# Per Cell Propagation Model Calibration Approach for Mobile Positioning

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**Abstract—This paper presents results of research on per cell propagation calibration-based mobile positioning for GSM. A novel mobile positioning system for GSM networks is proposed and assessed by field measurements and simulations. It utilizes timing advance, Received Signal Strength (RSS) and a per cell-tuned propagation prediction model. Clutter features are modelled to closely represent the real environment to enhance the accuracy of the signal strength prediction. The obtained results indicate that estimation of the mobile position at a sufficient accuracy for most of the location-based services does not have to involve significant changes in the terminals and in the network infrastructure. The performed field measurements and simulation of the designed mobile positioning system reveal that mobile users can be located with an accuracy of 40 meters. Furthermore, the method is computationally light-weight and can be integrated onto any RSS-based algorithm.**

**Index Terms—GSM network, per cell propagation, Propagation Calibration, Mobile positioning.**

## I. INTRODUCTION

An ultimate aim of the mobile positioning research is to find a method providing high estimation accuracy to the user with minimum delay and at minimum cost. Development of positioning techniques towards defined performance objectives is pushed by the perspective of high revenues through enabling attractive location-sensitive applications together with stated safety requirements.

Most of the Location Based Services (LBS) applications present the need for accurate techniques in estimating the position of the Mobile Stations (MS) within the network. Even though currently the Assisted Global Positioning System (A-GPS) provides the best accuracy [1], the challenge of coming up with GPS enabled mobile phones and the poor indoor coverage of GPS prevents GPS enabled phones from being used in LBS applications. Thus, positioning estimation based on the parameters available in the GSM cellular network itself has become a popular topic among the researchers all over the world [4].

So far, a wide variety of positioning techniques have been proposed using measurements taken within cellular networks such as received signal strength (RSS), time of arrival (TOA), angle of arrival (AOA), enhanced observed time difference (E-OTD). The TOA method is able to locate legacy handsets but requires installation of new network elements called location measurement units (LMUs) at each BTS. Similarly, the E-OTD method requires installation of an LMU for every 2-5 BTSs and software modification in the handsets [2].

The AOA method requires antenna arrays at the base transceiver stations (BTSs) or handsets [3, 4]. In most systems these arrays are usually arranged at the BTSs because it will be complex and economically not viable to have a handset-based solution. The A-GPS method requires installation of reference GPS receivers beside the integration of GPS receivers into handsets[5].

An RSS-based method basically estimates handset's coordinates by fusing cell identity (CI), timing advance (TA), and RSS information [1]. TA value corresponds to the time it takes for a signal to be transmitted from the mobile terminal to the serving BTS and it is used for synchronization purposes in GSM [3]. RSS levels are measurements of the strength (i.e., power) of signals received by the MS from the serving BTS and from up to the six strongest neighbour BTSs in GSM [3, 7]. Attenuation values from multiple neighbour BTSs are modelled in the RSS-based method through signal attenuation models such as Okumura-Hata [6], Longley-Rice [6], and Walfisch-Bertoni [8], and used to estimate the location of the MS [5].

Although positioning estimation algorithms based on signal attenuation may not be the most promising approach for providing LBSs, signal strength is the only common information available among various kinds of mobile networks. Together with the fact that the geographic conditions and the cell layout in metropolitan areas are not

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the same, new approaches for position estimation algorithms based on signal attenuation have to be investigated [1, 4].

The aim of this paper is to utilise RSS measurements in a 900MHz GSM network and data compiled from the outskirts of Pretoria City in South Africa to model the localized environmental features and then use the features to design a propagation model. The designed propagation model is then calibrated to characterise the area of study and then used for optimal predictions.

Predictions of RSS and propagation coverage area are vital aspects in the design of an accurate mobile positioning system [3, 4]. A mobile positioning system is also designed.

The performance of the developed positioning system is evaluated and compared with the naive RSS-based positioning system that uses Hata's generic suburban propagation model [6]. In this way the importance of per-cell propagation tuning for a RSS-based positioning algorithm is investigated.

## II. Modelling the Correction Factors

Due to its simplicity, popularity and ease of use, the Okumura-Hata path loss propagation model [6] was selected as a testing model. The algorithm is given by (1).

$$L_{dB} = 69.55 + 26.16\log f - 13.82(\log h_T) - \beta + (Q - 6.55\log h_T)\log d \tag{1}$$

where $Q = 44.9$, $\beta$ is the environment correction factor, $L_{dB}$ is the propagation loss and $f$ is the frequency in MHz.

This study was conducted in the outskirts of Pretoria city. Every clutter aspect the signal encounters after leaving the transmitting antenna affects the RSS and its direction [7].

Field measurement data was obtained through drive tests in the area of study. Signal predictions were performed using MATLAB based on the Okumura-Hata model.

Clutter and the digital terrain map of the area were utilised on the ATOLL planning tool to tune Hata propagation model to characterise the area of study. Since the region is sub urban the appropriate correction factor was used [8].

$$\beta_{urban} = 3.2(log(11.75h_R))^2 - 4.97 \tag{2}$$

$$\beta_{urban} = \beta_{urban} - 2\left(log\left(\frac{f}{28}\right)\right)^2 - 5.4 \tag{3}$$

### A. Terrain diffraction factor design

Path loss can be defined as the ratio of the transmitted to received power in decibels. From the equation for the Least Square (LS) regression analysis, the path loss at distance $d$ can be described in the form given below [6].

$$PL(dB) = PL(d_0) + 10n\log\left[\frac{d}{d_0}\right] \tag{4}$$

Where $d$ is the reference point at 1 km and $n$ is known as the path loss exponent.

To cater for the terrain diffraction factor, the diffraction loss for various points in different sectors was analysed. This was obtained by computing the free space path loss between the BTS and the MS and subtracting it from the path loss where diffraction loss is taken into account from ATOLL radio planning tool. Various diffraction losses were equated to (1), and from these values the value of $n$ was computed.

### B. Building correction factor

To be able to model the building correction factor that sufficiently accounts for diffraction power loss for the region under study, a combination of empirical and deterministic approaches were employed. This avenue was chosen purposely to harness the strengths of both these approaches, namely computational efficiency based on measurement accuracy of empirical methods and the flexibility of deterministic models since they present a close relationship with principles of physics. This renders the deterministic models more flexible to be applied to different environments without affecting their accuracy.

### C. Building diffraction model

Several built up cell sites were considered. Since buildings are opaque, only diffraction loss was taken into account. This is because we are dealing with outdoor propagation scenarios. The diffraction loss in this case is best described using Huygens principle, which states that each point on a wave front acts as a source of secondary wavelets, the combination of these wavelets produces a new wave front in the direction of propagation [6] .We can express the field strength of the resultant new wave by computing the integral of the field strength of wavelets and hence compute diffraction loss by (2).

$$L_{diff} = -20\log\sqrt{2} + 20\log\left(2\pi v\right) \tag{5}$$

Where $v$ is the Fresnel-Kirchoff parameter.

The building loss expression was applied on the building data obtained from the area under study. It was assumed that all the buildings have the same reflective, attenuation and conduction properties. The building loss corresponding to each radio path for all the cell sites was calculated. An average of these losses gave the average building loss that was used in this study. The loss was on average found to be 18dB.

The building density of the area was formulated by first estimating the length occupied by buildings on each radio path. Next, the length of the radio path to the measurement point was noted. The length of the buildings was divided by the corresponding length of the radio path. An average of these ratios was computed; the figure obtained was taken to represent the density of the buildings in the area under study. This approach was based on the fact that the greater the distance occupied by the building on the given radio path the more the buildings in the sector and hence it reflects the density of the buildings.

It was learnt from the area that different cell sites had different building concentrations. Thus it was imperative to come up with a sliding scale density to cater for the difference in building densities in the cell sites under consideration. This was realized by classifying the cells as having high, medium or low building densities. The procedure discussed above was again applied to the building data to establish the respective densities for the three density types. In order to obtain the diffraction loss due to buildings on each radio path the average building loss was multiplied by the respective building density of the cell sites under consideration.

### *D. Modelling Vegetation correction factor*

The same procedure as the one used to model the building correction factor was employed to model the vegetation correction factor. Equation (2) is used to compute diffraction loss due to trees. A similar procedure as the one used to calculate the building density was employed to get the vegetation density. This gave the three density scenarios of high, medium and low.

The various radio paths between the BTS and the measurement point were considered. The diffraction loss due to trees was computed using MATLAB. The diffraction loss corresponding to each radio path for all the cell sites was calculated. An average of these losses gave the average tree loss that was used in this study. The loss was on average found to be 8dB.

In the second case an empirical approach was used to calculate additional loss due to vegetation. The form of the formula used is supplied by (6).

$$\text{Vegetation loss} = \beta \text{ dB/m} \sum_{i=1}^{m} d_i \tag{6}$$

Where $\beta$ dB/m is the average vegetation loss per metre in dB and $d_i$ is the individual propagation distances in meters.

To ascertain the value of $\beta$ dB/m, field measurements were used. A site was first selected using clutter map. Then the particular site was located for field measurements. The signal strength at the measurement point was noted and then divided by the distance between the transmitter and the measurement point to give the loss in dB per meter. This was done for some selected sectors and an average of these values was taken as a representative of the vegetation loss per meter for that sector and finally for that cell and region.

This data was implemented in MATLAB where the distance is computed and hence the vegetation loss as explained above. An average value of 0.327 $\beta$ dB/m was realised as average vegetation loss.

The values obtained from the knife-edge part and the empirical part were added together to obtain the total vegetation loss for the cell being considered. An average of the two values was assumed to be the vegetation loss i.e. 4.1635 $\beta$ dB/m. To get the loss due to vegetation on each radio path, the average vegetation loss was multiplied by the respective densities of the sectors under study.

### *E. Additional Terrain loss Correction Factor*

To account for the terrain correction factor, the individual cells of the area under study were analysed using ATOLL planning tool on the point analysis window. This was done on a number of sectors; the average value was taken as the additional terrain loss for the area. To compute the additional terrain loss coefficient the data collected was analysed to find out how many of the measurement points had zero value and how many of them had a non-zero value.

The values of diffraction factor corresponding to each terrain obstacle were obtained using point analysis window on ATOLL planning tool.

The ratio of those measurements with non zero values to the total measurement points considered was taken as the coefficient of the additional terrain correction loss for that cell.

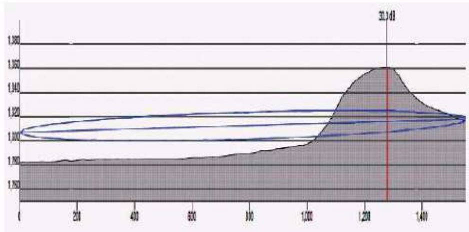

Figure 1: point analysis window estimation.

The same procedure was utilised in some more cells and an average of the values obtained was computed, a value of 0.382 was obtained. This is the value of the additional terrain loss correction factor for the area under study.

### *F. Modelled Propagation Prediction Model*

At this stage, all the parameters needed to model a propagation prediction model have been found. The best fit for the model predictions to the measured signal is found by introducing tuneable $p$-parameters into the path loss model. The modelled path loss formula would then be expressed as follows:

$$PL_{dB} = p_1 + p_2 \log d + p_3 \log\left(\frac{d}{d_0}\right) + p_4 * (Building\_Loss) + p_5 * (vegetation\_Loss) + p_6 * (ADD\_Loss) \tag{4}$$

Where $p_2$, $p_3$, $p_4$, $p_5$ and $p_6$ are the multiplying factors to be tuned and $p_1$ is the intercept value which introduces a constant offset in dBm to lower the mean error as close as possible to zero. $ADD\_Loss$, $vegetation\_Loss$ and $Building\_Loss$ are the additional terrain loss factor, vegetation correction factor and building correction factor. This is the propagation model that will be calibrated in the following section.

### *G. Calibration of the Propagation model*

The error between the measured and the predicted data was used to calibrate the model. First, the clutter information was obtained from ATOLL planning tool. This information was then loaded in the MATLAB work space. Based on this, the clutter loss was calculated for both vegetation and building for each measurement point. This was then averaged to get the clutter losses for vegetation and buildings separately.

In the clutter information file, each clutter type length between the BTS and the MS was included. This clutter length was divided by the total distance between the BTS and MS for each measurement point. The overall length of

given clutter type on any radio path was the sum of the individual clutter type length encountered on the radio path under consideration. This in turn reflects on how often the clutter type occurs in the region under study and hence its density. From this, the ratio of clutter length to the BTS-MS distance for all the measurement points under consideration was averaged and the results gave the clutter type density in the region under consideration. This became the multiplying factor for the building and vegetation losses respectively.
However, this was an optimistic approximation since the clutter density varies from one cell to another in the same region. To cater for this, we had to define whether the clutter density was high, medium or low. Based on this, the above procedure was repeated and each of the density types derived upon which the clutter loss calculation was based.

## III. Modelling Mobile Positioning System

### *A. Mobile Positioning Using Nonlinear Least Square Approach*

The calculation of the mobile position $(x, y)$ involves solving a nonlinear least squares problem given by (5).

$$Error = \sqrt{(X_i - x)^2 + (Y_i - y)^2} - d_{i,j} \tag{5}$$

Where: $(X_i, Y_j)$ are the BTS coordinates, $d_{i,j}$ is the computed distance from the BTSs to the approximate Mobile position using the modelled per cell propagation prediction model.
This method minimises the difference between distance calculated from the BTS coordinates to the estimated mobile position and the same distance calculated using the modelled propagation prediction model. Ideally this difference in distance should be equal to zero for very accurate MS positioning. The MATLAB *isqnonlin* function in the optimisation toolbox is used to implement this algorithm. The function *isqnonlin* solves nonlinear least squares problems of the form:

$$\min \ \mathrm{sum} \ \{\mathrm{FUN}_x(\mathrm{X})^2\} \tag{6}$$

Where $X$ and the values returned by FUN can be one dimensional or higher. A program was written in MATLAB utilising this function as shown below. The program utilises coordinates of six Base Transceiver Stations and the distances obtained from the prediction model to compute the mobile position.

```
function [err]=calerr(xy)

% function takes approximate mobile position
% xy, returns the calculated error in
 % distance.

global XYpos dist

% XYpos are the coordinates of BTS positions
% dist is the distances from the BTSs to the
% approximate mobile position

dxy=XYpos-ones(size(XYpos))*diag(xy);
dist2b=(dxy.*dxy)*[1;1];
distb=sqrt(dist2b);
err=distb-dist;

%.......................................................................................

% The MATLAB script file below is used to call the above
% MATLAB function

global XYpos dist

XYpos=[ 6.21230E+05 7.15670E+06
       6.20640E+05  7.15550E+06
       6.22340E+05 7.15540E+06
       6.21890E+05 7.153400E+06
       6.21230E+05 7.156700E+06
       6.20500E+05 7.15290E+06];

xy0=mean(XYpos) % Get mean of BTS coordinates

dxy=XYpos-ones(size(XYpos))*diag(xy0);
dist2=(dxy.*dxy)*[1;1]; dist=sqrt(dist2);

d=[1375,9840,15230,13800,14260,12930]';
% computed distances from the BTSs to mobile position.

dist=dist-d;
xy0=xy0.*(1+2*rand(1,2));
[xy,resn,resid,xf]=lsqnonlin(@calerr,xy0)
xt=xy+mean(XYpos)

% xt is the calculated mobile position
```

## IV. Results And Discussions

To obtain the predicted signal strength at the mobile position, total path loss was calculated using the modelled per cell propagation model and then deducted from the transmitted power values as shown by (7).

$$P\_received = P\_radiated - PL(dB) \tag{7}$$

Where $P\_received$ is the Received Power in dBm.
$P\_radiated$ is the Equivalent Radiated Power from the BTS antenna in dB. $PL(dB)$ is the path loss calculated using the modelled Path loss propagation model [3].
The values obtained for the predicted and measured signal SS before calibrating Hata propagation for a studied cell is depicted in figure (2).
Clearly there is no correlation between the predicted and the measured signal. Hence there is need to calibrate the propagation model for the best fit parameters that give predictions which are closest to the measured data. Evidently the predicted signal corresponded very well with the measured signal as can be seen in figure (3).
The related error between the predicted and the measured signal for this case was obtained as illustrated in figure (4). The corresponding mean error and the standard deviation error were found to be -0.1535dB and 2.2842 respectively.

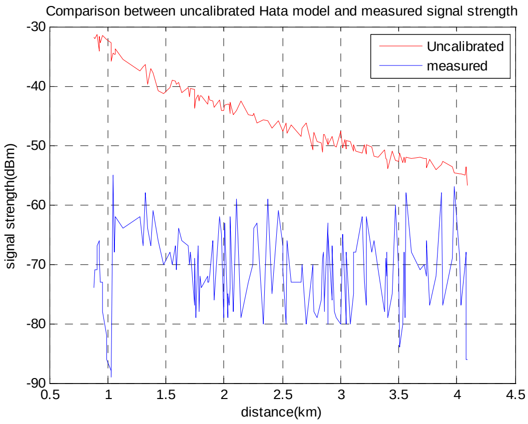


Figure 2: Measured and predicted SS before tuning.

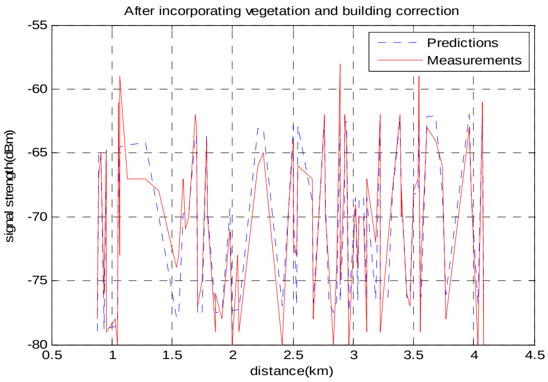


Figure 3: Vegetation and building correction effect

Thus the discrepancy between the predicted and measured signal strength is very small (compared to when generic tuning is utilized), all measurement points had a value of less than 10dB.

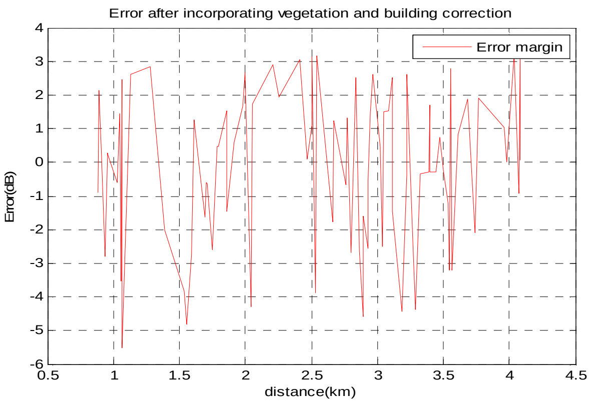


Figure 4: Error margin after clutter correction

When normal generic tuning procedure was applied on Hata model, most points did not correlate well compared to figure (3), though a few points did correspond well. The standard deviation error between the measured and the predicted signal levels was found to be 7.32 while the mean was 18.67dB.

Figure (5) gives a comparison between the values obtained when generic calibration is utilized on Hata propagation model and the field measured RSS. Thus, it is evident from figure (3) and figure (5) that the modelled per cell propagation model yields a close approximation to the real environment than the usual generic tuning. Based on localised environmental features, correctional factors can be used to tune propagation models for other similar cells in different locations if the characteristics are as the studied cell.

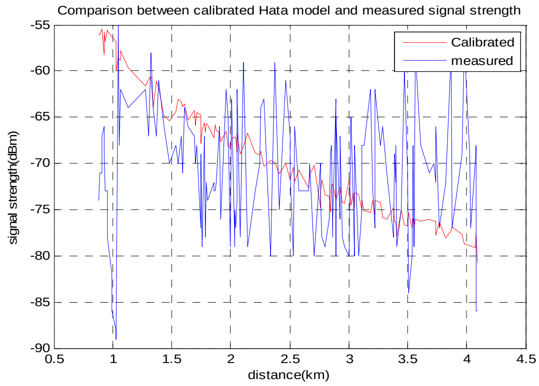


Figure 5: Average correction factor

An un-calibrated Hata model is used to compute the distance between the BTSs with the strongest RSS. The distance from the serving BTS was computed using the TA value. The computed distances from up to six BTSs together with the $(x, y)$ coordinates of the BTSs were applied on the positioning system. The accuracy of the designed MS positioning system was obtained has 210 meters.

The Hata propagation model was calibrated using ATOLL radio planning software. It was used to compute the BTSs-MS distances as discussed in the above section. The values obtained were applied on the location system. An improved accuracy of 173 meters was obtained for the MS position. This showed that when a propagation model is calibrated to characterise the terrain features of the area under study, the accuracy of the MS positioning is improved.

Figure (6) shows the measured MS position and the computed position using calibrated and un-calibrated Hata propagation model.

The calibrated propagation model using the modelled Path loss propagation model was used to compute the distance from the BTSs to the MS. The distances were again applied on the MS positioning system. The accuracy obtained for the area of study was 40 meters. Figure (7) shows the measured and computed MS position.

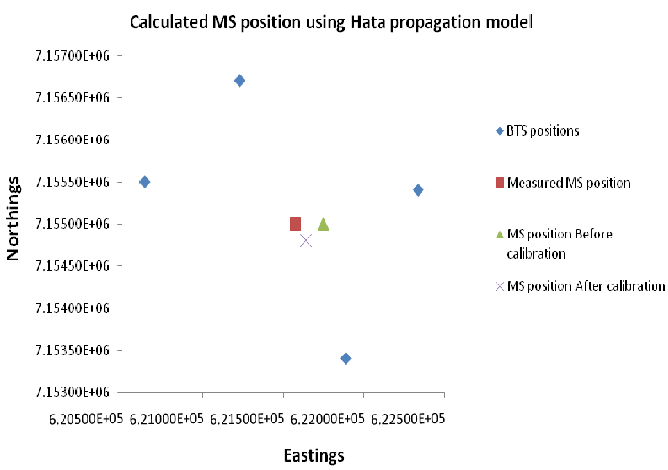


Figure 6: MS position based on conventional tuning.

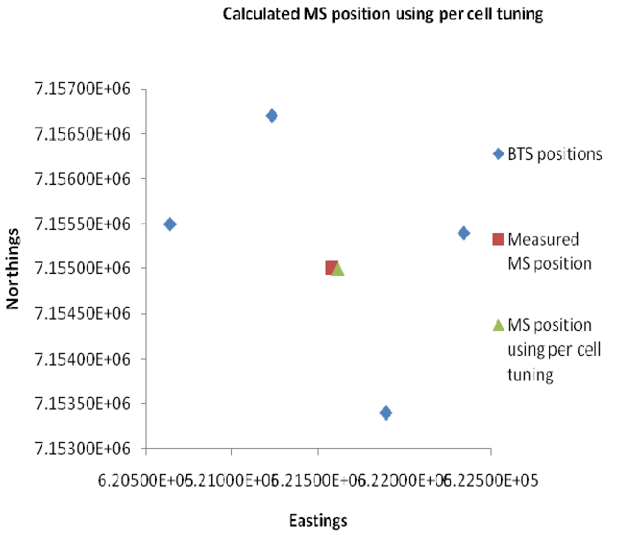


Figure 7: Computed MS position based on per cell tuning

## V. Conclusion

Per cell propagation positioning-based method is proposed and evaluated. Complexity of the developed positioning method is maintained at the minimum possible level in order to provide support for location sensitive applications in GSM networks. In classical cluster tuning approach standard propagation models are calibrated by utilizing radio planning tools without due regard to the contribution of the individual terrain and clutter factors. But in this work, a novel propagation system is modelled by taking into consideration specific clutter and terrain pattern in an area.

A positioning system is also designed which is used to compute the mobile position. An accurate and simple positioning system results therefore. The performance of the proposed method is assessed using simulations and field measurements. Comparatively the generic cluster calibration approach yielded a mobile position accuracy of 173 metres whereas per cell propagation-based positioning system gave an accuracy of 40 metres. Thus the computed results of the performance of the designed system are very close to the field measurements hence validating this proposed scheme. It has been shown that propagation prediction is vital in influencing the accuracy of mobile positioning.

The importance of tuning propagation prediction models taking into consideration specific clutter and terrain pattern in an area so as to achieve high accuracy level in positioning a mobile in GSM networks has been demonstrated. Locating disabled and elderly people for purposes of getting assistance from hospital personnel or their caretakers is certainly one of the most attractive domains that would benefit from such a system. Other possible applications include intelligent transport services, information on location of important landmarks and detection of fraudsters in GSM network.

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