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# Poynting Vector Joint with Weighted Least Square Regression Technique for Optimal Electric Field Strength Modelling

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**Abstract:** Telecommunication systems are presently at its lucrative growth-period in history; owing to supporting technologies and operational design that permit their wider deployment and acceptance. The need for better and robust telecommunication system networks design and management, estimating the strength of propagated field signal levels accurately at the user equipment terminal has become extremely important. In literature, one popular regression technique that is often engaged to perform field signal level predictive analysis and estimation of distributional strictures is the least square regression technique. This is probably due to its soft computational complexity and simplicity in graphical presentation procedure. Nonetheless, the resultant regression model may perform poorly owing to high stochastic nature and unequal noise variance (heteroskedastic) problems of most radio signal data. In this contribution, we proposed the application of weighted least square estimation approach combined with Poynting vector theory to model and estimate practical electric field strength data. The field strength data was obtained over radio frequency system interface which belongs to a commercial LTE cellular broadband networks service provider operating in typical urban area. In terms of reliability and precision, the outcome show that the employed hybrid weighted least square has the best performance compared to using the standard least square method. We also show that the precision performance improves as the power of the weighted least square method grows.

**Keywords:** eNodeB, Electric field strength, parametric estimation, highly stochastic, heteroskedastic, Weighted least square regression

## 1. INTRODUCTION

The deployment of long term evolution (LTE) networks, which is mainly a broadband internet protocol-based fourth generation (4G) telecommunication technology, has been on all over different parts of the world for a while now. This is to meet burst data transmission needs that was lacking in previous telecommunications systems such as Universal telecommunication systems networks and Code division multiple access systems.

Generally, in radio telecommunication systems networks, proper and continual cellular network monitoring and management requires the utilization of distinctive regression modelling techniques to perform a number of prognostic network performance assessments. However, accurate measurement and modelling-based estimation of the power of transmitted electromagnetic signal information through the cellular radio propagation channel has largely been one of foremost challenging parts in the network design and management [1-2].

In literature [3-14], least square regression based modelling procedure are often engaged in performing signal data predictive analysis and estimation of distributional parameters. For instance, in [3], the researchers proposed and adopted a least squares (LS) method to develop a more accurate quantitative measurement based model for path loss analysis in DVB-T2 systems. In [4], the authors applied a multi-linear regression method to develop a propagation model for acquired electromagnetic signals analysis over Ecuadorian jungle. This was specifically conducted by the Armed Forces in that jungle to optimise radio spectrum between 20 and 40 MHz transmission. The authors in [5] explored an ordinary least squares method base on experimental data to optimise COST 231 Hata model's vital parameters for enhanced predictive performance. A robust path loss fitting technique that

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employed least square algorithm for CDMA systems using Ghana environment as a case study is contained in [6]. Most recently, a linear-based Ridged/Lasso least square method and interrelated regression techniques were engaged for extrapolative analysis of propagated real-time field strength over ultra-high LTE frequency channels in [7-9]. Similar regression procedures were also previously adopted by authors in [10-18], to analyse and provide empirically adjusted channel loss models for in-depth radio propagation in Nigeria environment. The numerous applications of the least square regression technique in all these previous works may be due to its soft computational complexity and simplicity in data extrapolative analysis/graphical presentation. However, the resultant regression modelling precisions capacity are usually poor and low due to heteroskedastic (non-stochastic noise variance) complications and extremely stochastic nature of most empirical observations [18-20]. This in turn often results in poor precision/correlation problems [20-23]. A good alternative approach is the weighted least squares estimation which have to cater for both high variability [20] [24] and unequal noise variance nature of most signal data.

The research paper aims to propose a weighted least squares regression approach combined with Poynting vector theory for adaptive modelling and prognostic estimation of practical electric field strength data. The objectives are in twofold: to justify the need to exploring a better regression approach other than the commonly used least square regression models for accurate estimation of highly stochastic nature and unequal noise variance (heteroskedastic) problems of most practical radio signal datasets and, to propose an alternative hybrid approach which combines a weighted least squares regression approach with Poynting vector theory for adaptively solving the problem. This has been achieved by conducting a wide-ranged field strength dataset measurements over an operational microcellular LTE networks and employing the proposed hybrid approach to adaptively model the measured datasets. The resultant improved adaptive predictive modelling outcome using the proposed approach over the standard least square method is also clearly shown.

The remaining integral part of this research paper is structured as follows: the materials and research methodology adopted, which covers the basis of electric strength propagation, measurement and modelling based estimation using the proposed weighted least regression are contained in Section 2. Section 3 provides the resultant outcome using the weight regression approach over the standard least square method, while conclusion is shown in Section 4.

## 2. MATERIALS AND METHOD

### *A. Electric Field Strength Modelling*

The information flow from the transmitter via a propagation channel to the receiver is in radio telecommunication systems is in the form of electromagnetic waves consisting of electric and magnetic fields components. The time varying electric and magnetic fields components can be described using the Faraday's and Ampere's laws, both which constitute the first two parts of the core Maxwell's equations:

$$\nabla \times E = -\frac{\partial B}{\partial t} \tag{1}$$

$$\nabla \times H = \frac{\partial D}{\partial t} + J \tag{2}$$

where E and H are electric field intensity and magnetic field intensity (vectors); J and D indicate the displacement current density and electric displacement vector.

By multiplying equations (1) and (2) with H and E, respectively, we obtain the modified forms of Maxwell equations as:

$$H.\nabla \times E = -H.\frac{\partial B}{\partial t} \tag{3}$$

$$E.\nabla \times H = E.\frac{\partial D}{\partial t} + E.J \tag{4}$$

Also, by exploring the divergence of a cross product: $\nabla.(E \times H) = H.\nabla \times E - E.\nabla \times H$, equations (3) and (4) can be jointly written as:

$$\nabla.(E \times H) = H.\frac{\partial B}{\partial t} - E.\frac{\partial D}{\partial t} - E.J \tag{5}$$

To further simplify the Maxwell equations, we employ:

$$\frac{\partial}{\partial t}\left(\mu \frac{1}{2}\|H\|^2\right) = \frac{\partial}{\partial t}\mu\left(\frac{\partial H}{\partial t}.H + H\frac{\partial H}{\partial t}\right) = H\frac{\partial(\mu H)}{\partial t} = H.\frac{\partial B}{\partial t} \tag{6}$$

According, equation (5) becomes:

$$\nabla.(E \times H) + \frac{\partial}{\partial t}\left(\mu \frac{1}{2}\|H\|^2\right) + \frac{\partial}{\partial t}\left(\varepsilon \frac{1}{2}\|E\|^2\right) + \sigma E.E = 0 \tag{7}$$

By integrating equation (7) over a volume V and then applying the divergence theorem to the first part, gives:

$$\oint_S (E \times H) ds + \frac{\partial}{\partial t}\int_v \left(\frac{1}{2}\mu\|H\|^2 + \frac{1}{2}\varepsilon\|E\|^2\right) dv + \int_v \sigma\|E\|^2 dv = 0 \tag{8}$$

The expression in equation (8) simplifies the Poynting theorem which states that: the power leaving the volume plus the power going into heat plus rate of increase in the stored energy equals to zero, where:

$\int_v \sigma\|E\|^2 dv$ = power lost to heat inside V

$\frac{\partial}{\partial t}\int_v \left(\frac{1}{2}\mu\|H\|^2 + \frac{1}{2}\varepsilon\|E\|^2\right) dv$ =rate of increase of stored energy inside V

$\frac{1}{2}\mu\|H\|$ = stored magnetic energy density inside V

$\frac{1}{2}\varepsilon\|E\|^2$ = stored electric energy density inside V

$\oint_S (E\times H)ds$ = power leaving the volume V via the S surface

Thus, in terms of Poynting vector, the power carried by electromagnetic waves through a surface S, can be expressed as:

$$S = E\times H \quad (9)$$

For planes waves, $H = E/\eta$. Thus, equation (9) can be written as:

$$S = E\times H = E\times E/\eta = E^2/\eta \quad (10)$$

*Poynting vector* expression in equation (10) describes the direction and magnitude of energy flux density of the *electromagnetic* field.

### B. Data Collection

Signal power data collection, distribution analysis and modelling are key to performing robust radio frequency (RF) optimization over the cellular telecommunication network interface. The signal power data used in this work was acquired over RF telecommunication system air interface of a commercial LTE networks service provider operating in Port Harcourt City, Nigeria. By means of TEMS-empowered investigation tools (i.e. the laptop and the TEMS pocket phones) as displayed in figure 1, practical field signal power measurement was conducted at different receiver distances while driving along predefined routes round six LTE eNodeB microcellular sites which transmit at EIRP of 20 watts (43 dBm) in the 2600MHz frequency band. The TEMS is an acronym for telephone mobile software. The six eNodeBs whose heights ranges between 28m to 34m respectively, were randomly selected across the city. The eNodeBs are termed as eNodeB-1, eNodeB2, eNodeB3, eNodeB4, eNodeB5 and eNodeB6, in this work. The acquired drive test data are in logfile form and it contained all the measured signal data and other relevant parameters that can be explored to conduct a total network analysis and optimisation. With the aid of the TEMS empowered laptops, map info, Microsoft excel, and Matlab software, the log files were exported for further post processing.

At the receiving location, the measured signal power, $P_{rev}$ at the receiver point is related to S and the receiver point effective area, $A_r$ by [14][15]:

$$P_{rev} = S.A_r \quad (11)$$

where

$$A_r = \frac{G_a\lambda^2}{4\pi} \quad (12)$$

Substituting equations (9) and (10) into equation (9), gives

$$P_{evr} = \frac{E^2}{\eta}.\frac{G_a\lambda^2}{4\pi} \quad (13)$$

$$P_{rev} = \frac{E^2 G_a\lambda^2}{480\pi^2} \quad (14)$$

Equation (14) can be written in terms of E and after some simplification in $dB\mu V/m$, we obtain:

$$E(dB\mu V/m) = P_{rev}(dBm) + Cc \quad (15)$$

where

$$Cc = 20Logf(MHz) + 77.2(dB) - G_a(dB) \quad (16)$$

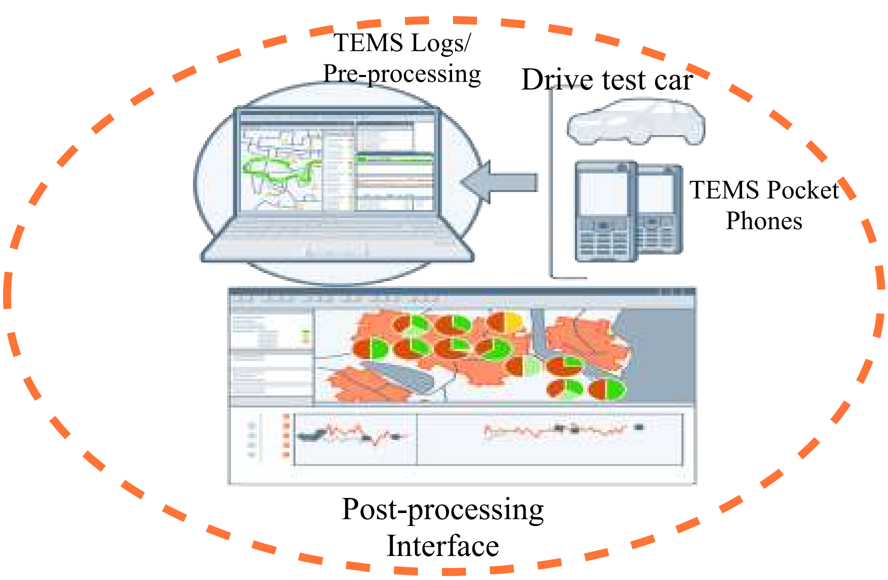


**Figure 1: TEMS Investigation Tools**

### C. Regression Methods

(i) Standard Least Square Regression Method

In computational sciences, social sciences and engineering, ordinary least squares (OLS) regression, also generally known as linear least squares (LLS) regression, is a special prognostic technique approximating a linear function to a data in least square sense. The LLS principle works by minimizing the sum of square differences between the values of observed data variables (i.e. the observed dependent variables) and the data values estimated by the linear function.

Consider the modeling of electric field strength data matrix [y: X], which involve N measurement observations. where, X and y denote the N×k matrix and N-vector data element yi. By starting with a linear model in (1), we have:

$$y_i = x_{1i}P_1 + x_{2i}P_i + x_{3i}P_i + \ldots x_{ki}P_i + e, (i = 1,2,\ldots,N) \quad (17)$$

where,

$N$ =Number of measurement observations

$x_i$ = independent variables

$y_i$ =response variable

$P_i$ =estimation parameters

$e$ =measurement errors

In Matrix form, equation (17) is given as:

$$y = XP + e \quad (18)$$

where

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, X = \begin{bmatrix} x_{1,1} \ldots x_{j,1} \\ x_{1,2} \ldots x_{j,2} \\ \vdots \quad \vdots \\ x_{1,n} \ldots x_{j,n} \end{bmatrix}, P = \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_n \end{bmatrix}, e = \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{bmatrix} \quad (19)$$

The residual error between the linear model and measurement data is obtained from equation (18) as:

$$e = y - XP \quad (20)$$

By means of least square regression, the estimation parameter, $P$ can be determined by minimizing the residual error, $y - XP$ in the least square sense as:

$$\min \sum e_i^2 = e^T e = (y - XP)^T (y - XP) \quad (21)$$

So, the cost function can be defined as:

$$S(P) = (y - XP)^T (y - XP)$$
$$= y^T y - y^T XP - P^T X^T y + P^T X^T XP \quad (22)$$

By differentiating with respect to $P$ and equate to zero gives:

$$\frac{\partial S(p)}{\partial P} = -2X^T y + 2X^T XP = 0 \quad (23)$$

Solving for $P$ gives:

$$P = \left(X^T X\right)^{-1} X^T y$$

Thus, LS solution is given by:

$$P = \left(X^T X\right)^{-1} X^T y \quad (24)$$

where the operator $T$ indicates the conjugate transpose (Hermitian Transpose)

(ii) Weighted Least Square Regression Method

The LS approach above is only efficient for unknown coefficients estimation if the observations possess unequal variance and if some level of correlation exist between the observations [18] [19]. In situations wherein the observations are uncorrelated, the weighted LS regression whose weighted covariance matrix is diagonal can be explored.

Therefore, the WLS component of equation (19) can be written as

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, P = \begin{bmatrix} p_{1,1} \ldots p_{j,1} \\ p_{1,2} \ldots p_{j,2} \\ \vdots \quad \vdots \\ p_{1,n} \ldots p_{j,n} \end{bmatrix}, X = \begin{bmatrix} x_{1,1} \ldots x_{j,1} \\ x_{1,2} \ldots x_{j,2} \\ \vdots \quad \vdots \\ x_{1,n} \ldots x_{j,n} \end{bmatrix}, P = \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_n \end{bmatrix} \text{ and } e = \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{bmatrix} \quad (25)$$

In terms of least square regression, the estimation parameter, $P$ can be determined by minimizing the residual error, $W(y - XP)$ in the least square sense as:

$$\min \sum W e_i^2 = W e^T e = W(y - XP)^T (y - XP) \quad (26)$$

So, the cost function can be defined as:

$$S(P) = W(y - XP)^T (y - XP) \quad (27)$$

By differentiating with respect to $P$ and equate to zero gives:

$$\frac{\partial S(p)}{\partial P} = -2WX^T y + 2WX^T XP = 0 \quad (28)$$

Solving for $P$ gives:

$$P = \left(X^T W X\right)^{-1} X^T W y$$

Thus, WLS solution is given by:

$$P = \left(X^T W X\right)^{-1} X^T W y \quad (29)$$

where the operator $T$ indicates the conjugate transpose (Hermitian Transpose) and $W$ the weighted covariance matrix.

### D. Measuring Estimation Accuracy

To measure the estimation accuracy of WLSR, we explore five statistical metrics. They are mean square error (MSE), root mean square error (RMSE), Mean absolute error (MAE), standard deviation error (STD) and coefficient of determination ($R^2$). The five metrics can be defined as:

$$MSE_{WLSR} = \frac{1}{N}\sum_{i=0}^{N} w_i \, [L(x_i) - y_i]^2 \tag{30}$$

$$RMSE_{WLSR} = \left\{\frac{1}{N}\sum_{i=0}^{N} w_i \, [L(x_i) - y_i]^2\right\}^{1/2} \tag{31}$$

$$MAE_{WLSR} = \frac{\sum_{i=1}^{N} |w_i(L(x_i) - y_i)|}{N} \tag{32}$$

$$STD_{WLSR} = (RMSE_{WLSR})^2 - ((MAE_{WLSR}))^{0.5} \tag{33}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (w_i(L(x_i) - y_i)^2}{\sum_{i=1}^{N} (w_i(L(x_i) - mean(y_i))^2} \tag{34}$$

## 3. RESULTS AND DISCUSSION

This section presents the field electric signal strength estimation results for eNode1 to eNode6, using weighted least square regression in comparison with standard least square model. The regression codes used and the graphical results, including their various statistical computations were accomplished using Matlab 2018a software. Figure 2 to 7 display the field strength estimation made using weighted and standard least square for eNode1 to eNode6. Also provides in each figure is their computed correlation coefficient, Rsq achieved with the weighted regression least square over the standard least square approach. In terms of the $R^2$. values, the results show that field strength estimation approach using the weighted least square outperform the standard least square approach by 20, 12, 25, 23, 26 and 15%, respectively, for eNode1 to eNode6. Further comparative analysis using, standard deviation, STD error, mean square error, MAE and Root mean square error, RMSE are shown in figures 8 to 11. The effect of increasing weighted power from 0 to 5, $(w^0, w^1, w^2, w^3, w^4 \text{ to } w^5)$, are shown in figures 10 to 11 and table 1. For $w^0 = 1$ indicates un-weighted least square, and this defines the standard SLR estimation approach. It can be found from the tabulated results that the field strength estimation errors with WLSR method decreases monotonically as the weighted parameter, $w$ increases in power. This also implies improving performances in field strength estimation accuracy.

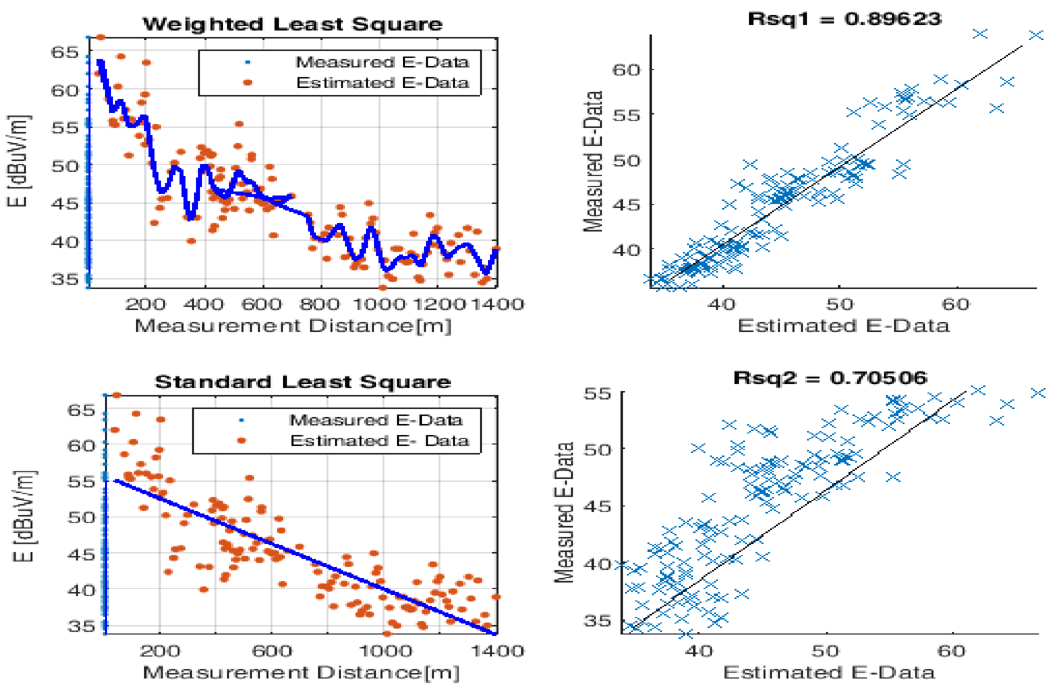


Figure 2: Estimated field strength using proposed and standard least square Approach for eNode1

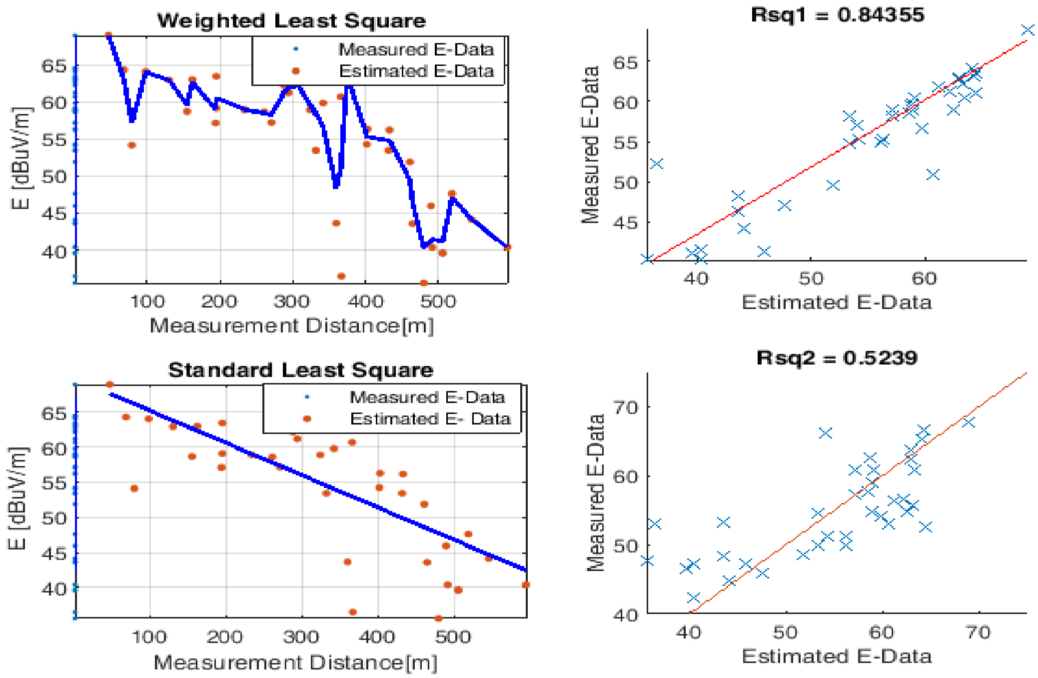


Figure 3: Estimated field strength using proposed and standard least square approach square for eNode2

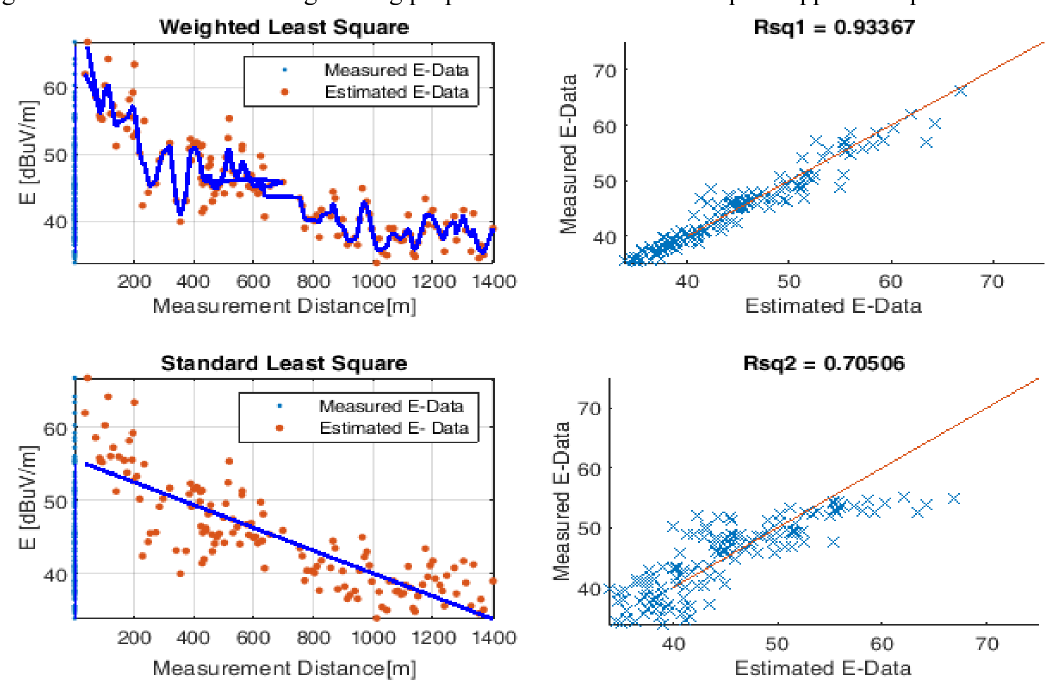


Figure 4: Estimated field strength using proposed and standard least square approach square for eNode3

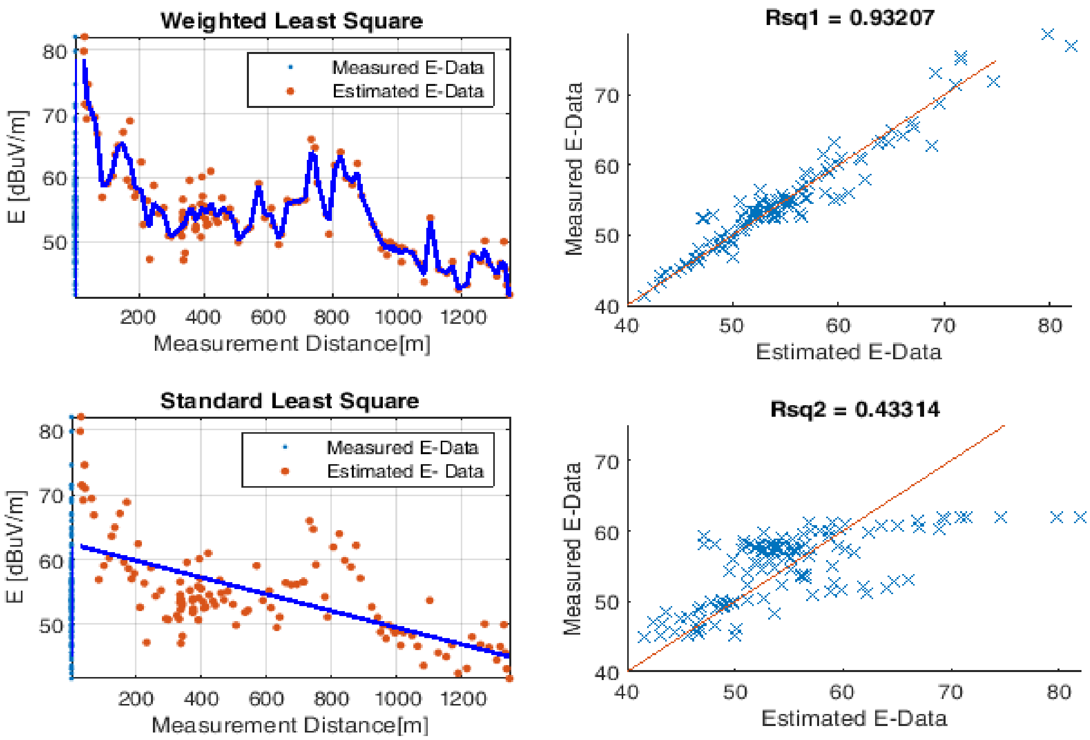


Figure 5: Estimated field strength using proposed and standard least square approach for eNode4

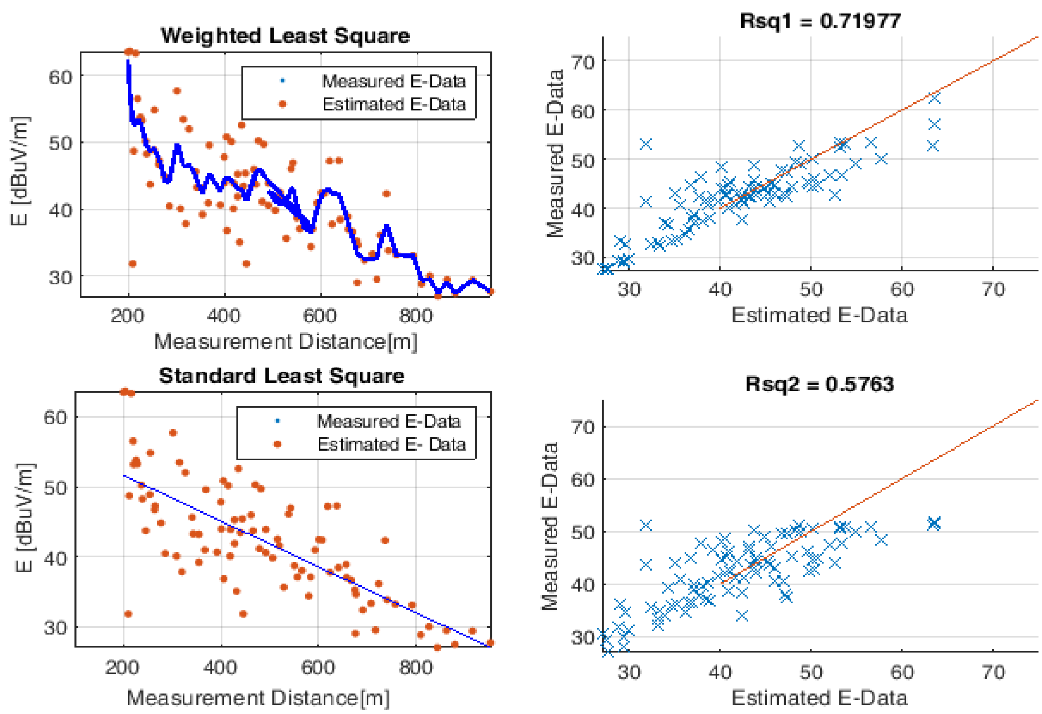


Figure 6: Estimated field strength using proposed and standard least square approach square for eNode5

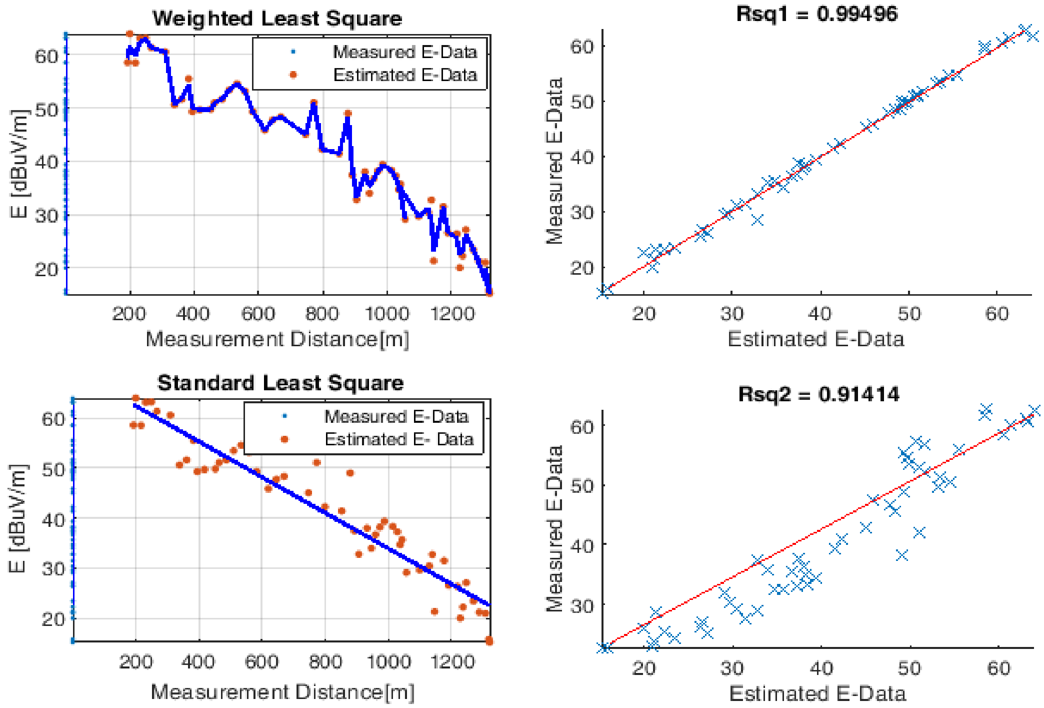


Figure 7: Estimated field strength using proposed and standard least square approach for eNode6

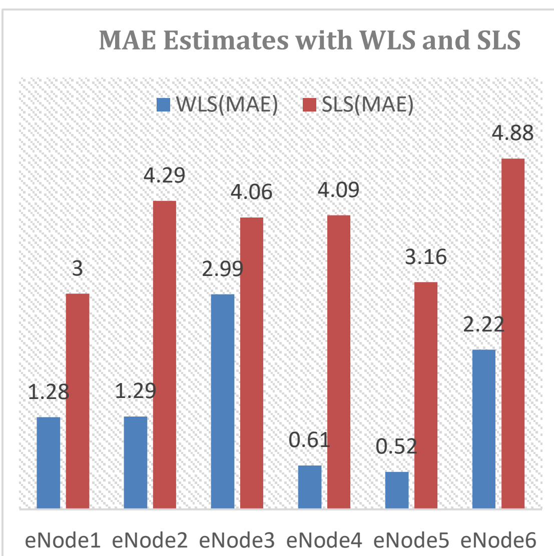


Figure 8: MAE values for estimated field strength using proposed and standard least square Approach

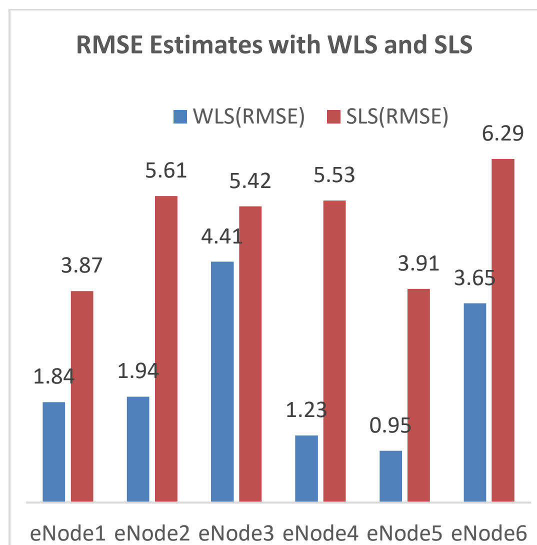


Figure 9: RMSE values for estimated field strength using proposed and standard least square Approach

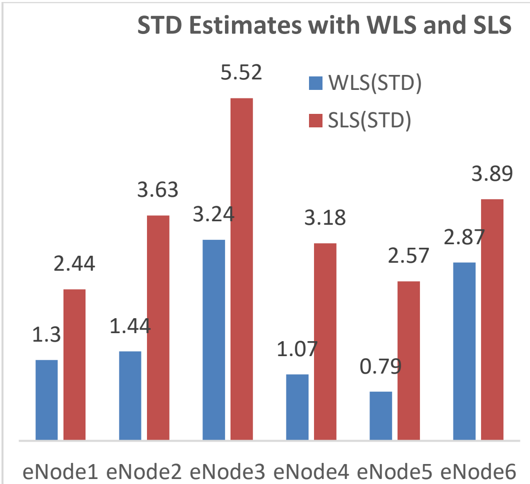


Figure 10: STD values for estimated field strength using proposed and standard least square Approach

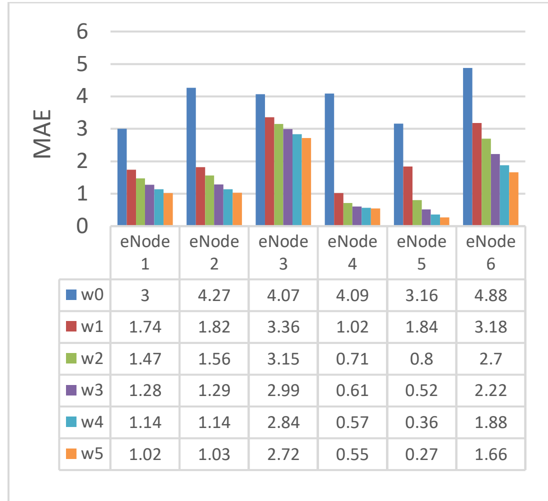


Figure 11: MAE estimated values as the weight grows from $w^0$ to $w^5$

Table I: Computed SLR and WSLR Accuracies at different weighted power for eNode1 to eNode6

| | Metric | $w^0$ | $w^1$ | $w^2$ | $w^3$ | $w^4$ | $w^5$ |
|---|---|---|---|---|---|---|---|
| eNode1 | Mae | 3 | 1.74 | 1.47 | 1.28 | 1.14 | 1.02 |
| | RMSE | 2.45 | 1.5 | 1.4 | 1.32 | 1.26 | 1.2 |
| | MSE | 6.00 | 2.25 | 1.96 | 1.74 | 1.58 | 1.44 |
| | STD | 2.45 | 1.59 | 1.4 | 1.32 | 1.26 | 1.2 |
| | R2 | 0.7051 | 0.8962 | 0.9195 | 0.9337 | 0.9436 | 0.9511 |
| | | | | | | | |
| eNode2 | Mae | 4.27 | 1.82 | 1.56 | 1.29 | 1.14 | 1.03 |
| | RMSE | 5.61 | 2.4 | 2.12 | 1.54 | 1.8 | 1.69 |
| | MSE | 31.47 | 5.76 | 4.49 | 2.37 | 3.24 | 2.85 |
| | STD | 3.63 | 1.57 | 1.49 | 1.44 | 1.39 | 1.34 |
| | R2 | 0.4331 | 0.896 | 0.917 | 0.932 | 0.9411 | 0.948 |
| | | | | | | | |
| eNode3 | Mae | 4.07 | 3.36 | 3.15 | 2.99 | 2.84 | 2.72 |
| | RMSE | 5.42 | 4.81 | 4.59 | 4.41 | 4.25 | 4.09 |
| | MSE | 12.81 | 11.83 | 11.15 | 10.49 | 9.92 | 9.36 |
| | STD | 3.58 | 3.44 | 3.34 | 3.24 | 3.15 | 3.06 |
| | R2 | 0.5763 | 0.6665 | 0.6959 | 0.7197 | 0.7401 | 0.7583 |
| | | | | | | | |
| eNode4 | Mae | 4.09 | 1.02 | 0.71 | 0.61 | 0.57 | 0.55 |
| | RMSE | 5.81 | 1.53 | 1.3 | 1.23 | 1.19 | 1.16 |
| | MSE | 10.11 | 1.27 | 1.18 | 1.14 | 1.08 | 1.04 |
| | STD | 3.18 | 1.13 | 1.09 | 1.07 | 1.04 | 1.02 |
| | R2 | 0.5034 | 0.9568 | 0.9684 | 0.9717 | 0.9736 | 0.9741 |
| | | | | | | | |
| eNode5 | Mae | 3.16 | 1.84 | 0.8 | 0.52 | 0.36 | 0.27 |
| | RMSE | 3.91 | 1.86 | 1.27 | 0.95 | 0.77 | 0.66 |
| | MSE | 5.29 | 1.82 | 0.96 | 0.56 | 0.46 | 0.36 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | STD | 2.3 | 1.35 | 0.98 | 0.75 | 0.68 | 0.6 |
| | R2 | 0.9141 | 0.9805 | 0.9909 | 0.9949 | 0.9966 | 0.9975 |
| | | | | | | | |
| eNode6 | Mae | 4.88 | 3.18 | 2.7 | 2.22 | 1.88 | 1.66 |
| | RMSE | 6.29 | 4.67 | 4.05 | 3.65 | 3.44 | 3.32 |
| | MSE | 15.76 | 11.69 | 9.12 | 8.35 | 8.23 | 8.12 |
| | STD | 3.97 | 3.42 | 3.02 | 2.89 | 2.87 | 2.85 |
| | R2 | 0.5239 | 0.7388 | 0.8069 | 0.8435 | 0.8601 | 0.8685 |

## 4. CONCUSSION

In radio telecommunication systems networks, proper and continual cellular network monitoring and management requires the utilization of distinctive regression modelling techniques to perform prognostic network performance assessment. However, accurate measurement and modelling-based estimation of the power of transmitted electromagnetic signal information through the cellular radio propagation channel has largely been one of foremost challenging parts in network design and management.

In this research paper, a weighted least squares estimation approach has been employed to model and estimate practical electric field strength data. The field strength data was obtained over radio frequency system interface which belongs to a commercial LTE cellular broadband networks service provider operating in typical urban area. In terms of reliability and precision, the outcome show that the employed weighted least square approach has the best performance in electric strength parameter estimation

## REFERENCES


[1] J. Isabona and K. Obahiagbon, ‘‘RF Propagation Measurement and Modelling to Support Adept Planning of Outdoor Wireless Local Area Networks in 2.4 GHz Band, American Journal of Engineering Research, vol. 3 (1), pp. 58-67, 2014.

[2] J. Isabona and S. Azi, ‘‘Measurement, Modeling and Analysis of Received Signal Strength at 800MHz and 1900MHz in Antenna Beam Tilt Cellular Environment’’, Elixir Computer Science and Engineering, vol.54, pp.12300-12303, 2013.

[3] P. Keawbunsong, S. Duangsuwan, P. Supanakoon, and S. Promwong, ‘‘Quantitative Measurement of Path Loss Model Adaptation Using the Least Squares Method in an Urban DVB-T2 System’’, International Journal of Antennas and Propagation, vol. 2018, pp. 1-8.

[4] F.R. Bajana, L.H. Lara, M. Paredes, and E.G. Ory, Promwong, ‘‘Quantitative Measurement of Path Loss Model ‘‘Multi Linear Regression applied to Communications systems Analysis’’. arXiv: Applications, pp.1-22, 2020 (https://arxiv.org/abs/2002.10573).

[5] V. G. Drozdova and R. V. Akhpashev Ordinary least squares in COST 231 Hata key parameters optimization base on experimental data,″ 2017 International Multi-Conference on Engineering, Computer and Information Sciences (SIBIRCON), *2017, pp. 236-238, doi: 10.1109/SIBIRCON.2017.8109878.*

[6] K. Diawuo, K.A. Dotche, and T. Cumberbatch, ‘‘Data Fitting to Propagation Model Using Least Square Algorithm: A Case Study in Ghana’’, International Journal of Engineering Sciences, 2(6), pp. 226-230, 2013.

[7] J. Isabona, ‘‘Wavelet Generalized Regression Neural Network Approach for robust Field Strength in Open and Shadow urban Microcells’’, Wireless Personal Communications, Vol. 114 (3), pp.3635–3653, 2020. DOI 10.1007/s11277-020-07550-5

[8] O. D. Ojuh and J.Isabona, ‘‘ Linear, Lasso and Ridge Regression Methods: A Quantitative Case Study with Spatial Electromagnetic Field Strength Signals’’. IOSR Journal Of Applied Physics (IOSR-JAP), vol.13, Issue 1 Ser. II (Jan. – Feb. 2021), pp.27-38, 2021 . DOI: 10.9790/4861-1301022738.

[9] O. D. Ojuh and J.Isabona, "Application of Levenberg-Marguardt Algorithm for Prime Radio Propagation Wave Attenuation Modelling in Typical Urban, Suburban and Rural Terrains", International Journal of Intelligent Systems and Applications(IJISA), vol.13, No.3, pp.35-42, 2021. DOI: 10.5815/ijisa.2021.03.04

[10] J.Isabona and S.O. Azi, ‘‘Optimised Walficsh-Bertoni Model for Pathloss Prediction in Urban Propagation Environment’’, International Journal of Engineering and Innovative Technology (IJEIT), vol. 2 (5), pp.14-20, 2012.

[11] J. Isabona and C.C. Konyeha, ‘‘Experimental Study of UMTS Radio Signal Propagation Characteristics by Field Measurement’’, American Journal of Engineering Research, vol. 2, (7), pp. 99-106, 2013.

[12] J. Isabona and C.C. Konyeha, ‘‘Urban Area Path loss Propagation Prediction and Optimisation Using Hata Model at 800MHz’’, IOSR Journal of Applied Physics (IOSR-JAP), vol. 3, Issue 4, pp. 8-18, 2013.

[13] J. Isabona and G.P. Isaiah, ‘‘CDMA2000 Radio Measurements at 1.9GHz and Comparison of Propagation Models in Three Built-Up Cities of South-South, Nigeria’’, American Journal of Engineering Research (AJER), vol. 2, Issue-05, pp-96-106, 2013.

[14] J. Isabona and S.O. Azi, ‘‘Enhanced Radio Signal Loss Prediction with Correction Factors for Urban Streets in the IMT-2000 Band’’, Elixir Space Science, vol. pp.15958-15962, 2013.

[15] J. Isabona and M. Babalola, ‘‘Statistical Tuning of Walfisch-Bertoni Pathloss Model based on Building and Street Geometry Parameters in Built-up Terrains’’. American Journal of Physics and Applications, vol. 1, pp. 10-16, 2013

[16] J. Isabona and C.C. Konyeha, C.B. Chinule, G.P. Isaiah, ‘‘Radio Field Strength Propagation Data and Pathloss calculation Methods in UMTS Network’’, Advances in Physics Theories and Applications, vol.21.pp 54-68, 2013.

[17] J. Isabona and P.G Isaiah, ''Computation and Verification of Propagation Loss Models based on Electric Field Data in Mobile Cellular Networks, Australian Journal of Basic and Applied Sciences, vol. 9 (29), pp.280-285,2015.
[18] N.O, Oyie and T.O.J. Afullo, ''Measurements and Analysis of Large-Scale Path Loss Model at 14 and 22 GHz in Indoor Corridor'', IEEE Access, vol.6, pp.17205-17214, 2018. Digital Object Identifier 10.1109/ACCESS.2018.2802038
[19] J. Isabona J and O. Enagbonmaa, ''Least Absolute Deviation Tuning Method to reduce Signal Loss Prediction Error in Electromagnetic Waves Propagation Channel'', BIU Journal of Basic and Applied Sciences vol.1 (1), pp.26 – 39, 2015.
[20] M.K.Yeliz, ''Generalized Least Square and Weighted Least Squares Estimation Methods for Distributional Parameters'' REVSTAT – Statistical Journal, vol. 13 (3), pp.263–282, November 2015.
[21] Boudt, K.; Caliskan, D. and Croux, C, ''Robust explicit estimators of Weibull parameters'', Metrika, vol. 73, pp.187–209, 2011.
[22] Zyl, J.M.V, ''A Median Regression Model to Estimate the Parameters of the Three-Parameter Generalized Pareto Distribution, Commun. Stat.-Simul. C., 41, 544–553, 2012.
[23] Zyl, J.M.V. and Schall, R. ''Parameter Estimation through Weighted Least-Squares Rank Regression with Specific Reference to the Weibull and Gumbel Distributions'', Commun. Stat.-Simul. C., 41, 1654–1666, 2012.
[24] Lu, H.L. and Tao, S.H, ''The Estimation of Pareto Distribution by a Weighted Least Square Method'', Quality & Quantity, 41, 913–926, 2007M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.

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