A Quasi-Moment-Method-Based Calibration of Basic Pathloss Models

Ike Mowete*, Michael Adedosu Adelabu, Ayotunde Abimbola Ayorinde, Hisham Abubakar Muhammed, and Francis Olutinji Okewole

Department of Electrical and Electronics Engineering, University of Lagos, Akoka, Lagos, Nigeria.

*Corresponding author: amowete@unilag.edu.ng

Abstract: Using a technique similar to Harrington’s method of moments, this paper develops a very simple but remarkably efficient approach to the calibration of established (basic) mobile radio propagation pathloss models. First, the theoretical foundations of the process, here referred to as the ‘Quasi-Moment-Method (QMM)’, is succinctly presented. Thereafter, for validation purposes, pathloss predictions due to its use are compared with corresponding data reported in the open literature, for a model that derived from the application of the Adaptive Neuro-Fuzzy Inference System, ANFIS. Results of the comparisons reveal that the root-mean-square error (RMSE) values for the QMM-models compare favorably with those reported for the more computationally involved ANFIS model; and that all the six QMM-calibrated models considered in the paper, provided better spread-correlated root-mean-square (SC-RMS) and standard deviation (SD) prediction errors. QMM cross-application prediction performance is also evaluated through comparisons with measurement data obtained by the authors, for the Nigerian cities of Ibadan and Abuja. Outcomes of the comparisons clearly show that the QMM cross-application performance, particularly for the calibrated ECC-33 models, may be described as excellent.

Keywords: Pathloss model, Calibration, Moment-Method, Cross-application, ANFIS.

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1. INTRODUCTION

In propagating from source to destination, electromagnetic waves are in varying degrees, invariably subjected to reflections, refractions, scattering, and absorption, with the consequence that signal degradation manifest as energy loss, conventionally referred to as ‘pathloss’, Ikegami and Yoshida, [1], Vieira et al., [2]; or channel propagation impairments, Sarkar et al. [3]. The radio link designer, in order to effectively plan, design, validate, and construct wireless communications networks, is consequently required to predict the nature and extent of signal quality degradation, and hence, account for the pathloss attributable to the system’s operational environment. This need, in the case of mobile cellular communications, is particularly underscored by the requirements of Site Placement Problem (SPP) and Site Selection Problem (SSP), as described, respectively, in two different publications by Khalek et al., [4], and by Calegari et al., [5]; the latter concerning the Software Tools for the Optimisation of Resources in Mobile Systems (STORMS) project. Both publications represent notable examples of the critical importance of optimum pathloss models to the design and implementation of schemes for network performance optimization.

Although it is, in principle, possible to accurately specify terrain propagation loss characteristics by solving Maxwell’s equations, subject to appropriate boundary conditions, this approach is decidedly mathematically rigorous and absolutely intractable in virtually all cases of practical interest, [3], [4]. A possible alternative is to utilize exhaustive measurements, which, in addition to being expensive, is clearly impractical. It is not surprising therefore, to find that researchers have, over the years, developed various methods and design tools in the form of empirical models Tutschku, [6]; Iskander and Yun, [7]; Fernandez et al., [8]; Gozalvez, Sepulcre and Palazon, [9], classified as either ‘large-scale pathloss models’ or ‘small-scale fading models’, with which to address these challenges. Unfortunately, it has been firmly established that it is impossible to find a model of such general applicability as to be independent of terrain, environmental conditions, and radio propagation scenario, [3]. Indeed, Erceg et al., [10], pointed out that classical pathloss models such as the Okumura-Hata [11] -and its derivatives-, rarely consider the needs of emerging communication systems and technology, and consequently inadequately provide for such needs, in network optimization schemes. Using a regression analysis approach, Erceg and his associates [10] analysed data available from comprehensive field measurements to obtain computational results, which suggest that this limitation may be addressed through the determination of optimum values for loss exponent and/or standard deviation of shadow fading indices, as may apply, in the model development process. One example that considered the needs of an emerging technology is offered by the contributions of Pitchaih [12], whose work addressed the limitations imposed by the channel on the performance of the Local Multipoint Distribution Systems (LMDS) as a last mile solution in a wireless
environment, utilizing the higher data rates. These contributions inform that pathloss prediction models are able to perform reliably, only to the extent that factors concerning the physical environment are suitably accounted for in the course of the model development process. This is the case with typical empirical modelling, in which data collection correctly reflects terrain and associated propagation characteristics.

Because the classical (basic) empirical models, despite the advantage of computational simplicity, often lack desirable levels of prediction accuracy, quite a few research efforts have been dedicated to ‘tuning’ or ‘calibration’ of the basic models, as a means of improving accuracy without losing ease of use. Notable examples of these optimization techniques include the contributions by Mardeni-Kwan [13], who implemented a regression-type ’Least Squares Method’; others are the regression analysis reported by Nissrat et al., [14], and the Genetic Algorithm optimization scheme, implemented by Garah and his associates, [15]. In the main, these approaches involve improving the Root Mean Square (RMS) prediction error due to such basic models as the Lee, [16], COST231-Hata [17], and COST231-Walfisch-Ikegami [18], and ECC-33 models, [19]. Although RMSE values as low as 3.08dB have been reported [15] as being due to the optimization of basic models with which RMSE values in excess of 20dB are otherwise associated, it is still held [20-22], that the associated prediction errors are in general, rather poor. As a consequence, research attention has been directed in recent times, to the development of empirical models, with basis in artificial intelligence techniques. These include the various Artificial Neural Networks (ANN)-based models described by Sotiroudis et al., [19], Cavalcanti and Cavacante, [21], and Eichie et al., [22]. Others are the variants of the Adaptive Neuro-Fuzzy Inference Systems (ANFIS)-based methods reported by Larijani, Curtis, and Wistex, [23], and the contributions by Faruk and his associates, [24 25]; as well as the Support Vector methods due to Timoteo [26], and Zhao, [27], and the Learning Machine approach introduced by Ayadi et al., [28].

As pointed out by Faruk et al., [25], and Surajudeen-Bakinde et al. [33], whereas the ANN and ANFIS-based models outperform the basic models in terms of Mean Prediction Error (MPE) and RMSE as performance metrics, the basic (Uncalibrated) models outperform the ANN/ANFIS models, when Standard Deviation Error (SDE) is utilized as performance metric. For this reason, [25] suggested that in practical situations a trade-off between simplicity and ease of use (due to optimized basic models) on one hand, and on the other, accuracy and computational complexity (attributed to the ANN/ANFIS models) should prove expedient. It was further suggested in [25] that a hybrid of these two approaches could be the best option. And indeed, this suggestion is very strongly supported by the results reported by Cavalcanti and Cavacante [21], who utilized a hybrid of ECC-33, Ericsson, and Tr-36.942 for pathloss prediction concerning LTE and LTE-A networks.

This paper presents a novel, a very simple, yet remarkably efficient approach to empirical pathloss calibration, which, on account of its similarity to the Matrix Methods originally developed by Harrington, [32], for the solution of field problems, is referred to as the ‘Quasi-Moment-METHOD’, or ‘QMM’. For the purposes of validating the correctness and efficacy of the approach, pathloss predicted with its use is compared with measurement (and associated) data published in [24], and the outcomes of the comparison revealed that the model compares favourably with the more computationally intensive ANFIS model utilized in [24]. For example, in terms of MPE, respective values of -0.0289 and 9.85x10^-6 were recorded for the best performing QMM-calibrated ECC-33 and ANFIS models; and in the case of RMSE, SC-RMSE, and SDE, values (in dB) obtained for the QMM-calibrated ECC-33 model are (4.9854, 3.7326, 1.9783), respectively, as against (2.5023, 4.4881, 6.0555) respectively, for ANFIS as published in [24].

2. THEORETICAL BACKGROUND

The generic pathloss empirical model is conceived in this paper, as a solution to the ‘approximation problem’, as defined by Dahlquist and Bjorck, [31]. Accordingly, we let \( P_i(d) \) represent the continuous function, which accurately specifies propagation pathloss for the region of interest, and which is to be approximated by the function

\[
P^*(d) = \alpha_1 \varphi_1(d) + \alpha_2 \varphi_2(d) + K + \alpha_3 \varphi_3(d),
\]

in which the set \( \{ \varphi_k \} \) represents a set of known functions, and \( \{ \alpha_k \} \), a set of unknown coefficients to be determined. The solution to this ‘approximation problem’ is considered optimum, when the unknown coefficients are so specified that the (weighted) Euclidean semi-norm of the error function defined as

\[
\varepsilon = P^*(d) - P(d),
\]

assumes its minimum possible value, for all values of the independent variable ‘d’. That is,

\[
\left| P^*(d) - P(d) \right|^2 = \sum_{i=1}^{N} \left| P^*(d) - P(d) \right|^2
\]

is as small as possible.

As shown in [31], when \( \{ \varphi_k \} \) is set of linearly independent functions, the solution to the approximation problem emerges as

\[
P^*_i(d) = \sum_{n=1}^{N} \alpha_n \varphi_n(d),
\]

provided that the unknown coefficients are solutions to the ‘normal equation’, given as

\[
\varepsilon = P^*(d) - P(d),
\]

assumes its minimum possible value, for all values of the independent variable ‘d’. That is,
\[ \langle \varphi_1, \varphi_2 \rangle \alpha \langle \varphi_1, \varphi_3 \rangle \alpha \langle \varphi_1, \varphi_4 \rangle \alpha = \langle \varphi_1, P_1 \rangle \]
\[ \langle \varphi_2, \varphi_3 \rangle \alpha \langle \varphi_2, \varphi_4 \rangle \alpha \langle \varphi_2, \varphi_5 \rangle \alpha = \langle \varphi_2, P_1 \rangle \]
\[ \langle \varphi_3, \varphi_4 \rangle \alpha \langle \varphi_3, \varphi_5 \rangle \alpha \langle \varphi_3, \varphi_6 \rangle \alpha = \langle \varphi_3, P_1 \rangle \]
\[ \langle \varphi_4, \varphi_5 \rangle \alpha \langle \varphi_4, \varphi_6 \rangle \alpha \langle \varphi_4, P_1 \rangle \]
\[ \langle \varphi_5, \varphi_6 \rangle \alpha \langle \varphi_5, P_1 \rangle \]  
\hfill (5)

The inner product terms appearing in Eqn. (5) admit description, according to [31],

\[ \langle \varphi_m, \varphi_n \rangle = \sum_{i=1}^{K} \varphi_m(d_i) \varphi_n(d_i) \]
\[ \langle \varphi_m, P_i \rangle = \sum_{i=1}^{K} \varphi_m(d_i) P_i(d_i) \]  
\hfill (6)

Equation (5) can be cast in matrix format, if the following definitions are utilized:

\[
[\Phi] = \begin{bmatrix}
\langle \varphi_1, \varphi_1 \rangle & \langle \varphi_1, \varphi_2 \rangle & \ldots & \langle \varphi_1, \varphi_K \rangle \\
\langle \varphi_2, \varphi_1 \rangle & \langle \varphi_2, \varphi_2 \rangle & \ldots & \langle \varphi_2, \varphi_K \rangle \\
\vdots & \vdots & \ddots & \vdots \\
\langle \varphi_K, \varphi_1 \rangle & \langle \varphi_K, \varphi_2 \rangle & \ldots & \langle \varphi_K, \varphi_K \rangle \\
\end{bmatrix}, \quad (7a)
\]

\[
[\Pi] = \begin{bmatrix}
\langle \varphi_1, P_1 \rangle \\
\langle \varphi_2, P_1 \rangle \\
\vdots \\
\langle \varphi_K, P_1 \rangle \\
\end{bmatrix}, \quad (7b)
\]

so that the desired unknown coefficients are obtained through the simple matrix operations of inversion and multiplication as

\[
[\mathbf{Y}] = [\Phi]^{-1} [\Pi] \]  
\hfill (8)

Equation (8) is similar to matrix equation for the moment-method, expressed in terms of generalized network parameters, [32].

Six of the more common basic pathloss models, namely, the Okumura-Hata, COST231-Hata, ECC-33, Egli, Ericsson, and Lee models, were selected as ‘base’ or ‘reference’ models, for the implementation of the QMM scheme described in the foregoing. In the case of the Okumura-Hata model, as illustrative example, the ‘base’ model is given, for urban centers, as, [13],

\[
P_{i}(Urban) = 69.55 + 26.16 \log_{10}(f) - 13.82 \log_{10}(h_{re}) - a(h_{re}) + (44.9 - 6.55 \log_{10}(h_{re})) \log_{10}(d) \]  
\hfill (9a)

In Eqn. (9a), \( h_{re} \) represents effective mobile receiver antenna height, both measured in meters. The parameter \( a(h_{re}) \) is a correction factor for effective mobile antenna height, and is given, for small-to-medium sized cities as

\[
a(h_{re}) = (1.1 \log_{10}(f) - 0.7) h_{re} - (1.56 \log_{10}(f) - 0.8) \]
\hfill (9b)

and for large cities,

\[
a(h_{re}) = 8.29 \left( (\log_{10}(1.55h_{re}))^2 - 1.1 \right), \quad f \leq 300MHz \]
\hfill (9c)

or

\[
a(h_{re}) = 3.2 \left( (\log_{10}(11.75h_{re}))^2 - 4.97 \right), \quad f \geq 300MHz \]
\hfill (9d)

For the sub-urban environment, Eqn. (9a) modifies to

\[
P_{i}(sub-urban) = P_{i}(urban) - 2 \left( \log_{10} \left( \frac{f}{28} \right) \right)^2 - 5.4 \]
\hfill (10)

Thus, in utilizing this ‘base’ model for the solution to the approximation problem of interest to the optimum model calibration process under discussion here, the following identification is made for the set \{\( \varphi_{k} \)\}:

\[
\begin{bmatrix}
\varphi_1 \\
\varphi_2 \\
\vdots \\
\varphi_K \\
\end{bmatrix} = \begin{bmatrix}
69.55 \\
26.16 \log_{10}(f) \\
-13.82 \log_{10}(h_{re}) \\
-a(h_{re}) \\
(44.9 - 6.55 \log_{10}(h_{re})) \log_{10}(d) \\
\end{bmatrix} \]
\hfill (11)

Since the \{\( P_i(d_i) \)\} are available from the processed field measurements, the only unknown quantities are the \{\( \alpha_k \)\}, which are readily determined from the matrix operations of inversion and multiplication.

### 2.1 Model Performance Evaluation and Validation

For the purposes of ascertaining the validity and efficacy of the formulation, prediction results due to QMM-calibrated basic models are compared with corresponding measurement results reported in [24], and with which the calibration of the basic models was effected. In addition, the performances of the various QMM-modified models are compared, in terms of MPE, RMSE, SC-RMSE, and SDE, with the performance of an ANFIS model, as reported in [24], for the same sets of measurement data.

Outcomes of this evaluation are displayed in the graphical formats of Fig. (1) and Fig. (2), as well as the statistical performance metrics shown in Table 1.

It is apparent from both Figs. (1) and (2) that the six QMM-calibrated reference models performed well-within the error bounds established by Phillips et al. [34]. This observation is supported by the associated computational results displayed in Table 1, concerning the statistical performance metrics of RMSE, SC-RMSE, MPE, and SDE, for the ANFIS and corresponding QMM-calibrated
models. These results reveal that whereas the ANFIS model recorded better RMSE and MPE metrics than the QMM-modified models, the latter models, in all cases, had better SC-RMSE and SDE metrics than the former. It should be remarked that even where the much more computationally intensive ANFIS model had better metrics, the corresponding metrics for the computationally inexpensive QMM models were comparable. And this observation is consistent with the remark in [25] that choice of use between ANFIS and efficiently calibrated

Figure 1. Comparison of prediction of QMM-models with measurement data from Fig 7 [24].

Figure 2. Comparison of prediction of QMM-models with measurement data from Fig 8 [24].
Table 1. Comparative performance evaluation of QMM-Models

<table>
<thead>
<tr>
<th>MODEL/METRIC</th>
<th>RMSE (dB)</th>
<th>SC-RMSE (dB)</th>
<th>MPE (dB)</th>
<th>SDE (dB)</th>
<th>RMSE (dB)</th>
<th>SC-RMSE (dB)</th>
<th>MPE (dB)</th>
<th>SDE (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>COST231-QMM</td>
<td>4.9854</td>
<td>3.9115</td>
<td>-0.0298</td>
<td>2.5816</td>
<td>7.5309</td>
<td>4.1702</td>
<td>-0.0097</td>
<td>5.5325</td>
</tr>
<tr>
<td>ECC-33-QMM</td>
<td>4.6105</td>
<td>3.7326</td>
<td>-0.8514</td>
<td>1.9781</td>
<td>5.1898</td>
<td>5.1559</td>
<td>0.0260</td>
<td>1.9911</td>
</tr>
<tr>
<td>ECC-33(LC)-QMM</td>
<td>4.5312</td>
<td>3.8729</td>
<td>-0.0266</td>
<td>1.9714</td>
<td>5.1924</td>
<td>5.1777</td>
<td>-0.1639</td>
<td>1.9177</td>
</tr>
<tr>
<td>EGLI-QMM</td>
<td>4.9853</td>
<td>3.9105</td>
<td>-0.0066</td>
<td>2.5814</td>
<td>7.5309</td>
<td>4.1722</td>
<td>-0.0090</td>
<td>5.5328</td>
</tr>
<tr>
<td>ERICSSON-QMM</td>
<td>4.9860</td>
<td>3.9753</td>
<td>-0.0858</td>
<td>2.5816</td>
<td>7.5321</td>
<td>4.1776</td>
<td>0.0532</td>
<td>5.5365</td>
</tr>
<tr>
<td>HATA-URB-QMM</td>
<td>4.9853</td>
<td>3.9112</td>
<td>-0.0234</td>
<td>2.5820</td>
<td>7.5310</td>
<td>4.1762</td>
<td>0.0428</td>
<td>5.5325</td>
</tr>
<tr>
<td>HATA(SUB)-QMM</td>
<td>4.9853</td>
<td>3.9085</td>
<td>0.0168</td>
<td>2.5822</td>
<td>7.5310</td>
<td>4.1759</td>
<td>0.0401</td>
<td>5.5329</td>
</tr>
<tr>
<td>LEE-QMM</td>
<td>4.9858</td>
<td>3.9137</td>
<td>-0.0724</td>
<td>2.5812</td>
<td>7.5310</td>
<td>4.1703</td>
<td>-0.0505</td>
<td>5.5327</td>
</tr>
</tbody>
</table>

basic models will depend on a trade-off between prediction accuracy and ease of model implementation.

With the validation, through the foregoing comparative analysis, of the QMM-calibration technique, its use with the calibration of basic models, using measurement results obtained for the Nigerian cities of Abuja and Ibadan as candidates, will be addressed in the ensuing sections.

3. MEASUREMENT CAMPAIGNS

Quite a few of the previously existing empirical models described in the open literature, [13, 14], have their bases in ‘optimization schemes’ designed to better fit basic models to measurement data for signal strength or power density collected for the terrain of interest. In the typical case, exemplified by the two references just cited, averages are taken, of measurements obtained from several base stations, and utilized as representative of the city for which a pathloss profile is to be established. A slight variation of this approach is adopted in this paper. Measurements taken for individual base stations are averaged for contiguous geographical locations, and this average is taken as representative of the geographical area covered by the base stations.

3.1 Data Collection

Two candidate Nigerian cities, Ibadan and Abuja, were considered for this paper, and the model calibration process was preceded by a phase of extensive data collection. Data sets were sourced from official measurement data on the existing networks of two major services providers in Nigeria, namely, MTN [29] and Airtel, [30]. In addition, field measurements were taken from 2009-2011 and later 2012-2013 at different times to cover the various seasons – wet rainy, and dry harmattan seasons. The measurements were informed by the distribution of the base stations across the locations, as made available by the services providers, and representative examples of which are displayed in Tables 2 (for Abuja) and Table 3 (for Ibadan).

Comprehensive data sets made available by the service providers included results of drive tests conducted on the two networks between 2007 and 2012, courtesy of engineering staff of the networks. Test equipment utilized for the field work include Lenovo ThinkPad and Toshiba Equium laptops, TEMS compatible mobile station – Sony Ericsson C702, USB GPS instrument, and TEMS dongle for real time drive-test data capture. A series of measurements were taken with SA2650 handheld spectrum analyzer having the frequency range 100kHz to 3.5GHz, and Carmin handheld GPS instrument were used as control data to verify the drive test results. Data capture and processing were carried out with the Toshiba laptop.

4. COMPUTATIONAL RESULTS AND DISCUSSIONS

For all computational results presented here, base station antenna height is 30m, and mobile station antenna height is 1.5m. All the base stations operated within the GSM-1800MHz frequency band.

4.1 Pathloss Prediction by the QMM-models for Abuja

Results presented in graphical formats in this section, concern the seven base stations, for which average pathloss, as earlier described, were obtained. The pathloss profiles in figure 3 refer to measured pathloss values obtained for BTS1, BTS2, BTS3, and BTS4 of Abuja, as identified in Table 2. And it is apparent from the profiles, that the best fit is due to the ECC-33 (QMM) models. Indeed, as can be seen from Table 4, the ECC-33 models (but for two exceptions) have the best performing statistical indices. The exceptions to this observation are in the cases of Mean Prediction Error (MPE) for the QMM-calibrated Lee model, which performed better; as well as Spread-Correlated RMSE (SC-RMSE), for which the QMM-modified Hata (Sub-Urban) model had the best index of $5.3397$dB. As a matter of fact, in terms of RMSE, the QMM-calibrated Lee model consistently came third, next to the ECC-33 and ECC-33 (Large City) models, in that order. One other remarkable feature of the results is that the Basic-COST231 model had a MPE (-1.4036dB) almost the same in magnitude (-1.3296dB) as its QMM-
4.1.1. Cross-Application performances of the QMM Pathloss Models - Abuja

In a recent publication, Zhang et al., [35], introduced ‘cross-application’ as a performance metric, defined as a measure of the ability of a basic model calibrated with measurements in a given area, to accurately predict pathloss in some other area with similar terrain features. A variation of that definition is adopted in this paper. ‘Cross-application’ is taken here, as referring to the ability of a QMM model, calibrated with pathloss averaged over a set of BTS’, to accurately predict pathloss for individual BTS within the set. Two different scenarios, based on this adaptation of the term, are examined in this section. The first involves BTS 1 to 5 (Garki), and the second, BTS 6 and 7, for Maitama. The pathloss profiles of Figs. (7) and (8), for BTS 1 to 5, and BTS 6 and 7, respectively, compare pathloss predicted on the basis of calibration with ‘BTS’ group averages’ on one hand, with measured pathloss for some BTS in the group, on the other.

In the case of the profiles of Fig. (7) and the corresponding statistical performance metrics displayed in Table 5, it is readily observed that the ECC-33 calibrated models are able to predict individual BTS pathloss with RMSE values ranging between 2.8973dB for BTS4, and 5.533dB for BTS3. All other models (with the exception of the sub-urban Hata model), in most of the cases, also performed creditably well in this regard. The same general trend is repeated for the group including BTS 6 and 7, whose pathloss profiles are displayed in Fig. (8). In this case though, a different calibrated version; though the latter recorded much better performances with the other indices.

Similar trends are displayed in the cases of BTS’ 2, 3, and 4, as can be seen from Figs. (4)-(6), and Table 4. The last column of Table 4 displays the statistical performance metrics of QMM models, calibrated with the use of pathloss, averaged over seven BTS’, at each radial distance away from the transmitting antenna. These results suggest that when average values, taken over a large data set are utilized for QMM pathloss calibration, performance improves remarkably.

As an example, for the best performing ECC-33 model, RMSE improved from the worst recorded case of 2.8505dB, for BTS1, to 0.4452dB, in the case of pathloss average. It is also readily observed that RMSE performances improved to below 5.0 dB for all the other models, except for the worst performing Hata (sub-urban) model, for which RMSE, nonetheless, improved from 11.5998 (for BTS2) to 7.8784dB. It may be concluded that this Hata (sub-urban) model is clearly a poor reference model, for use with pathloss model calibration for Abuja.

Table 2. Examples of the Abuja Cell Sites utilized in this study Source [30]

<table>
<thead>
<tr>
<th>New site ID</th>
<th>TAG</th>
<th>City/District</th>
<th>Capacity Dimension Area</th>
<th>Longitude</th>
<th>Latitude</th>
<th>BSC</th>
</tr>
</thead>
<tbody>
<tr>
<td>AB0009</td>
<td>BTS1</td>
<td>Garki</td>
<td>Abuja Metropolis</td>
<td>7.47268</td>
<td>9.01526</td>
<td>EABBS02</td>
</tr>
<tr>
<td>AB0043</td>
<td>BTS2</td>
<td>Garki</td>
<td>Abuja Metropolis</td>
<td>7.4930537</td>
<td>9.032386</td>
<td>EABBS01</td>
</tr>
<tr>
<td>AB0061</td>
<td>BTS3</td>
<td>Garki</td>
<td>Abuja Metropolis</td>
<td>7.4841082</td>
<td>9.037777</td>
<td>EABBS01</td>
</tr>
<tr>
<td>AB0063</td>
<td>BTS4</td>
<td>Garki II</td>
<td>Abuja Metropolis</td>
<td>7.497663</td>
<td>9.0395236</td>
<td>EABBS01</td>
</tr>
<tr>
<td>AB0006</td>
<td>BTS5</td>
<td>Garki II</td>
<td>Abuja Metropolis</td>
<td>7.48801</td>
<td>9.08198</td>
<td>EABBS01</td>
</tr>
<tr>
<td>AB0018</td>
<td>BTS6</td>
<td>Maitama</td>
<td>Abuja Metropolis</td>
<td>7.48091</td>
<td>9.10639</td>
<td>EABBS02</td>
</tr>
<tr>
<td>AB0019</td>
<td>BTS7</td>
<td>Maitama</td>
<td>Abuja Metropolis</td>
<td>7.50487</td>
<td>9.09258</td>
<td>EABBS01</td>
</tr>
</tbody>
</table>

Table 3. Examples of the Ibadan Cell Sites Utilized in this study Source [30]

<table>
<thead>
<tr>
<th>New site ID</th>
<th>TAG</th>
<th>City/District</th>
<th>Capacity Dimension Area</th>
<th>Longitude</th>
<th>Latitude</th>
<th>BSC</th>
</tr>
</thead>
<tbody>
<tr>
<td>OY0041</td>
<td>BTS1</td>
<td>Ibadan</td>
<td>Ibadan</td>
<td>3.8535035</td>
<td>7.3429193</td>
<td>EOYBS01</td>
</tr>
<tr>
<td>OY0030</td>
<td>BTS2</td>
<td>Ibadan</td>
<td>Ibadan</td>
<td>3.8536683</td>
<td>7.3794129</td>
<td>EOYBS01</td>
</tr>
<tr>
<td>OY0058</td>
<td>BTS3</td>
<td>Ibadan</td>
<td>Ibadan</td>
<td>3.8700244</td>
<td>7.3385585</td>
<td>EOYBS01</td>
</tr>
</tbody>
</table>
pattern of RMSE values emerged. For example, in the case of BTS 6, the best ‘cross-application’ performing QMM-calibrated model is the Egli model (3.0860dB) and the worst performing is the Ericsson model, for which a value of 4.8269dB was recorded, for RMSE.

Another interesting feature in the case of BTS 6, is that both the QMM-calibrated Egli and Hata (urban area) models, in that order, recorded better RMSE (3.0860dB; 3.3591dB) values than the ECC-33 calibrated models. And indeed, both models (Egli and Hata (urban)), again, in the same order, had better cross-application MPE values than the ECC-33 models.

4.2 Cross-Application performances of the QMM Pathloss Models -Ibadan

As a second example of the cross-application performances of the six QMM-calibrated models considered in this paper, the case of predicted pathloss profiles obtained from models calibrated with some measurements taken in Ibadan is presented in this section.

First, the performances of six calibrated models are compared with the measurement data from which they derive. The pathloss profiles of Fig. (9) graphically describe these performances, in the case of BTS2 of Table 3, as an example.

Computational results concerning statistical performance metrics for these cases further describe the performances of the calibrated models. For example, in the case of Fig. 9(a), 1.9872dB was recorded as RMSE for the two QMM-ECC-33 models, and for Fig. 9 (b), RMSE values of 7.2131dB and 7.5865dB were recorded, respectively, for the calibrated Ericsson and Egli models. For BTS’ 1 and 3, the ECC-33 models still give the best performances, though results for BTS 2, for the models represent the best.

Using the definition adopted in this paper for ‘cross-application’, the performances of the calibrated models for the three BTS’ considered for Ibadan, are described by the profiles of Fig. (10). The ‘QMM-models’ in the illustrations refer to the basic models, calibrated in this case, with average pathloss, taken over the three BTS’ listed for Ibadan.

As was the case for the two Abuja scenarios earlier described, the best performing ‘cross-application’ models for Ibadan are the ECC-33 models (RMSE(dB) = 3.0295; 2.3187; 5.1182; for BTS’ 1, 2, and 3, respectively), but a number of interesting departures occur in this case. For BTS1, the COST231 recorded the next best RMSE value of 5.8926dB, but for BTS’ 2 and 3, it was the calibrated Hata (urban-5.9536dB) and Ericsson (5.1128dB) models, respectively, that came after the ECC-33 models. In terms of MPE, the Lee models generally performed best, though corresponding values for the ECC-33 models were quite close. On the other hand, the ECC-33 models recorded far better Mean Absolute Error (MAE) results.

Figure 3. Predicted pathloss profiles for BTS 1 of Abuja
Table 4. Statistical performance metrics for the QMM models: Abuja

<table>
<thead>
<tr>
<th>Model/BTS</th>
<th>BTS1 (dB)</th>
<th>BTS2 (dB)</th>
<th>BTS 3 (dB)</th>
<th>BTS 4 (dB)</th>
<th>Average (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>COST231</td>
<td>MPE = -1.3286</td>
<td>RMSE = 6.2475</td>
<td>MAE = 5.0985</td>
<td>SDE = 1.7333</td>
<td>MPE = -1.3769</td>
</tr>
<tr>
<td>ECC-33 (LC)</td>
<td>MPE = -0.0777</td>
<td>RMSE = 2.8411</td>
<td>MAE = 2.1852</td>
<td>SDE = 0.3848</td>
<td>MPE = -0.0766</td>
</tr>
<tr>
<td>ECC-33</td>
<td>MPE = -0.0368</td>
<td>RMSE = 2.8405</td>
<td>MAE = 2.1820</td>
<td>SDE = 0.1775</td>
<td>MPE = -0.0373</td>
</tr>
<tr>
<td>HATA(URBAN)</td>
<td>MPE = -2.2595</td>
<td>RMSE = 6.5093</td>
<td>MAE = 5.5416</td>
<td>SDE = 1.5576</td>
<td>MPE = -2.3467</td>
</tr>
<tr>
<td>LEE</td>
<td>MPE = -0.0092</td>
<td>RMSE = 6.1604</td>
<td>MAE = 4.7408</td>
<td>SDE = 1.8266</td>
<td>MPE = -0.0056</td>
</tr>
</tbody>
</table>

Figure 4. Predicted pathloss profiles for BTS2 of Abuja
Figure 5. Predicted pathloss profiles for BTS 3 of Abuja

Figure 6. Predicted pathloss profiles for BTS 4 of Abuja
Table 5. Statistical Cross-Application performance metrics for the Abuja QMM-models

<table>
<thead>
<tr>
<th>Model/Cluster</th>
<th>BTS1 (dB) MPE</th>
<th>RMSE</th>
<th>MAE</th>
<th>SDE</th>
<th>BTS2 (dB) MPE</th>
<th>RMSE</th>
<th>MAE</th>
<th>SDE</th>
<th>BTS3 (dB) MPE</th>
<th>RMSE</th>
<th>MAE</th>
<th>SDE</th>
<th>BTS4 (dB) MPE</th>
<th>RMSE</th>
<th>MAE</th>
<th>SDE</th>
<th>BTS5 (dB) MPE</th>
<th>RMSE</th>
<th>MAE</th>
<th>SDE</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECC (LC)</td>
<td>MPE = -0.0845</td>
<td>RMSE = 3.4905</td>
<td>MAE = 6.2312</td>
<td>SDE = 0.5258</td>
<td>MPE = 3.3345</td>
<td>RMSE = 4.2076</td>
<td>MAE = 5.3752</td>
<td>SDE = 2.8514</td>
<td>MPE = -4.7453</td>
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<td>MAE = 6.2312</td>
<td>SDE = -0.2047</td>
<td>MPE = -2.5678</td>
<td>RMSE = 4.9052</td>
<td>MAE = 3.9318</td>
<td>SDE = -1.2348</td>
<td>MPE = -1.3453</td>
<td>RMSE = 9.3288</td>
<td>MAE = 8.1702</td>
<td>SDE = 3.8784</td>
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<tr>
<td>ECC-33</td>
<td>MPE = 0.1827</td>
<td>RMSE = 3.4939</td>
<td>MAE = 6.3034</td>
<td>SDE = 0.9873</td>
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<td>RMSE = 4.2076</td>
<td>MAE = 5.3752</td>
<td>SDE = 2.8514</td>
<td>MPE = 4.1470</td>
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<td>MAE = 6.3034</td>
<td>SDE = 3.8784</td>
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<td>MAE = 8.1702</td>
<td>SDE = 3.8784</td>
<td>MPE = 0.1656</td>
<td>RMSE = 4.4270</td>
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<td>SDE = 3.2811</td>
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<td>ERICSSON</td>
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<td>RMSE = 6.3842</td>
<td>MAE = 4.9100</td>
<td>SDE = 0.1032</td>
<td>MPE = -3.2572</td>
<td>RMSE = 4.2076</td>
<td>MAE = 6.3034</td>
<td>SDE = 3.8784</td>
<td>MPE = -1.0699</td>
<td>RMSE = 6.8301</td>
<td>MAE = 2.9719</td>
<td>SDE = 0.1032</td>
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<td>RMSE = 6.3842</td>
<td>MAE = 4.9100</td>
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<td>HATA-SUB</td>
<td>MPE = 7.2032</td>
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<td>MAE = 4.9100</td>
<td>SDE = 0.1032</td>
<td>MPE = -3.2572</td>
<td>RMSE = 4.2076</td>
<td>MAE = 6.3034</td>
<td>SDE = 3.8784</td>
<td>MPE = -1.0699</td>
<td>RMSE = 6.8301</td>
<td>MAE = 2.9719</td>
<td>SDE = 0.1032</td>
<td>MPE = 0.0072</td>
<td>RMSE = 6.3842</td>
<td>MAE = 4.9100</td>
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<td>MPE = -1.0699</td>
<td>RMSE = 6.8301</td>
<td>MAE = 2.9719</td>
<td>SDE = 0.1032</td>
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<tr>
<td>HATA(URBAN)</td>
<td>MPE = 2.4259</td>
<td>RMSE = 6.3842</td>
<td>MAE = 4.9100</td>
<td>SDE = 0.1032</td>
<td>MPE = -3.2572</td>
<td>RMSE = 4.2076</td>
<td>MAE = 6.3034</td>
<td>SDE = 3.8784</td>
<td>MPE = -1.0699</td>
<td>RMSE = 6.8301</td>
<td>MAE = 2.9719</td>
<td>SDE = 0.1032</td>
<td>MPE = 0.0072</td>
<td>RMSE = 6.3842</td>
<td>MAE = 4.9100</td>
<td>SDE = 0.1032</td>
<td>MPE = -1.0699</td>
<td>RMSE = 6.8301</td>
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<td>SDE = 0.1032</td>
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<tr>
<td>LEE</td>
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<td>RMSE = 6.3842</td>
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<td>RMSE = 6.8301</td>
<td>MAE = 2.9719</td>
<td>SDE = 0.1032</td>
</tr>
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</table>
Figure 8. Cross-application pathloss profiles: QMM-predicted Vs. BTS’ 6, and 7- Abuja

Figure 9. Comparison of pathloss profiles: QMM-predicted Vs. Measured BTS2- Ibadan
5. CONCLUDING REMARKS

This paper has presented the ‘Quasi-Moment-Method’ (QMM) as a very simple and remarkably efficient calibration tool for empirical radio propagation pathloss modeling. After a succinct description of the method’s characterizing features, predictions due to its use were compared with corresponding predictions published in [24], in which the ANFIS method was utilized. Results of that comparison revealed that in terms of RMSE and MPE, the QMM-calibrated models performed fairly closely to the ANFIS model, and recorded better SC-RMSE and SDE metrics.

Further evaluation of the QMM through calibration of six basic pathloss models, using measurement data for Abuja and Ibadan very clearly demonstrated that QMM-calibration of the basic models (particularly the ECC-33 models, in this case) provide excellent RMSE, MPE, MAE, and SDE results. Finally, and using a slight variation of the definition of ‘cross-application’ recently introduced by Zhang et al. [35], it was shown in the paper, that when the basic models are calibrated with the average of measurements taken over several base station pathloss data, the resulting models are able, with RMSE values well-within the error bounds established by Phillips et al. [34], to predict pathloss, for individual base stations involved in the averaging.

There is still a lot of scope for further investigations into the characteristic features of the QMM, including limitations and the physical interpretations of the calibration process, as may be available from the entries into the components of the matrix expression of Eqn. (8). It is also conceivable that QMM may represent a very good candidate for some hybrid modeling process, of the type proposed in the concluding remarks of [25].

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REFERENCES


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