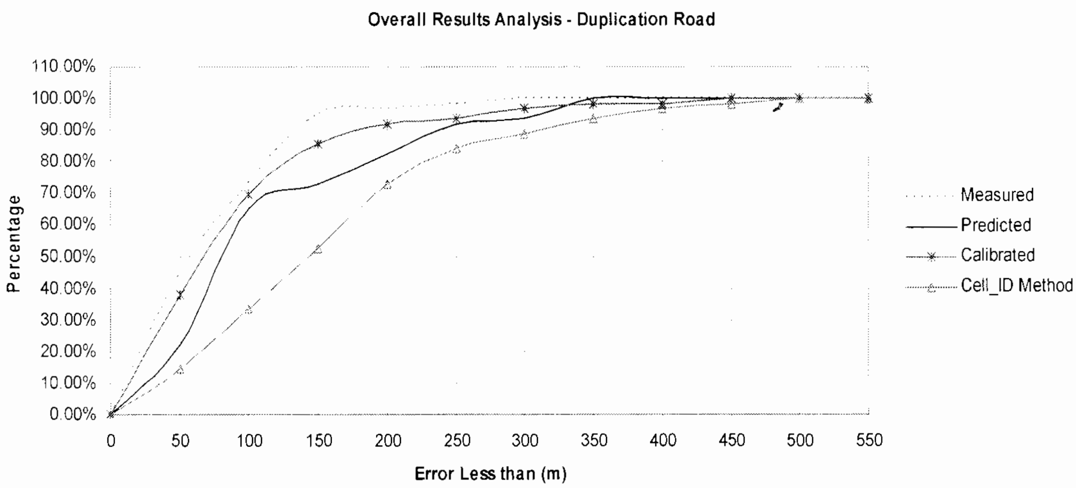


Figure 5.62: Overall results analysis – Duplication road

The best solution shows an error of 125m in 80% of the time and that of 180m in 90% of the time. The average error obtained in this work for normal urban environment is 89m while the median error is 65m.

Table 5.22: Overall results summary – Duplication road

	Measured	**Predicted**	**Calibrated**	**Cell_ID Method**
90% (m)	135	235	**180**	320
80% (m)	118	185	**125**	225
Maximum (m)	256	343	**433**	463
Minimum (m)	4	7	**9**	11
Average (m)	72	114	**89**	158
STD (m)	54	83	**83**	105
Median (m)	56	90	**65**	139

5.6.2 Suburban

Similarly, the performance has been enhanced by calibration in suburban environment. The improvement in 80th percentile is 150m while that in 90th percentile is 125m. In addition, the performance curve after calibration takes over the curve using a measured database near to 80th percentile.

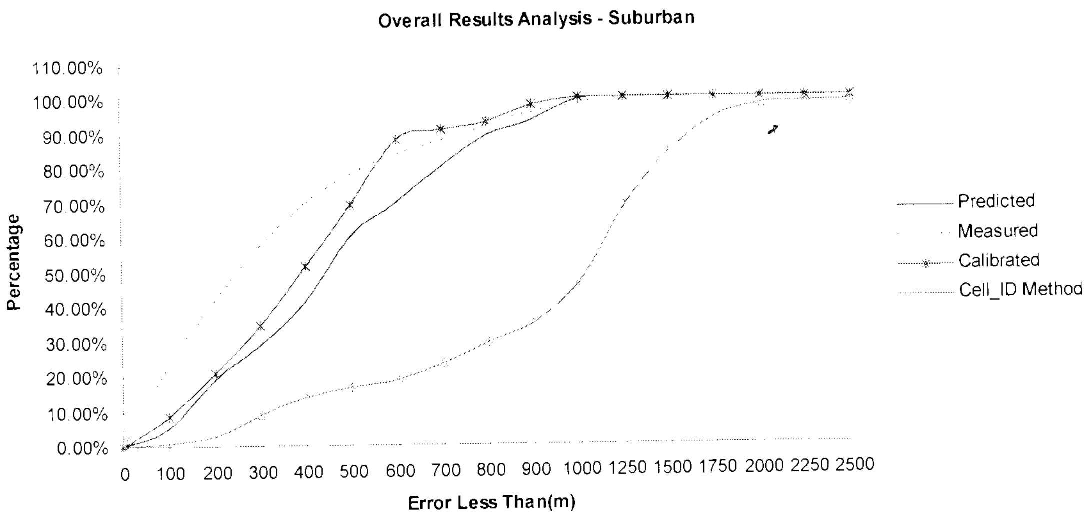


Figure 5.63: Overall results analysis – Suburban

The improvement in performance after calibration is clearly demonstrated by Table 5.23. However, the best results obtained for suburban environment is not that significant for most of the location based services.

Table 5.23: Overall results summary - Suburban

	Measured	**Predicted**	**Calibrated**	**Cell_ID Method**
80% (m)	525	700	**550**	1400
90% (m)	750	800	**625**	1675
Maximum (m)	1218	1293	**1363**	2699
Minimum (m)	5	24	**4**	31
Average (m)	325	482	**432**	1037
STD (m)	266	283	**287**	485
Median (m)	261	436	**391**	1030

5.6.3 Rural

A notable improvement in performance can be seen in rural environment after calibration. As it appears in Figure 5.64, the performance curve after calibration takes over that using both measured and predicted database in all percentages.

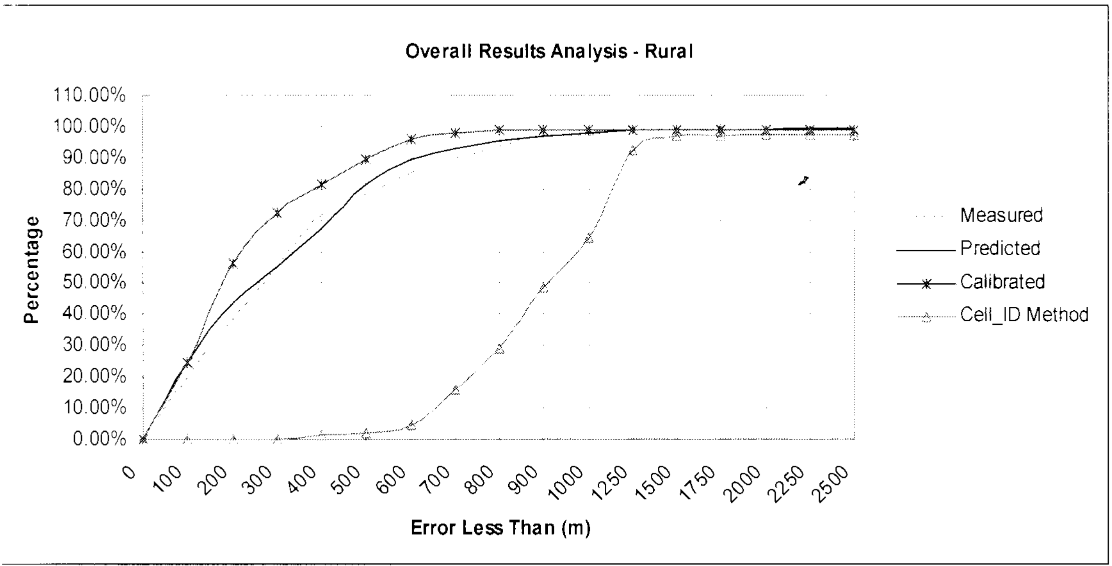


Figure 5.64: Overall results analysis – Rural

The positioning error is less than 385m in 80% of the time while that is less than 500m in 90% of the time in rural environment. This is significant for most of the location based services in rural environments.

Table 5.24: Overall results summary - Rural

	Measured	Predicted	Calibrated	Cell_ID Method
80% (m)	540	495	**385**	1125
90% (m)	700	600	**500**	1200
Maximum (m)	3424	3842	**3502**	4949
Minimum (m)	3	3	**4**	398
Average (m)	351	331	**318**	1003
STD (m)	384	393	**381**	606
Median (m)	260	274	**234**	907

5.6.4 Overall Results

This section is devoted for summarization of the performance of DCM in all three environments using measured, predicted and calibrated databases. A comprehensive results summary is shown in Table 5.25.

In addition, a comparison of the results of this work with the results published in [23] and [37] is shown in Table 5.26. The work in [23] is entirely based on a predicted database using wave propagation models whereas that in [37] involves a calibrated predicted database.

Table 5.26: Results comparison with other results in literature

	Urban			**Rural**		
	Results in this work	**Results in [23]**	**Results in [37]**	**Results in this work**	**Results in [23]**	**Results in [37]**
67% error (m)	95	83	175	270	607	Not available
95% error (m)	265	192	220	600	1021	Not available

Further more, a comparison of the final outcomes of this research with the outcomes of author's final year project (FYP) in similar title [29], is given in Table 5.27. Apparently, the performance in both urban and rural environments has been improved drastically by the new positioning approaches together with the calibration techniques. However, the performance in suburban environment is inferior to that obtained in FYP stage.

Furthermore, Figure 5.65 illustrates the estimated locations of one test trial together with the actual location in maps for four areas, along Galle road, along Duplication road, suburban and rural.

Table 5.2[illegible]: Overall results of three environments

	Bad Urban (Galle Road)			Urban (Duplication Road)			Suburban			Rural		
	Measured Database	Predicted Database	Calibrated Database	Measured Database	Predicted Database	Calibrated Database	Measured Database	Predicted Database	Calibrated Database	Measured Database	Predicted Database	Calibrated Database
Calibration Technique	-	-	**Curve Fitting- B**	-	-	**Neural Network for Error in loss**	-	-	**Neural Network for Error in Loss**	-	-	**Neural Network for Error in Loss**
Training Algorithm	-	-	-	-	-	**PSO type-2**	-	-	**PSO common type**	-	-	**PSO common type**
Positioning Technique	Approach-B with K=5 & Cost Function-4	Approach-B with K=8 & Cost Function-4	**Approach-B with K=5 & Cost Function-2**	Approach-A with Cost Function-3	Approach-A with Cost Function-4	**Approach-A with Cost Function-4**	Approach-B with K=3 & Cost Function-4	Approach-B with K=8 and Cost Function-0	**Approach-A with Cost Function-2**	Approach-B with K=2 & Cost Function-2	Approach-A with Cost Function-4	**Approach-A with Cost Function-2**
80% Error (m)	225	245	**200**	118	185	**125**	525	700	**550**	540	495	**385**
90% Error (m)	425	400	**330**	135	235	**180**	750	800	**625**	700	600	**500**
Median Error (m)	67	130	**106**	56	90	**65**	261	436	**391**	260	274	**234**
Average Error (m)	188	173	**149**	72	114	**89**	325	482	**432**	351	331	**318**
Maximum Error (m)	2070	616	**572**	256	343	**433**	1218	1293	**1363**	3424	3842	**3502**
Minimum Error (m)	13	31	**24**	4	7	**9**	5	24	**4**	3	3	**4**
Number of test points	50			63			312			154		

e 5.22: Comparison of current results and Final Year Project (FYP) results of three environments

	Urban			Suburban		Rural	
	FYP	**Current (Duplication road)**	**Current (Galle road)**	**FYP**	**Current**	**FYP**	**Current**
80% Error (m)	240	**125**	**200**	400	**550**	700	**385**
90% Error (m)	400	**180**	**330**	500	**625**	1300	**500**
Average Error (m)	138	**89**	**149**	202	**432**	513	**318**
Maximum Error (m)	801	**433**	**572**	391	**1363**	1700	**3502**
Minimum Error (m)	5	**9**	**24**	1.2	**4**	33	**4**

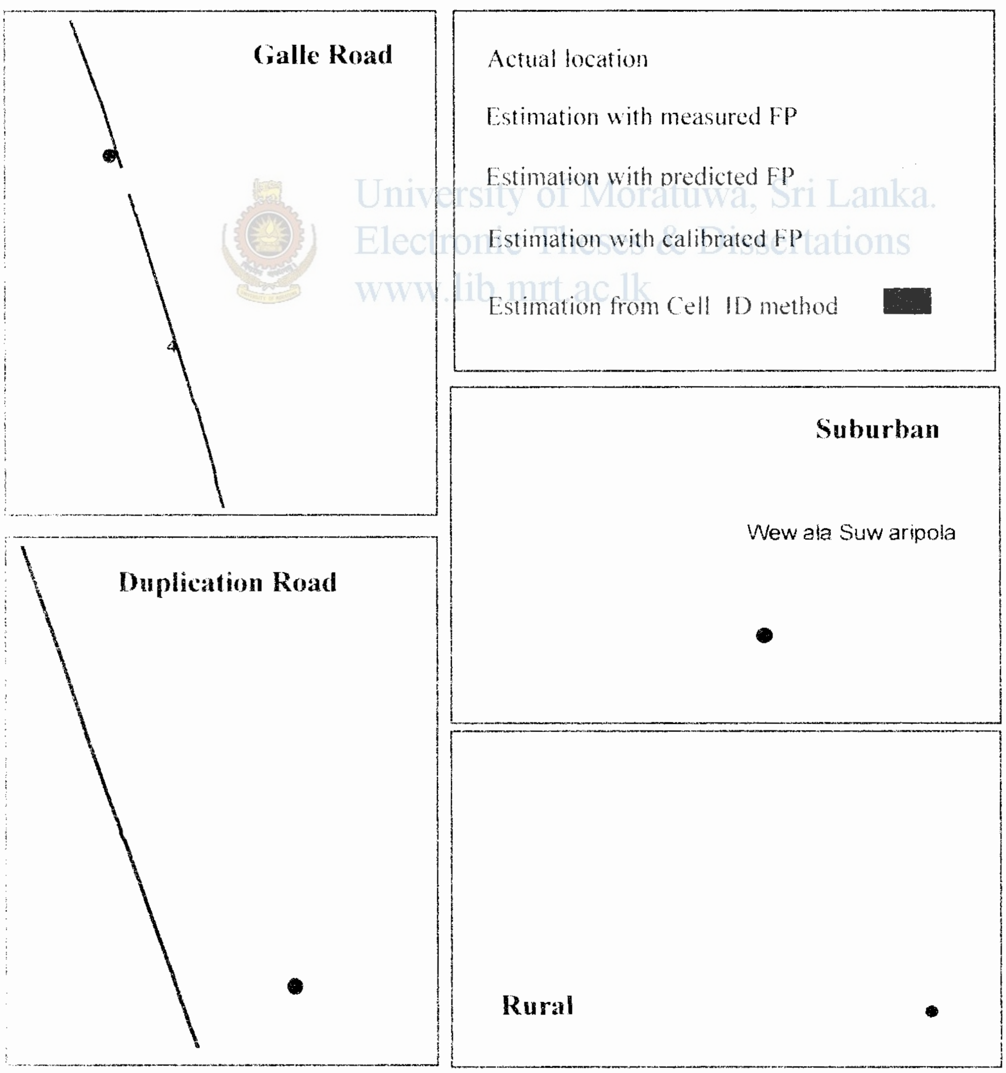


Figure 5.65: Plot of estimated locations of one test trial in four environments in maps
Original is in colour

Chapter -6

Conclusion

The major objectives of this work are to investigate the possibility of applying predictions obtained from theoretical propagation models/tool to create the fingerprint database for Database Correlation Method in local context and to come up with an improved technique for location estimation, which is feasible for the deployment in large dynamic networks.

This chapter summarizes the major contributions of this work while presenting a brief analysis of overall results, commercialization aspects and future directions for further research.

6.1 Contributions

At the very beginning, a comprehensive review of existing literature on the subject was carried out to get familiar with the status of positioning including all the technologies that have already been invented.

After that, a systematic methodology for creating a fingerprint database using network planning tool predictions has been introduced. In addition, an extensive measurement campaign was carried out for taking measurements in three different environments, urban, suburban and rural.

A detailed analysis of the deviation between network planning tool predictions and actual measurements shows that there exists a considerable deviation in urban environment, while the deviation in suburban is moderate and rural is even lower.

Methods for minimizing the above deviation, defined as calibration, were proposed based on neural network techniques and curve fitting techniques. The cell-wise calibration process proposed in this thesis is advantageous for deploying the technique in large, dynamic networks.

Furthermore, a novel fingerprint filtering method and a novel Cost Function (Cost Function-4) for fingerprint matching were proposed for location estimation and there validity has been proved with a measured and a predicted database.

In addition, the impact of RSS variation over different hours of the day on DCM algorithm was analyzed and the results show a negligible impact.

Finally, the performance of DCM algorithms using a measured database, a predicted database and a calibrated database was evaluated comprehensively, and the results show that the calibration process has been able to improve the performance noticeably.

6.2 Trial Results

The results analysis in chapter 5 shows that the performance of DCM using a predicted database is inferior to that using a measured database in all environments except the rural environment. But, the application of a calibration process has improved the performance considerably, by bringing the CDF curve with a calibrated database closer to that with a measured database in urban and suburban environment. A remarkable performance was observed in rural environment after calibration. The performance after calibration was even higher than that using a measured database in rural.

According to the results, the novel fingerprint filtering method is robust for bad urban environment, which was selected to be along Galle road. In addition, the proposed Cost Function (Cost Function-4) for location estimation has shown better results with a predicted database in all three environments. Furthermore, the calibration method based on neural network techniques has been succeeded in urban, suburban and rural, but for bad urban the best matching calibration methods was the one based on curve fitting.

Consequently, the best results obtained for bad urban environment show a positioning error less than 200m in 80% of the time while that is for urban environment is less than 125m (80%). A notable performance of positioning error less than 385m in 80% of the estimates was obtained for rural environment after calibration. This is an outstanding achievement of this research. The performance in suburban environment is inferior to that in both urban and rural environments, and the best accuracy was less than 550m in 80% of the estimates.

According to the accuracy requirements of different Location Based Services, as shown in Table 1.2, the accuracies achieved during this work for all three environments are sufficient to provide basic information services such as nearest ATM machine, nearest hospital, nearest petrol station, traffic information and location based advertising. The results in rural environment show a far better performance than the requirement shown in Table 1.2 for the same environment.

6.3 Commercialization Aspects

The proposed method for location estimation in cellular networks has been designed suitably for deploying in large dynamic networks. The method involves a predicted database of fingerprints instead of a measured one. This eliminates the initial deployment cost encountered in carrying out measurement campaigns for the formation of measured database as well as the maintenance burden involved in upgrading the network by introducing new cells and making changes to the existing infrastructure.

At the same time, the proposed calibration method, known as cell-wise calibration, is more applicable for the performance enhancement as well as for the ease of upgrading the database. If a new cell comes up, it's just a matter of calibrating the predictions of that particular cell and updating the database by inserting the calibrated predictions of new cell to existing fingerprints, without altering the existing ones. In addition, the proposed calibration process provides the flexibility of re-calibrating the fingerprints in cell-by-cell basis to make the database compatible with environmental variations.

Furthermore, the accuracies demonstrated by the developed method in three environments comply with the accuracy requirements for basic information services as illustrated in [9]. In addition, the accuracy obtained in urban environment complies with the accuracy requirement of FCC recommendations for network based solutions [2, 3].

Hence, the proposed solution is best suited for the deployment in large dynamic networks as a network based method for positioning to provide basic information services such as the nearest ATM, the petrol station etc.

6.4 Future Work

This research has demonstrated the possibility of applying network planning tool predictions for the formation of fingerprint database in local context. Since the calibration has shown to be a better way for performance enhancement, further research can be carried out towards improving the performance of calibration.

In addition, the analysis of RSS variation in Section 4.5 shows that the RSS variation of neighboring cells relative to that of the serving cell is some what similar throughout the day. This introduces a different direction for formation of fingerprints, in which the RSS of neighboring cells relative to serving cell are stored rather than absolute values; in order to reduce the effect comes with the variation of absolute values of RSS.

Furthermore, novel correlation algorithms can also be researched to be compatible with the novel database.

Since a significant improvement in performance can be observed in rural environment, it is worthwhile to carryout further research towards enhancing this performance further, which will help to a massive enhancement in location based services in rural environment.

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ABBRIVIATIONS

2G	Second Generation
3G	Third Generation
A-GPS	Assisted GPS
AOA	Angle of Arrival
ARFCN	Absolute Radio Frequency Channel Number
ATM	Automated Teller Machine
BCCH	Broadcast Control Channel
BS	Base Station
CDF	Cumulative Distribution Function
CEP	Circular Error Probability
CIR	Channel Impulse Response
DCM	Database Correlation Method
E-OTD	Enhance Observed Time Difference
FCC	Federal Communication Commission
FYP	Final Year Project
GDAL	Geospatial Data Abstraction Library
GPS	Global Positioning System
GSM	Global System for Mobile
LAR	Least Absolute Residuals
LBS	Location Based Services
LMS	Least Mean Square
LOS	Line Of Sight
MPM	Multi-path Model
MS	Mobile Station
NLOS	Non Line of Sight
NMR	Network Measurement Report
NN	Neural Networks
PSO	Particle Swarm Optimization
RMSE	Root Mean Square Error
RSS	Received Signal Strength
SEP	Error Probability
SMS	Short Message Service

TA	Timing Advance
TDOA	Time Difference of Arrival
TOA	Time of Arrival
UHF	Ultra High Frequency
VHF	Very High Frequency
VPM	Vertical Plane Model
WIM	Walfisch-Ikegami Model
WLAN	Wireless Local Area Network

Appendix A

PROPAGATION MODELS

A.1 Hata-Okumura Model

The median Path Loss equation of Hata-Okumura model is given in equation (A.1).

$$L(dB) = 69.55 + 26.16\log_{10} f_{MHz} - 13.82\log_{10} h_{BS} - a(h_{MS}) + (44.9 - 6.55\log_{10} h_{BS})\log_{10} d_{km} - K \tag{A.1}$$

Where h_1 (m) - Base station antenna height

h_2 (m) - Mobile antenna height

d_{km} (km)- Link distance

f_{MHz} (MHz) - Center frequency

$a(h_2)$ - MS Antenna height-gain correction factor

K - Correction factor for suburban and open areas.

Following are the range of parameters applicable for this model.

$$150 \text{ MHz} \leq f_{MHz} \leq 1500 \text{ MHz}$$

$$1 \text{ km} \leq d_{km} \leq 10 \text{ km}$$

$$30 \text{ m} \leq h_{BS} \leq 200 \text{ m}$$

$$1 \text{ m} \leq h_{MS} \leq 10 \text{ m}$$

The parameters of Hata model in different area types are given in table A.1 and table A.2

Table A.1: Hata Model Parameters: a (h_2)

Type of area		**a(h₂)**
Medium-small city		$(1.1 \log_{10} f_{MHz} - 0.7)\, h_2 - (1.56 \log_{10} f_{MHz} - 0.8)$
Large city	**(f_{MHz}>300 MHz)**	$3.2\,(\log_{10} 11.75\, h_2)^2 - 4.97$
	($f_{MHz} \leq$300 MHz)	$8.29(\log_{10} 1.54\, h_2)^2 - 1.1$

Table 2-A.2: Hata Model Parameters: *K*

Type of area	**K**
Open rural	$4.78 (\log_{10} f_{MHz})^2 - 18.33 \log_{10} f_{MHz} + 40.94$
Suburban	$2 [\log_{10} (f_{MHz}/28)]^2 + 5.4$

Large city is defined as a city having building heights greater than 15 m.

A.2 Walfisch-Ikegami Model (WIM)

WIM is a semi-deterministic model for medium-to-large cells in built-up areas. It has been shown to be a good fit to measured propagation data for frequencies in the range of 800 to 2000MHz and path distances in the range of 0.02 to 5 km.

WIM distinguished between LOS and NLOS propagation situations.

NLOS parameters

Table A.3: NLOS parameters for WIM

h_b	(m)	=	Base station antenna height over street level			4 – 50 m
h_m	(m)	=	Mobile antenna height..................................			1 – 3 m
h_B	(m)	=	Nominal height of building roofs			
Δh_b	(m)	=	h_b-h_B	=	Height of base station antenna above rooftops	
Δh_m	(m)	=	h_B-h_m	=	Height of mobile antenna below rooftops	
b	(m)	=	Building seperation			20–50m etc.
w	(m)	=	Width of street...			(b/2) if no data
Φ	(degrees)	=	Angle of incident wave with respect to street			90^0 if no data

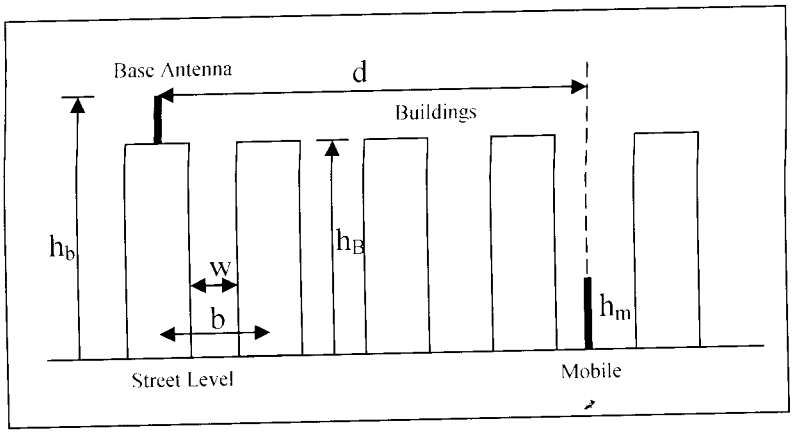

Figure A.1: WIM Parameters

In the absence of data, building height in meters can be estimated by three times the number of floors, plus 3m if the roof is pitched instead of flat. The model works best for base antennas well above the roof height.

For NLOS propagation paths the WIM gives the expression in equation (A.2) for the path loss in dB.

$$L_{NLOS} = \begin{cases} L_{fs} + L_{rts} + L_{mds}, & L_{rts} + L_{mds} \geq 0 \\ L_{fs}, & L_{rts} + L_{md} > 0 \end{cases} \quad (A.2)$$

Where L_{fs} - Free space loss

L_{rts} - Roof -to-street diffraction and scatter loss

L_{mds} - Multi-screen diffraction loss

L_{ori} - Orientation loss

$$L_{fs} = 32.45 + 20 \log_{10} d_{km} + 20 \log_{10} f_{MHz} \quad (A.3)$$

$$L_{rts} = -16.9 - 10 \log_{10} w + 10 \log_{10} f_{MHz} + 20 \log_{10} \Delta h_m + L_{ori} \quad (A.4)$$

Where

$$L_{ori} = \begin{cases} -10 + 0.354\Phi, & 0 \leq \Phi \leq 35^0 \\ 2.5 + 0.075(\Phi - 35^0), & 35^0 \leq \Phi \leq 55^0 \\ 4.0 - 0.114(\Phi - 55^0), & 55^0 \leq \Phi \leq 90^0 \end{cases}$$

$$L_{mds} = L_{bsh} + k_a + k_d \log_{10} d_{km} + k_f \log_{10} f_{MHz} - 9 \log_{10} b \quad (A.5)$$

where

L_{bsh} - Shadowing gain (negative loss)

$$L_{bsh} - \begin{cases} -18\log_{10}(1+\Delta h_b), & \Delta h_b > 0 \\ 0, & \Delta h_b \leq 0 \end{cases}$$

$$k_a = \begin{cases} 54, & \Delta h_b > 0 \\ 54 + 0.8\,|\Delta h_b|, & \Delta h_b \leq 0 \text{ and } d_{km} \geq 0.5 \\ 54 + 0.8\,|\Delta h_b|(d_{km}/0.5), & \Delta h_b \leq 0 \text{ and } d_{km} < 0.5 \end{cases}$$

$$k_d = \begin{cases} 18, & \Delta h_b > 0 \\ 18 + 15\,(|\Delta h_b| / h_B), & \Delta h_b \leq 0 \end{cases}$$

$$k_f = -4 + \begin{cases} 0.7\left(\frac{f_{MHz}}{925} - 1\right), & \text{medium city and suburban} \\ 1.5\left(\frac{f_{MHz}}{925} - 1\right), & \text{metropolitan area} \end{cases}$$

A.3 Outdoor and Outdoor-to-Indoor Coverage in urban areas at 1.8 GHz

In the Vertical Plane Model (VPM), if the antenna height h_b is below 70m or the length of the propagation path (l) over buildings exceeds a selected field distance d_s, the *COST-231-Walfisch-Ikegami-Model* is selected. If the height of the diffracting edges are not homogeneously distributed ad the MS is not located within a street canyon, the *Knife-Edge Model* is applied.

In the case of non line-of-sight, the path loss is computed by equation (A.6).

$$L_{VPM} = (1-g)(L_K + L_B) + gL_W \tag{A.6}$$

Where:

L_K – Diffraction loss of the knife edge model

L_B – Basic path loss using the dual-slope approach

L_W – Path Loss due to the Walfisch Type Model

$g = g_h . g_w$ (Gain calculated based on the antenna heights)

For the line-of-sight situation, the path loss is calculated based on the LOS part of the Walfisch-Ikegami Model.

Determination of path loss using Multi Path Model (MPM) is given in [43]. Vector data format is used in considering the scattering areas. MPM considers paths due to single scattering process and the path loss from the BS to scattering area and from scattering area to the MS is assumed to be equal to Free-Space Loss.

A.4 CRC- Predict Propagation Model

This model defines the received signal strength at the mobile by equation (A.7).

$$P_{RX} = P_{TX} + K_1 + K_2 \log(d) + K_3 \log(H_{eff}) + K_4 Diffraction + K_5 \log(H_{eff}) \log(d) + K_6 (H_{meff}) + K_{clutter} \quad (A.7)$$

Where

P_{RX} – The received Power in dBm

P_{TX} – Transmit Power (EIRP) in dBm

K_1 – A constant off-set in dB

K_2 – Multiplying Factor for Log(d)

K_3 – The Multiplying factor for log(Heff). Compensates for gain due to Antenna height

K_4 – Multiplying Factor for Diffraction Losses

K_5 – Okumura Hata type of Multiplying factor for Log(Heff)log(d)

H_{eff} – Effective height of base station Antenna from ground

Diffration – Loss due to diffraction over an obstructed path

$K_{clutter}$ – Loss in dB for the clutter type

H_{meff} – Mobile Effective Antenna height

Appendix B

NEURAL NETWORKS

B.1 Neural Network Training Algorithms

It is desirable to modify the connection weights of the network until the desired output is obtained, during the training phase. Since the network weights are initially random, it is likely that the initial output value will be very far from the desired output. Hence, an algorithm should be used which efficiently modifies the different connection weights to minimize the errors at the output. Such algorithms are called Neural Network Training Algorithms.

Numerous training algorithms have been presented in literature [47, 52, 53] with their pros and cons in relation with the application. One algorithm may work better in one application and may be worst in another. Therefore, it is needed to select the algorithm which performs well in the particular application. Several training functions studied by the author during this research are given below.

Most training algorithms use the gradient of the performance function to determine the weight adjustment towards the minimum of the performance function. The gradient is determined using a technique called back-propagation, which involves performing computations backwards through the network.

i. Back-propagation Algorithm (Gradient Descent)

The simplest implementation of back-propagation learning, updates the network weights and biases in the direction in which the performance function decreases most rapidly (the negative of the gradient). An iteration of this algorithm can be written as:

$$X_{k+1} = X_k - (lr \cdot g_k) \tag{B.1}$$

Where X_k - vector of current weights and biases

g_k - current gradient

lr - learning rate

This is also called as *Gradient Descent training function*. Here, the learning rate is used to determine the amount of changes to the weight and biases. The larger the learning rate, the bigger the step. If the learning rate is made too large, the algorithm becomes unstable. If the learning rate is set too small, the algorithm takes a long time to converge [47].

ii. Gradient Descent with Momentum

This is a derivative of Gradient Descent Algorithm, which is used to provide a faster convergence in the training process by using a momentum. Momentum allows a network to respond not only to the local gradient, but also to recent trends in the error surface. Acting like a low-pass filter, momentum allows the network to ignore small features in the error surface.

The major problem with gradient descent is that, the training process may get stuck in a shallow local minimum. This can be avoided using momentum. With momentum a network can slide through such a minimum.

Momentum can be added to back-propagation learning by making weight changes equal to the sum of a fraction of the last weight change and the new change suggested by the back-propagation rule. The magnitude of the effect that the last weight change is allowed to have is mediated by a momentum constant (mc), which can be any number between 0 and 1. When the momentum constant is 0, a weight change is based solely on the gradient. When the momentum constant is 1, the new weight change is set to equal the last weight change and the gradient is simply ignored [47].

The new weight change dX is given by equation (B.2).

$$dX = (mc \cdot dX_{prev}) + (lr \cdot (1 - mc) \cdot g_k) \tag{B.2}$$

where dX_{prev} - Previous change to the weight or bias

g_k - Current gradient

mc - Momentum Costant

lr - Learning Rate

iii. Resilient Back-propagation

Multilayer networks typically use sigmoid transfer functions in the hidden layers. These functions compress an infinite input range into a finite output range. Sigmoid functions are characterized by the fact that their slope must approach zero as the input gets large. This causes a problem when using steepest descent to train a multilayer network with sigmoid functions, since the gradient can have a very small magnitude; and therefore, cause small changes in the weights and biases, even though the weights and biases are far from their optimal values.

The purpose of the resilient back-propagation (Rprop) training algorithm is to eliminate these harmful effects of the magnitudes of the partial derivatives.

In this algorithm, the magnitude of the derivative has no effect on the weight update and only the sign of the derivative is used to determine the direction of the weight update. The size of the weight change is determined by a separate update value.

The update value for each weight and bias is increased by a factor ***delt_inc*** whenever the derivative of the performance function with respect to that weight has the same sign for two successive iterations. The update value is decreased by a factor ***delt_dec*** whenever the derivative with respect that weight changes sign from the previous iteration. If the derivative is zero, then the update value remains the same. Whenever the weights are oscillating the weight change will be reduced. If the weight continues to change in the same direction for several iterations, then the magnitude of the weight change will be increased [47].

iv. BFGS Algorithm

This is a Quasi-Newton algorithm of Numerical Optimization category. This is an alternative to conjugate gradient methods for fast optimization.

The basic step of Newton's method is:

$$X_{k+1} = X_k - A_k^{-1} g_k \tag{B.3}$$

Where $\mathbf{A_k}$ is the Hessian matrix (second derivatives) of the performance index at the current values of the weights and biases.

Newton's method often converges faster than conjugate gradient methods. Unfortunately, it is complex and expensive to compute the Hessian matrix for feed-forward neural networks.

There is a class of algorithms that is based on Newton's method, but which doesn't require calculation of second derivatives. These are called quasi-Newton (or secant) methods. They update an approximate Hessian matrix at each iteration of the algorithm. The update is computed as a function of the gradient. The quasi-Newton method that has been most successful in published studies is the Broyden, Fletcher, Goldfarb, and Shanno (BFGS) update.

The BFGS algorithm requires more computation in each iteration and more storage than the conjugate gradient methods, although it generally converges in fewer iterations. The approximate Hessian must be stored, and its dimension is $n * n$, where n is equal to the number of weights and biases in the network. For very large networks it may be better to use Rprop or one of the conjugate gradient algorithms [47].

v. Particle Swarm Optimization algorithm (PSO)

Particle Swarm Optimization is a population based optimization algorithm that is motivated from the simulation of the social behavior [54]. If the optimization problem is regarded as a bird swarm looking for food in the sky, then one bird is a particle of PSO algorithm which conducts the search in the solution space. In this regard, the PSO algorithm consists of particles which are flown through the solution space towards the global optimum value.

Every particle of the PSO algorithm is one of the solutions, and it adjusts its flying according to its own experience and others. The best position that every particle has experienced during flying is the best solution found by itself. And the best position that group has experienced is the best solution found by the swarm. The first is called personal best (pBest), the last is called global extreme (gBest). The fitness value decided by optimization is used to evaluate that the particle is good or bad. Every particle can adjust itself according to pBest and gBest, which makes the particle swarm move to good area.

Particles can adjust its velocity and the position according to equation (B.4) and (B.5).

$$v_{id} = w * v_{id} + c_1 * rand() * (p_{id} - x_{id}) + c_2 * Rand() * (p_{gd} - x_{gd}) \tag{B.4}$$

$$x_{id} = x_{id} + v_{id} \tag{B.5}$$

Where,	C1 & C2	– Acceleration constants
	Rand() & rand()	– two random functions in the range [0 1]
	W	- Inertia weight
	x_i	- Position of i^{th} particle

p_i - pBest position of i^{th} particle

p_g - gBest postion of the swarm

There is a Toolbox for particle swarm optimization in Matlab [55, 56]. Three types of algorithms have been developed in that for Neural Network training. Those are called Common type, Type-1 and Type-2.

The Common type algorithm uses the general equation given in equation (B.4) with user defined inputs for w, c_1 and c_2. Type-1 and Type-2 uses pre-defined values for those variables. Those are given in table B.1.

Table B-1: Values for PSO variables

Variable	Type-1	Type-2
W	0.6	0.729
C_1	1.7	1.494
C_2	1.7	1.494