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# Optimizing Propagation Models on Railway Communications using Genetic Algorithms

Ana Rita Beire\*, Helder Pita, Nuno Cota

*Área Departamental de Engenharia Eletrónica e Telecomunicações e de Computadores  
Instituto Superior de Engenharia de Lisboa – ISEL  
Lisboa, Portugal*

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## Abstract

Although the Okumura-Hata prediction model has been a widely used model to estimate radio network coverage, its application in railways environment requires calibration. The objective of this work is to present Genetic Algorithms as a solution in optimizing propagation models, proving that it can be used for optimizing the Okumura-Hata model on railway communications in order to improve its prediction of radio coverage.

Several tests were carried out using different conditions allowing to establish the conditions that maximize the gain of the algorithm for this particular problem. The algorithm was applied to training samples and the resulting parameters were applied to different scenarios, showing improvements in the prediction results.

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*Keywords:* Optimization; Propagation Model; Okumura-Hata; Genetic Algorithms; Railway Communications.

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## 1. Introduction

The radio signal coverage prediction is an essential step in planning all radio networks and it is still an intense topic in research. A wide variety of empirically and theoretically based models have been developed to estimate the radio propagation in mobile communications. One of the most popular empirical approaches has been proposed by Okumura [1]. Later, in order to put Okumura's curves into suitable form for computer implementation, Hata

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\* Corresponding author. Tel.: +351 917 945 218

*E-mail address:* [anaritabeire@gmail.com](mailto:anaritabeire@gmail.com)

introduced a set of equations for path loss estimation [2].

Given the maturity of current GSM systems, the radio network planning and optimization methodologies and propagation models are currently well defined and documented, and are used by all public mobile network operators. These conventional models are based on assumptions and objectives which are different of railway reality. These differences are not only related to quality of service and coverage probability requirements, but also in architecture, capacity, among others [3].

The suitability of the Okumura-Hata propagation model for radio coverage prediction in GSM-R railway communications has been demonstrated in [4]. However, tuning the model based on linear iterative tuning methods with a large number of tuning parameters is relatively complicated, once it requires changing one variable at a time in small steps and then doing an analysis for each setting.

The objective of this work is to present Genetic Algorithms as solution in optimizing propagation models, proving that it can be used for optimizing the Okumura-Hata prediction model on railway communications in order to make it more fit to perform the prediction of radio coverage.

The concept of optimization is identified as a mechanism for analyzing complex decisions involving the selection of values for variables, with the simple aim of quantifying performance and measure the quality of decisions. The goal is to find the best solution, while respecting the restrictions of the problem parameters. In the case of complex problems, search methods are not always the best solution. There are several methods, each more suited to a class of problems. Among the most effective methods and the most suitable for solving the problem in question are the Genetic Algorithms, due to its ability of prosecuting different search paths simultaneously.

The Genetic Algorithm (GA) is a search and optimization method inspired on the natural evolution process. This algorithm belongs to the group of Evolutionary Algorithms that, as the name implies, use techniques inspired by evolutionary biology such as inheritance, mutation, natural selection and crossover. This method was introduced in 1975 by John Holland [5]. Subsequently, the methodology was developed in greater detail by David Goldberg, [6].

## 2. Propagation Model

The Okumura-Hata model for medium-sized city environment is formulated as following:

$$L_{[dB]} = a_1 + a_2 \log(f) + a_3 \log(h_{be}) + b_1 \log(d) + b_2 \log(h_{be}) \log(d) - (1.1 \log(f) - 0.7)h_m - (1.56 \log(f) - 0.8) \quad (1)$$

where  $a_k$  and  $b_k$  are model tuning parameters,  $d$  is propagation distance (km),  $f$  is frequency (MHz),  $h_{be}$  is effective height of base station antenna (m) and  $h_m$  is mobile antenna height (m).

In addition to the basic equation of the Okumura-Hata model, there is a set of correction terms, such as, the influence of water, the undulation of the terrain, the presence of vegetation, etc, which characterize different environments [1,2].

It was also added to the Okumura-Hata model the obstacles correction, given by the Deygout method (2), which has been proved to improve the quality of the results [9].

$$A_{ol [dB]} = x_1 + x_2 \log\left(\sqrt{(v - 0.1)^2 + 1} + v - 0.1\right), \quad v > -0.7 \quad (2)$$

$$v = \pm h \sqrt{\frac{2d_p}{\lambda d_1 d_2}} \quad (3)$$

where  $x_k$  are tuning parameters,  $d_p$  is propagation distance (m),  $d_1$  is propagation distance between the base station and the obstacle (m),  $d_2$  is propagation distance between the obstacle and the mobile station (m),  $h$  is the height of the obstacle above the direct ray between base station and mobile station (m) and  $\lambda$  is wavelength (m).

All these formulas contain parameters that can be adjusted, depending on the environment (see Table 1). However, manual adjustment of these parameters is time consuming and not very efficient, so the concept of optimization is introduced.

Table 1. Parameters from the Okumura-Hata to optimize.

Formula	Parameters
Okumura	$a_1, a_2, a_3, b_1, b_2$
Deygout	$x_1, x_2$
Water	$m_1, m_2$
Terrain Undulation	$u_1, u_2, u_3$
Position in Terrain Undulation	$p_1, p_2, p_3$
Orientation	$c_1, c_2$
Vegetation	$v_1, v_2$

### 3. Problem Formulation

The objective of this work is to use a Genetic Algorithm that based on measurements optimize the Okumura-Hata model parameters, represented in Table 1, in order to obtain a prediction as similar to the measurements as possible. The more reliable is the prediction, the more the margins used by public networks operators can be reduced. This will lead to a smaller number of base stations, to be considered in the planning process, and, consequently, lower costs associated to its implementation.

Genetic algorithms have proved to be far more robust at handling complex and non-linear problems [7]. In this work, an intelligent GA technique has been experimented in an attempt to find out the best optimization mechanism for the problem. The algorithm will use a training sample (based on measurements) to obtain the optimized model parameters. These parameters are then applied to a bigger sample and the new error statistics are calculated, proving the validity of the algorithm.

Measurements were provided by REFER Telecom, the Portuguese railway communications operator, and were carried out in four different railways.

#### 3.1. Population Initialization

The algorithm starts from an initial set of individuals (initial population) representing possible solutions to the problem. The initial population is randomly generated, according to a uniform distribution.

Each individual ( $X$ ) is represented as follows:

$$X = [s_1, s_2, \dots, s_n] \quad (4)$$

where  $s_k \dots$  are the parameters of the Okumura-Hata model to optimize.

Both real and binary representations were used. In Figure 1 we can compare results from the two representations, in two different scenarios. In both figures it is clear that binary representation allows lower values of RMSE, although in Figure 1 (b) real representation converges faster.

#### 3.2. Evaluation of Individuals

For each iteration (generation in AG) individuals are evaluated based on the objective function, in relation to their level of adaptability to the environment and the fittest are selected to generate descendants.

The smaller the deviation between the resulting prediction and the measures, the more suited is the individual. In order to quantify this deviation, first order statistics and the correlation coefficient have been used. The first order statistics implemented were mean error (ME), root mean square error (RMSE) and error's standard deviation (ESD), calculated according to (5), (6) and (7) respectively.

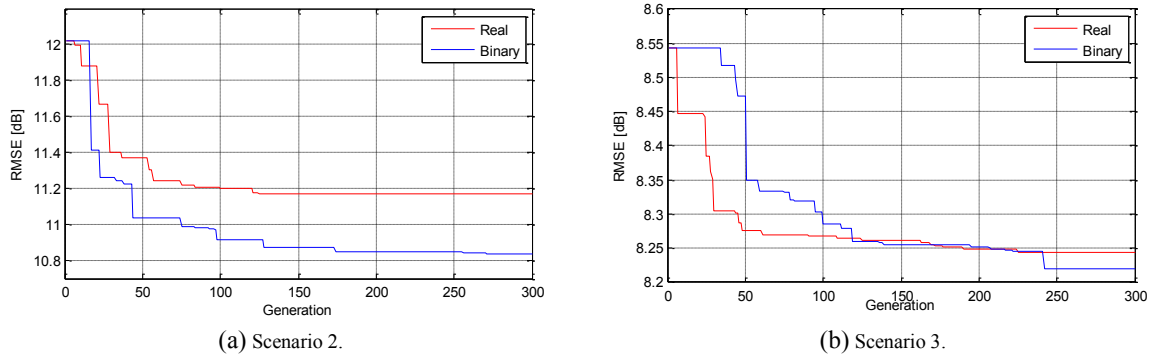


Fig. 1. Comparison between real and binary representations.

$$ME = \frac{1}{n} \sum_{i=1}^n |P_{meas_i} - P_{pred_i}| \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n |P_{meas_i} - P_{pred_i}|^2} \tag{6}$$

$$ESD = \sqrt{\frac{1}{n} \sum_{i=1}^n (|P_{meas_i} - P_{pred_i}| - ME)^2} \tag{7}$$

where  $P_{meas_i}$  is the signal strength (in dBm) of measured signal at  $i$ th point,  $n$  is the number of data points and  $P_{pred_i}$  is the corresponding predicted value.

The correlation coefficient provides a measure of the degree of linear relationship between measured and predicted variables and is calculated as:

$$RE = \frac{\sum_{i=1}^n (P_{meas_i} - \bar{P}_{meas})(P_{pred_i} - \bar{P}_{pred})}{\sqrt{\sum_{i=1}^n (P_{meas_i} - \bar{P}_{meas})^2} \sqrt{\sum_{i=1}^n (P_{pred_i} - \bar{P}_{pred})^2}} \tag{8}$$

In Figure 2 we can observe the convergence of the first order statistics implemented and the correlation factor. The RMSE statistic was used to evaluate the fitness of each solution as it has been the one that presented better results, minimizing the other statistics (ESD and ME) and maximizing the correlation (RE).

The dispersion observed in ESD and ME statistics and RE are due to the fact that they are not used as evaluation methods, and therefore do not use the concept of elitism, as RMSE. The elitism allows that the best individual, which is the one with the lowest RMSE, has place in the next generation.

### 3.3. Crossover and Mutation

Individuals are selected as parents based on their fitness values using the tournament method. An individual with higher fitness value is likely to be selected. Then reproductions are carried out among individuals generating permutations of the genetic material through crosses and by inserting new genetic material through mutations. Depending on the representation of the variables, different methods must be used. Basic crossover methods include one-point crossover, multi-point crossover, and uniform crossover [8]. The uniform crossover is used in this paper. On the mutation a percentage of bits is inverted, changing one or more parameters of the individuals.

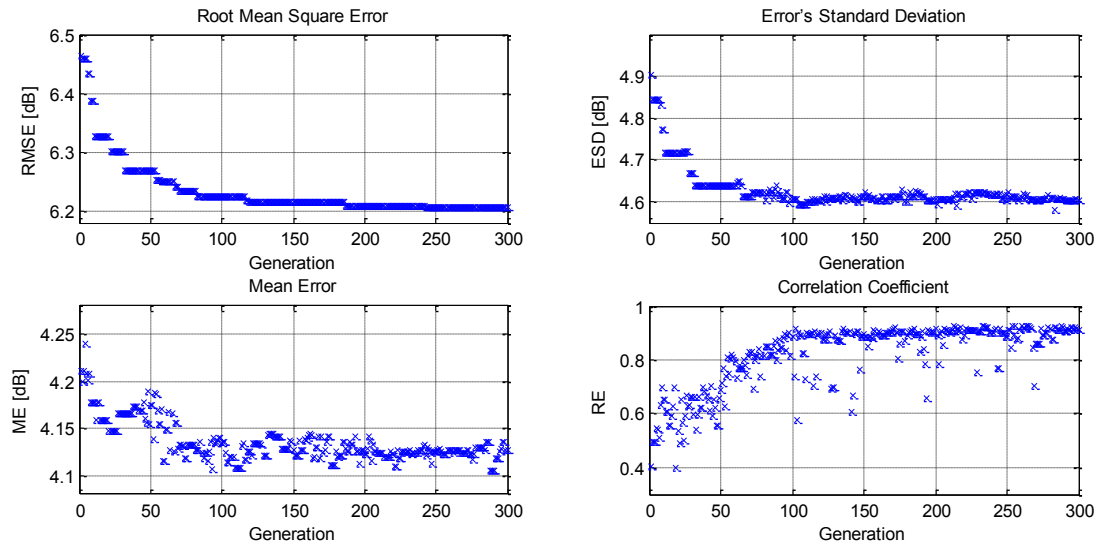


Fig. 2. Statistical parameters used to evaluate individuals (scenario 4).

With these two methods we get to improve the initial population, until we obtain convergence. The number of iterations has been selected as the number of iterations that insure that the root mean square error reaches a stable value.

#### 4. Tuning Results

A succession of tests was carried out using different conditions, such as, crossover probability, crossover method, mutation probability, mutation method, elitism, etc, which allowed to maximize the gain of the algorithm for this particular problem.

Figure 3 (a) shows the RMSE for different values of crossing probability. A probability of 40% produces a faster convergence to a lower value of RMSE. Figure 3 (b) shows the variation of the number of individuals with elitism. If no elitism is used (Elitism=0) there is the possibility of the algorithm to move to a worst solution. Although the algorithm eventually converges, the final value is far worse than the ones obtained by using elitism.

The conditions that maximize the algorithm are presented in Table 2.

Table 2. Condition that maximize the gain of the algorithm.

Variable	Value
Representation	Binary
Crossing Probability	40%
Number of Crossing Points	Uniform
Mutation Probability	2%
Number of Mutation Points	10% of the Bits
Elitism	3 Individuals

Once the conditions of the algorithm were established, four scenarios were tested: Cascais – 1, Sintra – 2, Oeste – 3 and Évora – 4. These railways were chosen in order to measure the signal in different propagation environments, such as, suburban environments, water paths, urban environments, rural environments, hilly terrains, open areas, etc. In these tests, the algorithm was applied to a training sample, corresponding to only 80% of the measurements. The

resulting tuned parameters were applied to all of the measurement points. This process was repeated for each scenario.

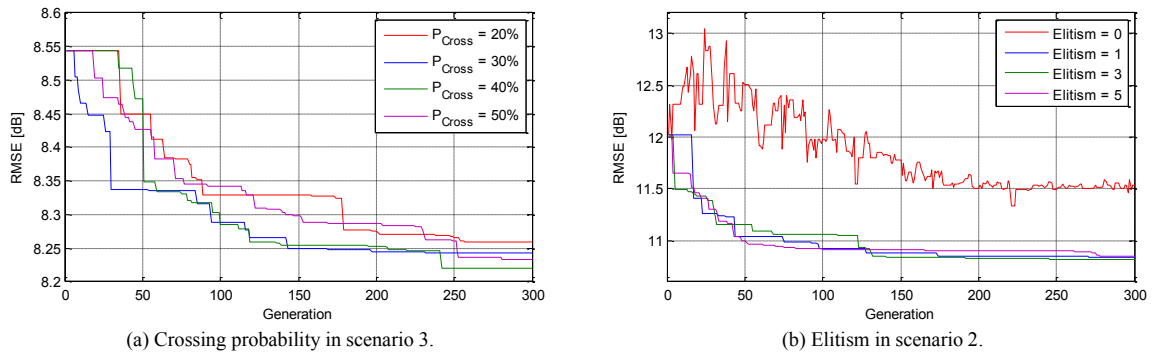


Fig. 3 Variation of the conditions of the algorithm.

In order to compare the predictions with the measurements, the received power in the measurement points is computed by both original Okumura-Hata and tuned model parameters. Two sets of field strengths are resulted from these computations. In Figure 4 it is possible to compare the original and the tuned model prediction with measurements from two different scenarios and conclude that the prediction with the tuned parameters is more similar to the measurements than the prediction with the original model parameters.

Statistical parameters of the error between predictions and measurements represented in Table 3 enforce these visual assumptions. In this table is performed a comparison between the statistical parameters obtained from predictions using original and tuned parameters, for each scenario. In all scenarios significant improvements can be observed with the introduction of the algorithm.

Table 3. Original model versus tuned model statistics, for each scenario.

Scenario	Model	RMSE	ESD	RE	ME
1	Original	13,278	8,342	0,840	10,331
	Tuned	10,003	6,033	0,850	7,979
	Gain	<b>24,7%</b>	<b>27,7%</b>	<b>1,0%</b>	<b>22,8%</b>
2	Original	14,497	8,600	0,857	11,670
	Tuned	10,804	6,305	0,826	8,774
	Gain	<b>25,5%</b>	<b>26,7%</b>	<b>-3,1%</b>	<b>24,8%</b>
3	Original	9,183	6,850	0,913	6,116
	Tuned	8,188	6,121	0,920	5,439
	Gain	<b>10,8%</b>	<b>10,6%</b>	<b>0,7%</b>	<b>11,1%</b>
4	Original	9,719	7,502	0,907	6,178
	Tuned	6,158	4,573	0,945	4,125
	Gain	<b>36,6%</b>	<b>39,0%</b>	<b>3,8%</b>	<b>33,2%</b>

Figure 4 (a) is related to scenario 2 while Figure 4 (b) is related to scenario 4, both in Table 3.

Afterwards, an overall tuning, containing the same proportion of measurements of each scenario, was performed in the algorithm. The resulting tuned parameters were applied to each scenario individually. Table 4 presents a comparison between the statistical parameters obtained from predictions using original and overall tuned parameters. Once again, it is possible to observe improvements with the introduction of the algorithm, although,

they are not as pronounced as the previous ones, which have been obtained through the use of individual tuned parameters. This test was important to demonstrate that it is not easy to have a model that fits to all types of environments.

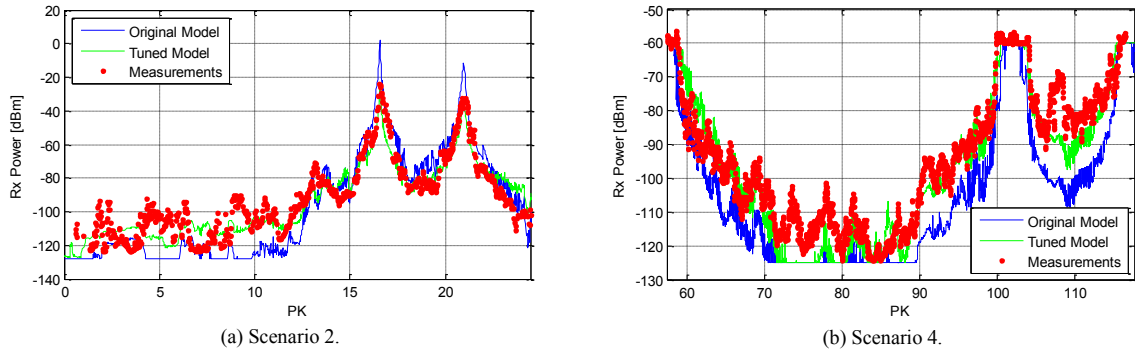


Fig. 4. Overlap between original and tuned predictions and measures.

In Figure 5 the difference between the prediction with the original model, individual tuning and overall tuning can be observed, from scenario 1. Globally there is a better adjustment between the individual tuning prediction and measurements.

Table 4. Original model versus tuned model statistics, for overall tuning.

Scenario	Model Parameters	RMSE	ESD	RE	ME
1	Original	13,278	8,342	0,840	10,331
	Tuned	11,470	7,063	0,826	9,038
	Gain	<b>13,6%</b>	<b>15,3%</b>	<b>-1,3%</b>	<b>12,5%</b>
2	Original	14,497	8,600	0,857	11,670
	Tuned	12,297	7,560	0,839	9,698
	Gain	<b>15,2%</b>	<b>12,1%</b>	<b>-1,8%</b>	<b>16,9%</b>
3	Original	9,183	6,850	0,913	6,116
	Tuned	8,437	6,218	0,913	5,703
	Gain	<b>8,1%</b>	<b>9,2%</b>	<b>0,0%</b>	<b>6,7%</b>
4	Original	9,719	7,502	0,907	6,178
	Tuned	6,504	4,790	0,942	4,399
	Gain	<b>33,1%</b>	<b>36,2%</b>	<b>3,5%</b>	<b>28,8%</b>

## 5. Conclusions

This work purpose was to create an algorithm that, based on a small number of measures, was able to adapt the Okumura-Hata model to each environment.

Based on measurements provided by REFER Telecom, carried out in several railways it was possible to create an algorithm more suited for the optimization of the propagation model of Okumura-Hata on railways environments. After several tests performed with measurements from different railways we were able to find the conditions that maximize the performance of the algorithm for this type of application.

Four performance indicators were used: mean error, root mean square error, error's standard deviation and correlation coefficient.

We have shown that the proposed GA is able to produce significant improvements over the original model. The improvements are more significant when the algorithm is applied to each railway individually.

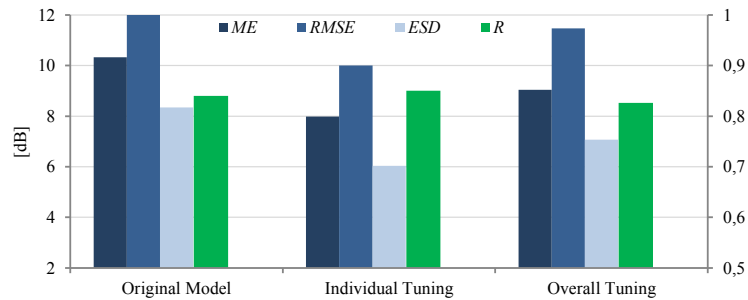


Fig. 5. Statistical metrics.

Computation time depends on the number of measurement points, the number of individuals of the population and the number of generations. For example, with a population of 200 individuals and a maximum of 300 generations, the processing time is, for each scenario, represented in Table 5.

Table 5. Algorithm processing time.

Scenario	Number of Measurement Points	Processing Time
1	33300	~ 2,5 h
2	6708	~ 25 min
3	27314	~ 1 h 20 min
4	40752	~ 1 h 45 min

Taking into account that, in the planning process, the optimization of the parameters is performed only once, processing times are quite acceptable.

With this algorithm it is intended that in the future, based on further measures, it is possible to find a pattern between the parameters and environments so no measures are necessary to calibrate the propagation model.

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