Suitable Propagation Loss Models for Mobile Communications in Jordan

M. S. H. Al Salameh and M. M. Al-Zu'bi
Department of Electrical Engineering
Jordan University of Science and Technology
Irbid 22110, Jordan
salameh@just.edu.jo

Abstract— Extensive outdoor measurements for mobile phone base stations in Irbid city, Jordan, were performed by the authors. In order to determine the model that can accurately predict the propagation in this environment, different well-known propagation models are compared with these measurements. Among these models, the comparison reveals that the COST-231 Hata model is the most suitable model for Irbid city, Jordan. To further improve the prediction accuracy, this paper proposes a propagation model based on optimizing the COST-231 Hata model by the particle swarm optimization (PSO) method. The proposed model is validated by comparison with measurements conducted in other locations in Irbid. It is shown that the root mean square error (RMSE) between the predicted and the measured data for the proposed model, is improved by up to 5 dB compared with Hata model and by up to 29 dB compared with Egli model, in all the areas under study. Furthermore, this model is expected to be suitable for other areas in Jordan similar to Irbid.

Keywords— Mobile communications, Measurements, Propagation, Hata, Wireless, PSO.

I. INTRODUCTION

Mobile phone communications are the most widely used systems across the world. For efficient communication network planning, accurate radio frequency (RF) propagation models are needed. In fact, many propagation models are available. However, every model is mainly suitable for the area conditions under which the measurements were performed. Thus, it is important to determine the most suitable model for a specific environment.

Various propagation models were optimized to match specific areas in different parts of the world. For instance, Hata model was customized by the least squares (LS) method for suburban areas within Cyberjaya and Putrajaya areas in Malaysia [1]. The Bertoni-Walfisch model was tuned using the mean square error (MSE) method for global system for mobile communications (GSM) at 900 MHz in Istanbul, Turkey [2]. Hata model was also tuned using the MSE method for Brno, Czech Republic [3]. In [4], Lee model was calibrated by the least square regression method for Jiza town in Jordan based on data supplied by the mobile operators. Okumura model was optimized by the use of the regression fitting method for code division multiple access (CDMA) network in Kuala Lumpur, Malaysia [5]. The COST-231 Hata model was optimized for 3G radio network in Banciao city, Taiwan [6]. In [7], COST-231 Walfisch-Ikegami (WI) path loss model was tuned by the particle swarm optimization (PSO) method for 3G network in the south-western Amman, Jordan.

In this paper, different well-known propagation models are compared with extensive measurements performed by the authors for mobile communications in Irbid, Jordan. Among these models, the comparison reveals that the COST-231 Hata model is the most suitable model for Irbid city, Jordan. To further improve the prediction accuracy, this paper proposes a propagation model based on optimizing the COST-231 Hata model by the particle swarm optimization (PSO) method. The proposed model is validated by comparison with measurements conducted in other locations in Irbid. It is shown that the prediction accuracy of the proposed model is enhanced by up to 5 dB compared with Hata model and by up to 29 dB compared with Egli model, in all the areas under study. This model should be suitable for other areas in Jordan similar to Irbid. As a matter of fact, the COST-231 Hata model was also optimized by the least squares (LS) method, but due to the limit placed on the paper number of pages, only the PSO optimization results will be shown here.

II. PROPAGATION LOSS MODELS AND THE DRIVE TEST

The propagation loss models considered here are COST-231 Hata [3, 6], COST-231 WI [8, 9], and Egli models [10]. Details of these models can be found in [3], [6], [8],[9], [10].

The path loss in dB is calculated from the measured received power using the following equation [8]:

$$PL = P_t + G_t + G_r - P_r - L_t - L_r \qquad (1)$$

Where, P_t is the transmitted power, P_r is the received power, G_t is the transmitter antenna gain, G_r is the receiver antenna gain, L_t is the transmitter feeder losses (e.g., cables and connector losses), and L_r is the receiver feeder losses (e.g., cables and car body losses). In this paper, the values of these

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parameters are: P_t= 42 dBm, G_t= 18 dB, G_r= 2.15 dB, L_t= 2 dB, and L_r=8 dB. The value of L_r is due to the car body penetration loss and it equals to 8 dB on average based on the experiments and this value is similar to the car body loss reported in [11], [12]. The values of L_t, P_t, and G_t were obtained from the mobile communications operators in Jordan.

The definitions of the parameters used in this paper are: f_c: the operating frequency in MHz, d: the distance between the transmitter and the receiver in km, h_m: the receiver antenna height in m, h_b: the transmitter antenna height in m.

The measurements have been carried out, for over a year, by using RF measuring tools while driving a car on many routes in Irbid city around cellular phone base stations for Umniah mobile operator in Jordan at 1800 MHz. The measuring tools consist of TEMS (Test Mobile System) RF measuring software [13], GPS receiver, Laptop, and mobile phone. The mobile phone is equipped with RF measuring firmware [14] in order to extract the received RF signal strengths and deliver these readings to the laptop. The collected data mainly include the received signal strength levels of the serving base stations for each ARFCN (Absolute Radio Frequency Channel Number) scanned channel, cell-ID, and mobile station (MS) location coordinates.

III. OPTIMIZATION PROCESS

The optimization process is intended to enhance the accuracy of the path loss model in order to suit the environmental area under consideration. To that end, the COST-231 Hata model consists of three parts: initial offset, initial system design parameter and slope of model curve, which are expressed as:

$P_{offset} = 54.27$

$P_{system} = 33.9 \log_{10}(f_c) - 13.82 \log_{10}(h_b) - 3.2[\log_{10}(11.755 h_m)]^2$

$$P_{slope} = 44.9 - 6.55 \log(h_b) \tag{2}$$

Thus, COST-231 Hata model can be written as follows:

$$PL = [P_{offset} + P_{system}] + [P_{slope}] \log_{10}(d) \tag{3}$$

The role of the optimization process is to modify the expressions between the square brackets in equation (3) so that a better match will be created between the resulting optimized equation and the measured data. This can alternatively be done through introducing two coefficients, say $\acute{x}$ and $\acute{y}$, associated with the square brackets. According to that, equation (3) becomes:

$$PL = \acute{x}\,[P_{offset} + P_{system}] + \acute{y}\, P_{slope} \log_{10}(d) \tag{4}$$

The PSO method will be used to find the optimum values of $\acute{x}$ and $\acute{y}$.

Particle Swarm Optimization (PSO)

The PSO algorithm is a recently developed, in 1995, global optimization technique for the solution of non-linear problems [15]. The idea is related to the social intelligent behavior of organisms such as swarms of bees, flocks of birds, schools of fish, herds of animals, colonies of ants, molds, and bacterial growth. Each particle in the search space of PSO consists of position vector (**x**), velocity vector (**v**) and personal best vector (i.e., best previous position) and its fitness value. The PSO algorithm is applied in two phases: initialization and iteration [16]. In the initialization phase, the initial velocity and position vectors of each particle are randomly assigned in n-dimensional search space. Each particle moves toward the best solution by modifying its velocity and position in accordance with its best previous experience. The best solution of each particle is called personal or local best (X_{pbest}). The best solution among all particles in the search space is called global best (X_{gbest}). In the iterations phase, each coordinate component of n-dimensional search space for a specific particle, updates its velocity and position according to the following equations [17]:

$$v^{n+1}{}_{id} = C\,[\,\omega\, v^{n}{}_{id} + c_1\, r^{n}{}_{1d}\,(X^{n}_{pbest\ id} - X^{n}{}_{id}) + c_2\, r^{n}{}_{2d}\,(X^{n}_{gbest\ d} - X^{n}{}_{id})\,] \tag{5}$$

$$X^{n+1}{}_{id} = X^{n}{}_{id} + v^{n+1}{}_{id}\,\Delta t \tag{6}$$

Where,

- $v^{n+1}{}_{id}$, $v^{n}{}_{id}$: Velocity of d^{th} coordinate in velocity vector of i^{th} particle at the $n+1^{th}$ and n^{th} iterations, respectively.
- $X^{n+1}{}_{id}$, $X^{n}{}_{id}$: Position of d^{th} coordinate in position vector of i^{th} particle at the $n+1^{th}$ and n^{th} iterations, respectively.
- $X^{n}{}_{pbest\ id}$: Personal best position of d^{th} coordinate in the personal best vector of i^{th} particle at n^{th} iteration.
- $X^{n}{}_{gbest\ d}$: Global best position of d^{th} coordinate in the global best vector at n^{th} iteration.
- Δt: Time step; as usual it is chosen here to be 1 s.
- $i = 1,..,N_p$, where N_p is the swarm size
- $d = 1,\ldots,N_d$, where N_d is the search space dimension

The inertia weight ω and the convergence factor C in (5) above are given by [17], [18]:

$$\omega = \omega_{max} - \frac{(\omega_{max} - \omega_{min})}{N_j}\, j \tag{7}$$

$$C = \frac{2}{\left|2 - \alpha - \sqrt{\alpha^2 - 4\alpha}\right|} \qquad (8)$$

Where N_j is the maximum number of iterations, and j is the current iteration number. In this paper, $\omega_{min}= 0$, $\omega_{max}= 1$; where the experiments have shown that when the value of ω_{max} falls between 0.8 and 1.2, the PSO algorithm has the largest convergence speed.

The cognitive parameter c_1 and social parameter c_2 are positive acceleration constants used to increase the new velocity towards personal best (X_{pbest}) and global best (X_{gbest}). The parameter $\alpha= c_1+c_2$, and c_1, c_2 are chosen to be: $c_1=2$, $c_2=2$, accordingly $\alpha=4$, C=1. The experiments showed that the acceleration coefficients should be selected as $c_1=c_2=2$ in order to obtain the best performance. The parameters, r^n_{1d} and r^n_{2d}, are random numbers of the d^{th} coordinate at the n^{th} iteration that are uniformly distributed between 0 and 1.

In each iteration, the fitness function is evaluated for all the particles. For each particle, if the current fitness value is better than the local best value, then the local best position is replaced by the current position value. Moreover, all local best values are examined in order to determine the global best position.

IV. RESULTS

The location map of the ten cellular phone base stations (BS1 to BS10) under study in Irbid city is shown in Fig. 1.

Fig. 1: Locations of the ten cellular phone base stations (BS1 to BS10) under study in Irbid City.

The COST-231 Hata model is optimized using PSO. In this work, the swarm size value is selected to be 10; this choice is based on several trials in order to get the best results. For all the cases examined in this paper, the optimal solution is reached, on average, after 40 iterations. The optimization process is implemented through the use of the measurements accomplished in six sites (BS1 to BS6) in Irbid city, see Fig. 1. The measurements in the remaining four base stations (BS7 to BS10) are used to validate the optimized model. Figures 2 and 3 show a comparison between the existing path loss models, the measured path loss data, and the proposed optimized model for BS1 and BS2 sites at different frequencies and different sectors. The results of base stations BS3-BS6 are not shown here due to the limit on the number of paper pages. The accuracy of the path loss models are calculated in terms of the root mean square error RMSE [10]:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} [PL_{mi} - PL_i]^2}{N-1}} \qquad (9)$$

Where, PL_{mi} is the measured path loss at position i in dB, PL_i is the calculated path loss at position i in dB, and N is the number of measured path loss samples. Due to the huge number of measured samples for each base station and in order to remove the effects of fast fading, the measured data were averaged over every 1 m of the path between the base station and the receiver.

The optimization process of the COST-231 Hata model gives the optimized values of ẋ and ẏ in (4) as listed in Table 1 for each base station.

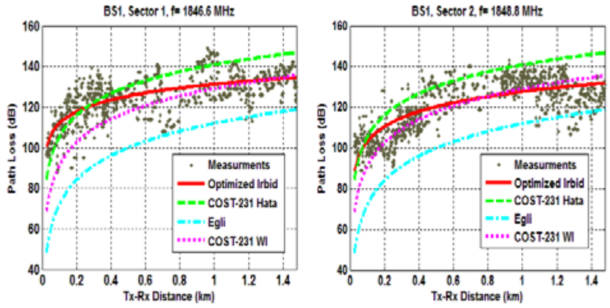

Fig. 2: Path loss vs. distance in kilometres for BS1 site.

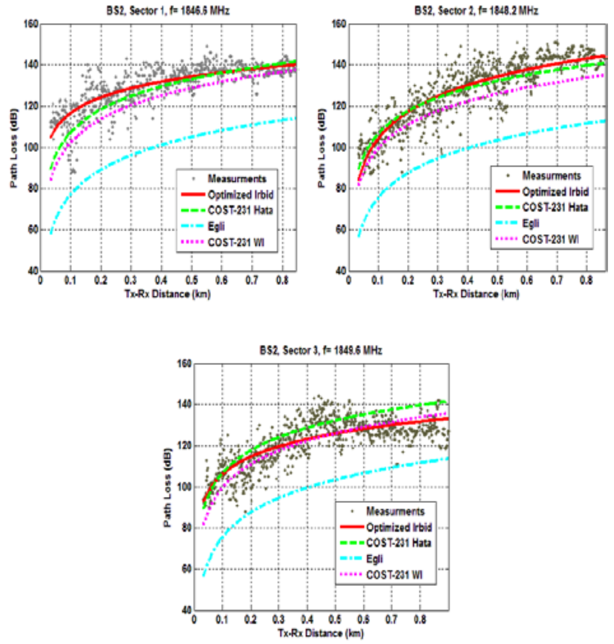

Fig. 3: Path loss vs. distance in kilometres for BS2 site.

Table 1: The RMSE values and optimized coefficients for base stations: BS1 to BS6.

	RMSE (dB)				Optimized coefficients	
Base Station	Proposed optimized Model	Hata	Egli	WI	$\acute{x}$	$\acute{y}$
BS1	8.09	12.6	25.02	11.65	0.92	0.62
BS2	6.92	8.32	29.81	9.73	0.95	0.68
BS3	8.16	10.8	29.81	10.91	0.91	0.50
BS4	7.69	9.32	35.88	16.28	0.95	0.62
BS5	8.74	10.9	30.46	14.87	0.93	0.69
BS6	8.31	9.91	30.69	11.73	0.92	0.70

From Table 1, we can see that the proposed optimized model has the best RMSE values in all the base station sites compared with the other examined models. Substituting the average values of $\acute{x}$ and $\acute{y}$ from Table 1 into equation (4), the proposed optimized model can be written as follows:

$$PL = \acute{x}\,[P_{offset} + P_{system}] + \acute{y}\,[P_{slope}]\,\log_{10}(d)$$

$$= 50.57 + 31.59\log_{10}(f_c) - 12.88\log_{10}(h_b) - 2.98\,[\log_{10}(11.755h_m)]^2 + [29 - 4.23\log(h_b)]\log(d) \qquad (10)$$

The measured data in the remaining four locations in Irbid city, i.e., BS7-BS10, are utilized to verify the validity and accuracy of the proposed optimized model. Fig. 4 compares the optimized model with the COST-231 Hata model for base station BS8. Table 2 shows the root mean square error (RMSE), between the predicted and the measured data, of the proposed optimized model as well as the other models.

Table 2: The RMSE values for the base station sites (BS7 to BS10), which were used to validate the proposed model.

	RMSE (dB)			
Base station	Optimized model	Hata	Egli	WI
BS7	8.38	11.82	37.43	11.81
BS8	7.26	10.19	29.27	11.19
BS9	7.89	13.04	29.24	13.69
BS10	9.58	13.09	24.68	11.27

Table 2 confirms that the proposed optimized model has the best RMSE values in all the base station sites compared with the other models. In particular, the prediction accuracy of the proposed model is improved by up to 5.15 dB as compared with Hata model, and by up to 29.05 dB as compared with Egli model. Moreover, it is expected that this new model will be suitable for other similar areas in Jordan.

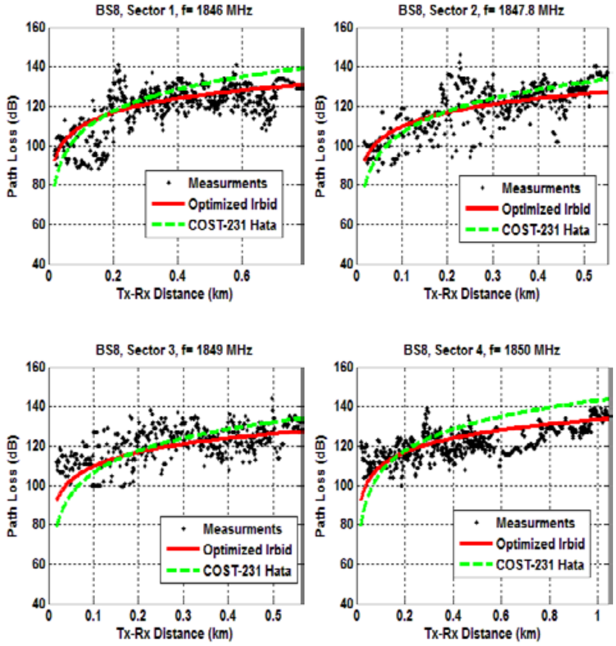

Fig. 4: Path loss vs. distance in kilometres for BS8 site.

V. CONCLUSIONS

This study proposes an optimized path loss model for Irbid city in Jordan. The optimization is based on the particle swarm optimization (PSO) technique in addition to outdoor measurements for mobile phone base stations performed by the authors for over a year. The measured path loss data for other base stations are used to confirm the validity and accuracy of the optimized model, where the path loss predictions of the proposed model show enhanced accuracy of up to 5 dB as compared with Hata model and up to 29 dB as compared with Egli model.

Finally, the optimized model is expected to suit other similar areas in Jordan. The proposed model can help the mobile operator companies in Jordan to make accurate predictions for many system design parameters.

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