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by Augustinus Bayu Primawan

Submission date: 16-Nov-2023 08:54AM (UTC+0700)
Submission ID: 2226476686
File name: X_PRIMAWAN_FinalVersion.PDF (4.43M)
Word count: 4213
Character count: 21708

The study of access point outdoor coverage deployment for wireless digital campus network

Augustinus B. Primawan*

Information and Communications Technologies,
School of Engineering and Technology,
Asian Institute of Technology,
Thailand
and
Teknik Elektro, Fakultas Sains dan Teknologi,
Universitas Sanata Dharma,
Indonesia
Email: bayu.prima@gmail.com
*Corresponding author

Nitin K.Tripathi

Remote Sensing and Geographic Information System,
School of Engineering and Technology,
Asian Institute of Technology,
Thailand
Email: nitingis@gmail.com

Abstract: Wireless local area network design needs more development to obtain appropriate and effective results. Site surveys in the design process give realistic results, but require time and effort. Developing ways of predicting signal strength using empirical models can give appropriate results in access point placement to get good signal coverage. Geospatial analysis, such as inverse distance weighting, Kriging and global polynomial interpolation, has been compared. This study showed that Kriging analysis is an appropriate method to predict value the coverage area. Furthermore, predictive signal strength models such as classical, empirical and COST 231 Hatta models have been studied. The empirical model was shown to do the best predictive calculations. The empirical model used to predict signal strength combined with Kriging geographical statistical analysis gave usable signal coverage prediction for access point placement. This model will support GIS spatial analysis tools to perform effective planning in access point placement.

Keywords: access point placement; GIS spatial analysis; received signal level.

Reference to this paper should be made as follows: Primawan, A.B. and Tripathi, N.K. (xxxx) 'The study of access point outdoor coverage deployment for wireless digital campus network', *Int. J. Information and Communication Technology*, Vol. X, No. Y, pp.000–000.

Biographical notes: Augustinus B. Primawan is a Doctoral candidate in Information and Communications Technologies in Asian Institute of Technology, Thailand. He received his Bachelor degree in Electrical Engineering from Institute of Technology Sepuluh Nopember, Surabaya,

Indonesia. His Master in Electronics and Communication Engineering was received from De La Salle University, Manila, Philippines. His research interests are wireless network deployment and optimisation, GIS for communication infrastructure.

Nitin K. Tripathi is currently a Full Professor in Remote Sensing and Geographic Information Systems in Asian Institute of Technology, Thailand. He received his Bachelor degree in Civil Engineering from the National Institute of Technology Warangal. His Master and Doctoral in Remote Sensing was received from the Indian Institute of Technology, Kanpur, India. His research interests include remote sensing, GIS, GPS and data photogrammetry.

1 Introduction

Deploying wireless LAN enables users to access network applications and resources anytime and anywhere. Wireless access points nowadays can be found in public service areas, buildings, and campus areas, among many others. A digital campus network is the most appropriate way to provide internet access over an area where access points are dense. It is a bit more difficult to do this over wider areas since a huge number of access points will be required. Models for coverage mapping and prediction still need to be better designed (Phillips et al., 2013). Site surveys help define the contour of radio frequency coverage in a particular facility or area. Some propagation models from site survey data have been proposed (Phillips et al., 2013).

In some situations, such as campus area or shopping centre area, the outdoor coverage mode may be the best to use. It is essential to use WLAN radio transmission models (Hou and Gao, 2011). Currently, methods of signal strength prediction to model the path loss form are classified into three general categories. The first is a deterministic model. This model uses Maxwell's equations with reflection and diffraction laws. The second is a statistical model using probability analysis to perform signal prediction. The last model is an empirical model that uses existing equation obtained from results of field measurements.

Some commercially available programming tools that consolidate site survey and radio frequency propagation do not have the quantity of data needed. GIS analysis has been proposed as a way to develop signal coverage visualisations (Barrile et al., 2009). Methods such as neural network prediction and Kriging prediction have been used to predict strength of received signals (Sen et al., 2008). Kolyaie et al. (2011) discussed about geo-statistical evaluation in wireless signal propagation. Nearest distance analysis was used in performing connection from received point to access point in term of coverage radius. The result of nearest distance analysis is a table of reception points located in the coverage area of each access point. Spatial interpolation methods (SIM) have been developed including inverse distance weighting (IDW), spline, natural neighbours, and Kriging, among others. These techniques are classified as geographical statistics and non-geographical statistics (Chen and Liu, 2012). Non-geographical statistical methods include IDW and global polynomials. Alternatively, the Kriging method is a geographical statistical method. Geospatial Kriging analysis is a method of geospatial analysis that uses spatial interpolation. Spatial interpolation is a way of estimating values of un-sampled properties from unknown locations based on observed values at known locations.

This paper discusses simulation and analysis of access point placement based on coverage analysis of signal strength. The predicted signal strength for coverage was determined with IDW and Kriging. Comparison of field measurements and computations gives precise results for network design. Comparison of an interpolation method was done. This method gave a reproducible approach to modelling wireless access point coverage, as well as techniques for predicting signal strength with a propagation model.

2 Research background

2.1 *Analysis of signal strength prediction*

In WLAN deployment, the free space propagation model usually is used to predict the signal strength at a receiver where there is no obstruction or attenuation between the accessing point (AP) and receiving point (RP). In terms of received signal power, the propagation model of the received signal strength indication (RSSI) calculation uses a one slope model in path loss and is given by:

$$P_{dBm} = P_{0,\,dBm} - 10n\log_{10} d \tag{1}$$

where $P_{0,dBm}$ is the power signal level obtained at 1 meter from the access point, d is the distance from RP to the access point and n is an experimental result determined by interpolation (Andrade et al., 2010). This model is a classical propagation model and is widely used in a large number of environments, including industrial and wide area networks.

The second model is an empirical propagation model that can be given as:

$$P_{dBm} = P_{0,\,dBm} - 10n\log_{10} d - EF \tag{2}$$

EF is an environment factor calculated from the received signal strength difference between propagation with and without environment attenuation. The values of signal strength come from field measurements. This model used to accommodate environment attenuation that impacts the signal quality at the receiver. Some models have been proposed using different conditions (Sharma and Singh, 2013; McGibney et al., 2010).

Another empirical model that has been formulated to simplify calculation of path loss is the Hatta model (Sharma and Singh, 2013). This is used in the frequency band from 500–2,000 MHz. It is also known as the COST-231 Hatta model and is given as:

$$P_{dBm} = P_{0,\,dBm} - L_p \tag{3}$$

where

$$\begin{aligned} L_p = {} & 46.3 + 33.9\log_{10}(f) - 13.82\log_{10}(h_b) - a(h_m) \\ & + \left(44.9 - 6.55\log_{10}(h_b)\right)\log_{10} d + c_m \end{aligned} \tag{4}$$

f is frequency in MHz, d is the distance between the AP and RP in *km*, h_b is the AP antenna high above the ground level in *meters*, c_m is defined as 0 dB for suburban or open environments and 3 dB for urban environment, and $a(h_m)$ is defined for urban environments as:

$$a(h_m) = 3.20\left(\log_{10}(11.75h_r)\right)^2 - 4.97 \tag{5}$$

It is for urban conditions and $f > 40$ MHz. When the environment is suburban or rural, the following is used:

$$a(h_m) = \left(1.1\log_{10} f - 0.7\right)h_r - \left(1.56\log_{10} f - 0.8\right) \tag{6}$$

h_r is the RP antenna height above the ground level in *metres*.

The COST 231 Hatta model uses $f = 2400$ MHz, $h_b = 3$ m, $c_m = 3$ dB, $h_r = 1$ m in an urban environment with frequencies greater than 400 MHz.

2.2 *Spatial interpolation method*

The study spatial interpolation in coverage signal was done by Molinari et al. (2015) for cellular coverage prediction. That study found the comparative result in spatial interpolation technique especially with Kriging. Another Kriging technique was also discussed in coverage mapping of radio network by Braham et al. (2015). They also used Kriging technique for developed prediction coverage radio network.

SIM becomes essential for estimating coverage signal strength map. Spatial interpolation was defined for prediction value sample of the primary variable at point within same region of the sampled location (Li and Heap, 2014). There are three categories for spatial interpolation known as

1. geostatistical methods
2. non-geostatistical methods
3. combination methods.

These methods nearly use same estimation formula as follows:

$$\hat{Z}(X_0) = \sum_{i=1}^{n} \lambda_i Z(X_i) \tag{7}$$

where $\hat{Z}$ is the estimated value of the primary variable at the point of interest X_0, z is the observed value at the sampled point x_i, λ_i is the weight assigned to the sampled point and n represent the number of sample points.

A taxonomy of spatial interpolation that proposed by Molinari et al. (2015) can be explained as Table 1.

Table 1 A taxonomy of spatial interpolation

Interpolation	Global	Classification	Inexact, deterministic
		Trend surface	Inexact, deterministic
		Regression	Inexact, stochastic
		Others	Inexact, depending
	Local	Thiessen polygon	Exact, deterministic
		Weighted moving average	Exact, deterministic
		Spline	Exact, deterministic
		Kriging	Exact, stochastic

Source: Molinari et al. (2015)

3 Method

3.1 Study area

The study area of this experiment was a student dormitory area and an administrative building on the Asian Institute of Technology campus in the Eastern and Northern UTM WGS 1984 N47. This campus is located in Pathumthani Province, Thailand. The student dormitory already had so many access points, as seen in Figure 1. In Figure 2, the location of RPs was determined during field measurements. The coverage of access points was analysed using coverage prediction with geo-statistical analysis and a predictive signal strength model.

Figure 1 Access point location of the study area

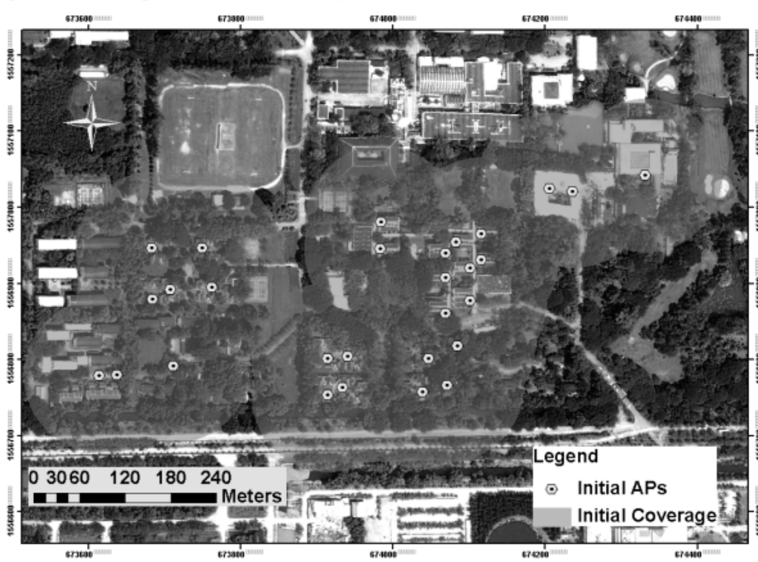
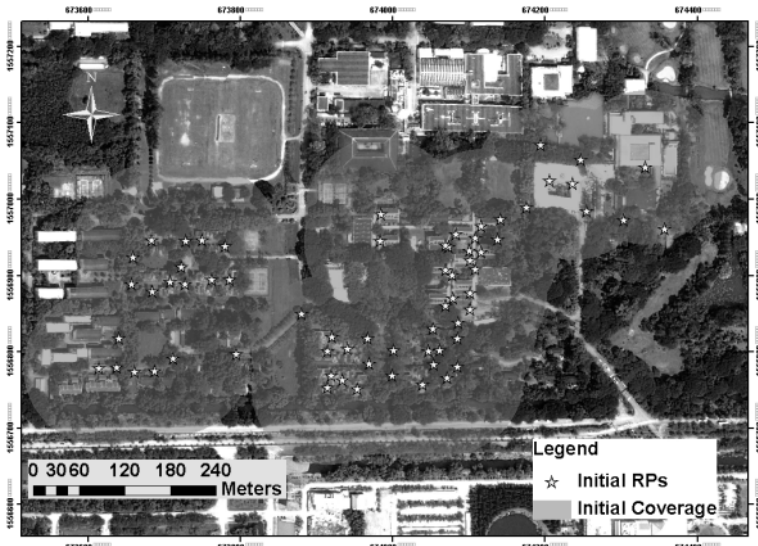


Figure 2 Receive point test-bed of the study area



Drive tests were done to quantify signal strength in certain areas for which the field strength model was to be used. Useful field estimations were taken in the dense zone of the study area. All field information was taken from a portable terminal utilising a signal strength analyser instrument. The network device specifications for this analysis and simulation were a maximum power output of the AP (1,000 mW), maximum coverage radius (100 m), coverage signal direction (omni-directional), height of the AP antenna (3 metres), and height of the RP antenna (1 metre).

The procedures of field strength analysis are described as follows:

Firstly, GIS modelling was done for interconnection of RP and AP and the Euclidean distance was determined. Secondly, the RSSI value for each RP was calculated. The deterministic coverage area was calculated using the classical model of determining path loss where *L0*, *dbm* is the RSSI of the received signal with a distance, *d0*, equal to 1 m, *n* is a correction factor for the environment interpolated from the measured signal strength given by equation (2), and *d* is the distance between receiving and access point locations.

Database of APs and RPs in Table 2 provides information about location and measured RSSI for each RP location from each connected AP. This database includes location of access point (longitude and latitude in UTM), location of received point (longitude and latitude in UTM), calculated distance between APs and RPs covered, measured field strength of the RP to the assessed APs in a certain location of each covered area, MAC Address of the accessed APs, and the Location name of each assessed AP.

Table 2 Database information of APs and RPs

ID	*X_Point*	*Y_Point*	*AP_ID*	*MAC_Addr*	*X_Point_1*	*Y_Point_1*	*RP_ID*	*Signal_Str*
0	674,332	1557,042	AP_1	0c_85_25_ab_02_d6	674,358	1,556,961	RP_1	–73
1	674,117	1556,931	AP_5	68_bc_0c_0a_6b_31	674,101	1,556,933	RP_10	–86
2	674,070	1556,907	AP_8	3c_ce_73_9b_06_21	674,074	1,556,938	RP_12	–81
3	674,070	1556,861	AP_9	3c_ce_73_09_7f_41	674,079	1,556,901	RP_13	–86
…								
203	674,102	1556,920	AP_7	3c_ce_73_c5_ea_21	674,109	1,556,949	RP_9	–92
204	674,070	1556,907	AP_8	3c_ce_73_9b_06_21	674,109	1,556,949	RP_9	–100
205	674,070	1556,861	AP_9	3c_ce_73_09_7f_41	674,109	1,556,949	RP_9	–100

ID is the identification of data number. X_Point and Y_Point are longitude and latitude of the access point location, whether X_Point_1 and Y_Point_1 are longitude and latitude of the received point location. MAC_Addr is the device address information of the access point. Signal_Str is the measured signal strength from the received point to the access point.

The data collected in the current study were analysed to find adjusted variables for the empirical prediction model for equation (2). Empirical outdoor signal level with environment attenuation was determined from the difference in signal strength with and without environment factors, as shown in Figure 3. This value is an average of the difference power output converted from *dBm* shown in Table 3. The difference of signal strength with the same distance was converted into antilog of the *dBm*. Then, the average value of the difference signal strength was reconverted into *dBm* that became the *EF* value.

Figure 3 Received signal level with environmental factor (see online version for colours)

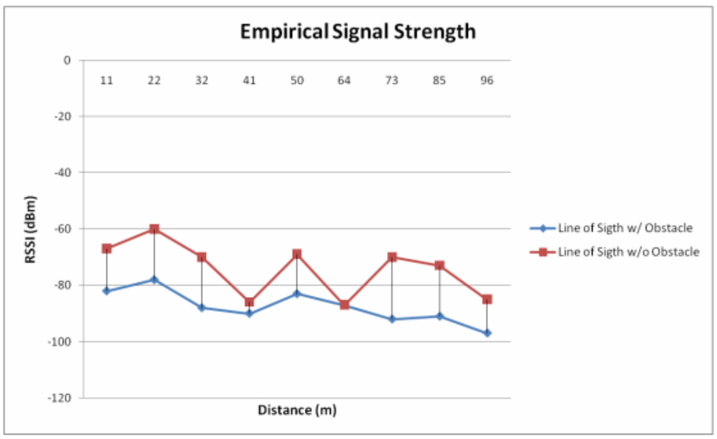


Table 3 Environment factor calculation

Distance (m)	*Signal strength (dBm)*		*Difference*		
	Line of sight w/ obstacle	*Line of sight w/o obstacle*	*dBm*	*Antilog (dBm)*	
13	–82	–67	15	3.16E-02	
21	–78	–60	18	1.58E-02	
32	–88	–70	18	1.58E-02	
41	–90	–86	4	3.98E-01	
50	–83	–69	14	3.98E-02	
62	–87	–87	0	1.00E+00	
72	–92	–70	22	6.31E-03	
82	–91	–73	18	1.58E-02	
		Average of the differences		1.90E-01	–7.20

Based on the calculations, a value of –7.20 was added to environmental factor predictive models in equation (2). The received signal level predicted by the empirical model is given as:

$$P_{dBm} = P_{0,\,dBm} - 10n\log_{10} d - 7.20$$

4 Coverage prediction result

The measurement of RSSI field strength and collection of field data were done to determine the RSSI field strength from several RPs to access the APs. This measured field strength was used to determine network strength and develop coverage prediction for the study area. Finally, a coverage map of field strength was developed using Geospatial Analysis. The prediction technique is a set of geospatial calculations to predict values over an entire area based on relatively few known values. Data collected for the RSSI from sample RPs in the study area was used to predict the signal coverage of the entire study area. The final analysis was done comparing calculations and field measurements with the output of the empirical propagation model to evaluate the coverage area.

The predictive models were then compared against data from field measurement. The results are displayed graphically in Figure 4. From this comparison, it appears that the behaviour of the COST-231Hatta model was similar to the field measurements. However, the empirical model had closer predicted values. The prediction accuracy of empirical model was better than either log-distance or COST-231 Hatta model. Table 4 shows that of the empirical model for predicting attenuation with and without obstacles showed the smallest error.

Figure 4 Comparison measured and predicted signal (see online version for colours)

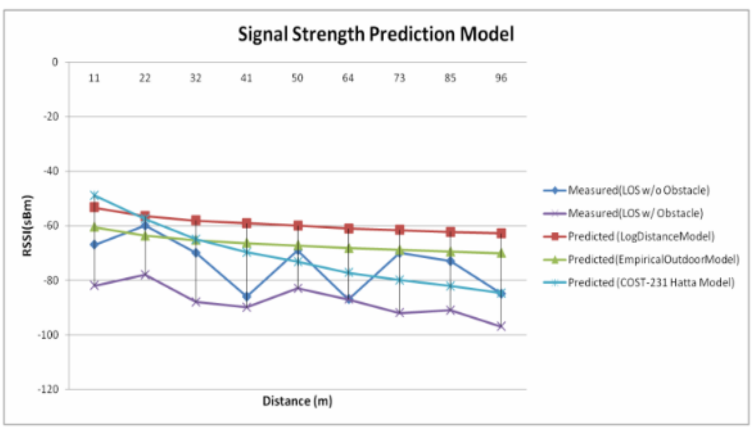


Table 4 Root mean square error of the predicted RSSI to measured RSSI

M-LD	*M-E*	*M-C*	*(W/ obstacle)*
14.71	11.31	12.16	
M-LD	*M-E*	*M-C*	*(W/o obstacle)*
9.95	7.68	10.79	

where,

M-LD is log of distance predicted to measured

M-E is empirical predicted to measured

MC is COST-231 Hatta predicted to measured

The comparative study for error prediction gives the appropriate model for prediction model. Furthermore, the data distribution from each predictive model displayed by Table 5 and Table 6. These cumulative probabilities of the prediction model give normal distribution so that these models will be implemented into coverage prediction map by using interpolation technique.

Table 5 Cumulative probability function

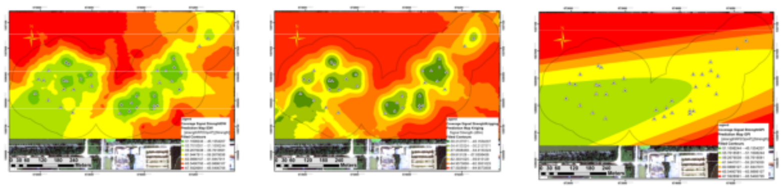
(W/ obstacle)	*M-LD*	*M-E*	*M-C*	*CPF*
	27.71	18.68	9.71	11%
	27.92	19.03	11.19	22%
	29.94	21.65	11.72	33%
	31.73	23.81	12.62	44%
	33.05	25.17	13.11	56%
	33.96	25.21	22.51	67%
	34.07	25.87	26.12	78%
	34.28	26.26	26.28	89%
	35.31	27.88	40.43	100%
(W/o obstacle)	*M-LD*	*M-E*	*M-C*	*CPF*
	5.81	1.64	0.17	11%
	11.94	2.58	2.12	22%
	13.03	4.78	6.27	33%
	14.66	6.21	6.63	44%
	16.99	6.69	10.67	56%
	20.39	9.63	13.53	67%
	26.07	17.59	14.47	78%
	29.81	21.53	19.03	89%
	31.25	22.86	32.15	100%

Table 6 Data signal strength distribution

No	*Model*	*Min*	*Max*	*Mean*	*Std. dev*	*Skewness*	*Kurtosis*	*Median*
1	Measurement	–100	–62.6	–81.29	6.7939	–0.18646	3.2363	–81.25
2	Classical	–135	–105	–125.38	4.7905	0.78865	4.2629	–126
3	Empirical	–53	–23	–32.623	4.7905	–0.78865	4.2629	–35.837
4	Cost231Hatta	–110.33	–100.75	–107.41	1.579	0.77207	4.1921	–107.64

A coverage map was developed from geospatial interpolation with measured RSSI data from each RP. The comparative study using the interpolation method is shown in Figure 5. The methods consisted of IDW, Kriging and global polynomial interpolation (GPI). These methods were provided as part of the GIS analytical tools.

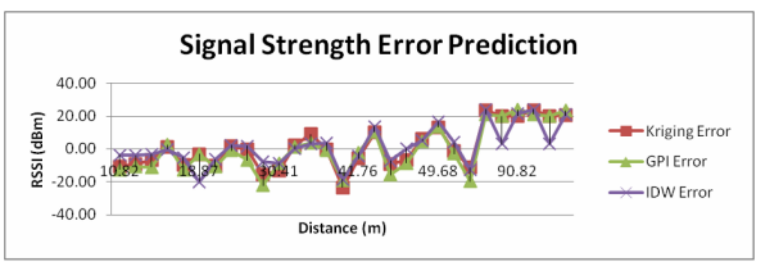
Figure 5 Predicted signal strength of the coverage area with (a) IDW (b) Kriging and (c) GPI (see online version for colours)



(a) (b) (c)

The root mean square error from geographical statistic methods in Figure 6 were 10.79 (Kriging), 10.58 (GPI), and 12.16 (IDW). Thus GPI gave less error than Kriging or IDW, but the coverage prediction of Kriging was better visualising than for IDW or GPI.

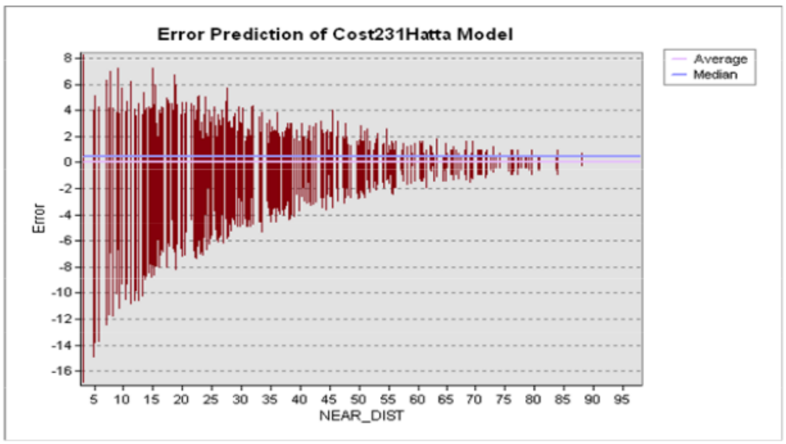
Figure 6 Error prediction signal strength of the coverage area with (a) Kriging (b) GPI and (c) IDW (see online version for colours)



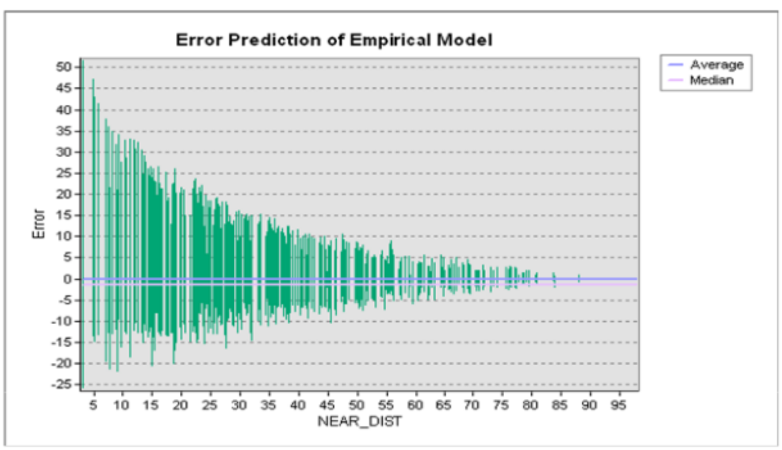
Although both IDW and Kriging had similar results, Kriging gave more realistic results than IDW. Thus, Kriging Interpolation was chosen to use as a prediction method in this coverage area. Which is this option have been proposed in Kolyaie and Yaghooti (2011). Otherwise, the calculated coverage map would need to be determined from calculated RSSI field strength values for each RP from deterministic calculation of the signal strength.

Figure 7 shows the error prediction from cross validation for predictive model. These distance error for prediction model of Cost231Hatta model (a) and empirical model (b) gave similar result in which the biggest error happen for the small distance and then was reduced for bigger distance. It can happen that the further distance between received point and access point, the better prediction of signal strength. Furthermore, this prediction model and interpolation technique can be implemented into coverage prediction map for access point placement.

Figure 7 Error prediction for (a) COST231Hatta and (b) empirical (see online version for colours)



(a)



(b)

The coverage prediction of measured RSSI and predicted RSSI from the empirical method are shown in Figure 8 and Figure 9. The results show that the coverage area prediction by the empirical method can be better than field measurements. By this empirical method, access point placement can be done as effectively as previously used methods (Hou and Gao, 2011; Arya and Sharma, 2013). In comparison with measured signals of the classical model, the empirical method gave better results. This is because the classical model uses general modelling in predicting propagation of signal strength.

Figure 8 Measured of the RSSI in the study area and its coverage area (see online version for colours)

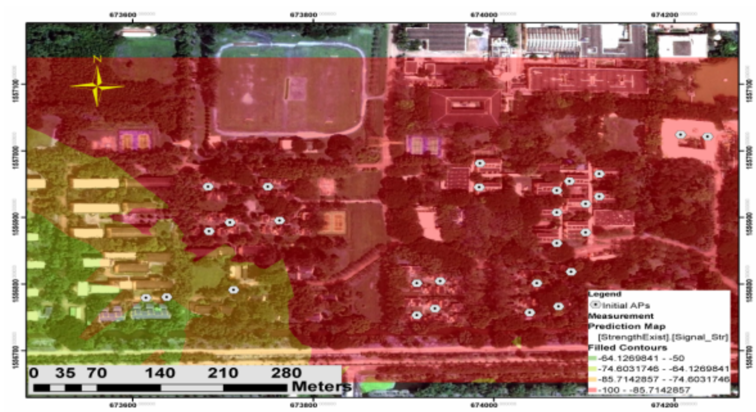
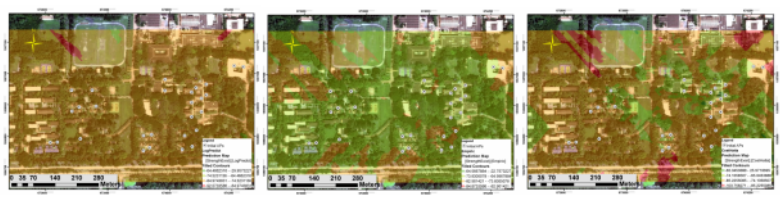


Figure 9 Predicted signal strength of the coverage area with (a) classical model (b) empirical model and (c) COST-231Hatta model (see online version for colours)



(a) (b) (c)

4 Conclusions

This paper first reviewed prediction models their implications to coverage simulation. Secondly, analysis of signal strength prediction models was explored. The analysis results showed that the empirical model was a better approach to the measurement of field data collection. Finally, a comparative study about coverage signal prediction was done. It was found that the Kriging method gave more realistic predictions. Coverage models based on empirical environmental data can be used in the deployment of access points for dense areas using GIS interpolation tools. This GIS application and analysis can be very useful in implementation of wireless networks. This technique was adequate in design, implementation and analysis for wireless LAN access point placement. The analysis of this paper contributes to the body of knowledge about design and deployment of wireless access points in a campus area.

References

Andrade, C.B., Pierre, R. and Hoefel, F. (2010) 'IEEE 802. 11 WLANS: a comparison on indoor coverage models', *23rd Canadian Conference on Electrical and Computer Engineering*, Calgary, Canada, pp.1–6.

Arya, L. and Sharma, S.C. (2013) 'Coverage and analysis of obstructed indoor WLAN using simulation software and optimization technique 1', *Conference on Advances in Communication and Control System*, Atlantis Press, Dehradun, India, pp.631–637.

Barrile, V., Bilotta, G. and Di, F. (2009) 'GIS for calculating electromagnetic field', *2nd WSEAS International Conference on Urban Planning and Transportation*, Rodos Island, Greece: WSEAS, pp.117–124.

Braham, H. et al. (2015) *Spatial Prediction under Location Uncertainty in Cellular Networks* [online] http://arxiv.org/abs/1510.03638 (accessed 14 March 2016).

Chen, F.W. and Liu, C.W. (2012) 'Estimation of the spatial rainfall distribution using inverse distance weighting (IDW) in the middle of Taiwan', *Paddy and Water Environment*, Vol. 10, No. 3, pp.209–222.

Hou, Q. and Gao, L. (2011) 'The simulation of WLAN outdoor coverage in hot spot area for wireless digital city', *2011 7th International Conference on Wireless Communications, Networking and Mobile Computing*, Wuhan, IEEE, pp.1–4 [online] http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6036676 (accessed 23 June 2014).

Kolyaie, S. and Yaghooti, M. (2011) 'Evaluation of geostatistical analysis capability in wireless signal propagation modeling', *Geocomputation*, pp.76–83, *Proceedings of the 11th International Conference on Geo Computation*, London, UK [online] http://www.geocomputation.org/2011/papers/kolyaie.pdf (accessed 30 August 2015).

Kolyaie, S., Yaghooti, M. and Majidi, G. (2011) 'Analysis and simulation of wireless signal propagation', *Archives of Photogrammetry, Cartography and Remote Sensing*, Vol. 22, No. 1, pp.261–270.

Li, J. and Heap, A.D. (2014) 'Spatial interpolation methods applied in the environmental sciences: a review', *Environmental Modelling and Software*, Vol. 53, pp.173–189 [online] http://dx.doi.org/10.1016/j.envsoft.2013.12.008 (accessed 30 August 2015).

McGibney, A., Klepal, M. and Pesch, D. (2010) 'A wireless local area network modeling tool for scalable indoor access point placement optimization', *Proceedings of the 2010 Spring Simulation Multiconference*, pp.1–8, ACM Press, New York, USA [online] http://portal.acm.org/citation.cfm?doid=1878537.1878707 (accessed 23 June 2014).

Molinari, M. et al. (2015) 'Spatial interpolation based cellular coverage prediction with crowdsourced measurements', *ACM SIGCOMM Workshop on Crowdsourcing and Crowdsharing of Big (Internet) Data*, pp.33–38.

Phillips, C., Sicker, D. and Grunwald, D. (2013) 'A survey of wireless path loss prediction and coverage mapping methods', *IEEE Communications Surveys & Tutorials*, Vol. 15, No. 1, pp.255–270 [online] http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6165627 (accessed 30 August 2015).

Sen, A. et al. (2008) 'Programming an artificial neural network tool for spatial interpolation in GIS – a case study for indoor radio wave propagation of WLAN', *Sensors*, Vol. 8, No. 9, pp.5996–6014 [online] http://www.mdpi.com/1424-8220/8/9/5996/ (accessed 23 March 2012).

Sharma, P.K. and Singh, R.K. (2013) 'Comparative analysis of propagation path loss models with field measured data', *International Journal of Engineering Science and Technology*, Vol. 2, No. 6, pp.2008–2013.

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