A Metaheuristic Approach for Propagation-Model Tuning in LTE Networks

Lucas Benedičič and Marko Pesko
Research and Development Department
Telekom Slovenije, d.d., Cigaletova 15, SI-1000 Ljubljana, Slovenia
E-mail: {lucas.benedicic, marko.pesko}@telekom.si

Tomaž Javornik
Communication Systems Department
Jožef Stefan Institute, Jamova cesta 39, SI-1000 Ljubljana, Slovenia

Peter Korošec
Computer Systems Department
Jožef Stefan Institute, Jamova cesta 39, SI-1000 Ljubljana, Slovenia

Keywords: LTE, coverage planning, semi-empirical propagation models, metaheuristics, optimization

Received: November 28, 2013

When deploying a new mobile technology such as LTE, it is crucial to identify the factors that affect the radio network in terms of capacity and quality of service. In this context, network coverage is arguably the single most influential factor. This work presents a metaheuristic-optimization approach that automatically adapts the parameters of a signal-propagation model. The optimization procedure is performed per cell, enabling the calculation of accurate network-coverage predictions. The evaluation of the proposed approach is carried out on two different regions in Slovenia, where Telekom Slovenije, d.d., provides LTE coverage. The results show radio-propagation predictions of improved quality when compared to manual and analytical methods.

Povzetek: Avtorji predstavljajo metahevristično metodo za samodejno optimizacijo parametrov semi-empiričnih modelov razširjanja radijskega valovanja. Rezultati številnih poskusov v omrežjih LTE kažejo izboljšano natančnost izračunanih napovedi razširjanja radijskega valovanja.

1 Introduction

One of the primary objectives of radio-coverage planning is to efficiently use the allocated frequency band. To this end, radio-coverage prediction tools are of great importance, as they allow network engineers to test different configurations before physically implementing the changes. However, predicting the radio coverage of a mobile network is a complex task, hence the importance of fast and accurate prediction tools. The precision achieved by the software tool of choice is directly related to the accuracy of the signal-propagation model used. For this reason, signal-propagation models that support configurable parameters are preferred, since they allow the model to adapt to different environments and thus to improve the accuracy of the calculated coverage predictions.

The effectiveness of the decision-making process during radio-network planning is tightly coupled with the precision achieved by the propagation model used. In order to obtain a radio-propagation model that accurately reflects the characteristics of the area covered by the mobile network, the parameters of the signal-propagation model are adjusted using data from field-measurement campaigns. Signal-loss adjustment using this method depends on existing field-measurement data, which are collected in advance for the area covered by the target network cells.

In order to adapt the parameters of a signal-propagation model, mainly analytical approaches were proposed in the related literature [1, 8, 27]. These works confirm the suitability of methods based on least-squares theory for the parameter tuning of signal-propagation models.

In this work, we propose the automatic optimization of the parameters of a signal-propagation model using a metaheuristic approach. The objective of such optimization is four-fold. First, using a stochastic optimization approach, the parameters are optimized in order to reflect the local characteristics of the terrain, thus adapting the model to the local environment of a given network cell. Second, based on a set of field measurements, the automatic optimization of model parameters improves the accuracy of the calculated radio-propagation predictions of each network cell, as well as the radio network as a whole. Third, the proposed metaheuristic method improves, under certain geographical conditions, the results achieved by a traditional linear-least-squares approach [1, 8, 27], the application of which only adapts the linear part of the propagation model, i.e., $y = c + mx$. Fourth, tuning the complete parameter set per network cell shows improved results especially in rugged-terrain areas.

As the working schema for tackling the presented problem, we use PRATO, a parallel framework for coverage planning of cellular networks [5]. The framework flexibility allows for coverage planning and optimization of radio networks in general, and LTE in particular. The optimization component featured by PRATO enables the parallel optimization of several parameters, e.g., the parameters of the signal-propagation model.

The remaining of this paper is organized as follows. Section 2 introduces some principles of radio-propagation prediction and the signal-propagation model used. Section 3 describes the optimization problem involving the parameter-tuning of the signal-propagation model, followed by the performed simulations and the achieved results in Section 4. Finally, in Section 5 we draw some conclusions and give guidelines for further work.

2 Radio-propagation prediction

To calculate the radio-propagation predictions, we use a mathematical model based on the well-known Okumura-Hata formula [14, 22]. Other more accurate methods exist, like the ones based on ray tracing [7, 25]. However, these methods are still inefficient in terms of the computational effort required to achieve satisfying results.

On the other hand, (semi-)empirical methods for radio-propagation predictions give acceptable results within a feasible amount of time. For this reason, they became the industry standard for non-deterministic, signal-propagation calculations [3, 6, 14, 21, 22, 23].

2.1 Signal-propagation model

The Okumura-Hata model has been largely studied and shown to be suitable for predicting the signal propagation of LTE networks [2]. In its primary form, the model distinguishes the distance from the receiver to the transmitter, the frequency used and the effective antenna height, i.e., the antenna height above the receiver's level. These variables are taken into account in order to calculate the path loss in open areas (OA), as described in Equation (1).

$$\begin{aligned} L_{\mathrm{OA}}(x,y,\vec{\beta}) &= \beta_1 + \beta_2 \log(d_{(x,y)}) + \beta_3 \log(H_{\mathrm{A}}) \\ &+ \beta_4 \log(d_{(x,y)}) \log(H_{\mathrm{A}}) - 3.2\,(\log(11.75 \cdot H_{\mathrm{R}}))^2 \\ &+ 44.49 \log(F) - 4.78\,(\log(F))^2\,, \end{aligned} \quad (1)$$

where $\vec{\beta} = (\beta_1, \beta_2, \beta_3, \beta_4)$ are the adaptable parameters of the model, $d_{(x,y)}$ is the distance from the transmitter to the topography point with coordinates (x, y) (expressed in kilometers), H_{A} is the effective antenna height of the transmitter (expressed in meters), H_{R} is the antenna height of the receiver (expressed in meters), and F is the frequency (expressed in MHz).

In this work, as well as in [11], the terrain profile is used for non-line-of-sight (NLOS) determination, i.e., the loss due to an obstacle obstruction in the first Fresnel zone of the transmitter [26]. In such case, additional path-loss factors due to the terrain profile and the Earth shape are added to the original formula, the values of which are calculated as in Equation (2).

$$L_{\mathrm{NLOS}}(x,y) = \sqrt{\left(\alpha K(d_{(x,y)})\right)^2 + E(d_{(x,y)})^2}, \quad (2)$$

where α is the knife-edge diffraction control parameter, the value of which is calculated based on the level of obstruction of the Fresnel zone, $K(d_{(x,y)})$ is the knife-edge diffraction loss (in dB), and $E(d_{(x,y)})$ is the correction due to the Earth sphere, the value of which improves the calculated prediction especially for higher base-station towers and distances over 10 kilometers. All three values depend on the characteristics of the topography point with coordinates (x, y). The euclidean distance between the transmitter and the receiver is intentionally calculated using two-dimensional coordinates due to simplicity and the negligible difference when compared to its three-dimensional counterpart.

In order to adequately predict signal-loss effects due to foliage, buildings and other fabricated structures, a supplementary factor based on the land usage (clutter) is included. This technique is adopted by several propagation models for radio networks, e.g., [1, 3, 19, 22]. Consequently, we introduce an extra term for signal loss due to clutter, thus defining the total model-predicted path loss, which is expressed in dB, as in Equation (3).

$$L(x,y,\vec{\beta}) = L_{\mathrm{OA}}(x,y,\vec{\beta}) + L_{\mathrm{NLOS}}(x,y) + L_{\mathrm{CLUT}}(x,y), \quad (3)$$

where $L_{\mathrm{CLUT}}(x, y)$ represents the clutter loss at the topography point with coordinates (x, y).

2.2 Field measurements

In mobile networks, a moving mobile device (or user equipment, UE) constantly performs cell selection/reselection and handover in order to keep the best possible connection to the network. In this context, the best connection is selected by measuring the signal strength or quality of the neighboring cells. In LTE networks, the UE measures two parameters from the reference signal of the network, namely the Reference Signal Received Power (RSRP) and the Reference Signal Received Quality (RSRQ) [23].

For a certain frequency bandwidth, RSRP measures the average received power over the resource elements that carry cell-specific reference signals. RSRP is applicable in both idle (e.g., waiting for a call) and connected (e.g., during a call) modes. During the procedure of cell selection/reselection in idle mode, RSRP is used. On the other hand, RSRQ is only applicable when the UE is in connected mode.

The radio-coverage calculation involves predicting the network coverage over a certain region, and thus over the UEs within it. Hence, in the first place, we are interested on accurately predicting the best connection the UE would select in idle mode and the RSRP field measurements it uses.

In our case, the field measurements representing the RSRP at a given location were collected using a small truck equipped with the spectrum analyzer Rohde & Schwarz, the functionality of which supports LTE signal analysis. The spectrum analyzer was connected to an external omnidirectional antenna mounted on the roof of the truck, at roughly 2 m above the ground, taking measurements at a rate of 2 Hz. The measurement locations were established using a GPS unit. These GPS-informed locations were tested to be compliant with the 60-meter limit mentioned in [1]. The measurements covered a considerable proportion of the target area, with over 100,000 individual points, collected from more than 30 network cells.

To minimize the deviation in the measured RSRP values, and the impact that small-scale fading has in larger-scale path loss [10], all field measurements were post-processed so that a single value, the median, was calculated for each of the measured locations. The resulting RSRP was then used as the field measurement representing the given location, the resolution of which matches the digital elevation model (DEM) and clutter maps used as input data of the optimization process. Note that the DEM data represents the terrain profile of the geographical area of interest.

3 Parameter tuning of the radio-prediction model

The procedure to adapt the parameters of the mathematical model for each of the cells in the target network involves minimizing the deviation of the radio-propagation prediction compared to a given set of field measurements.

In the context of our work, this means that we have to fine tune the parameters of $L_{\mathrm{OA}}(x, y, \vec{\beta})$, as defined in Equation (3). The adjustable parameters are the elements of vector $\vec{\beta} = (\beta_1, \beta_2, \beta_3, \beta_4) \in \mathbb{R}^4$, namely

β_1 the reference loss or offset;

β_2 the loss slope due to distance of the receiver from the transmitter;

β_3 the loss slope due to height of the transmitter antenna;

β_4 the loss slope due to the combined effect of the distance and height of the antenna.

The parameter tuning is performed per cell to improve local fitting of the radio predictions, being its resulting solution a vector $\vec{\beta}^*$ of the target cell.

The analytical approach for tuning of the radio-prediction model consists of correlating the field measurements with the predicted received-signal values. The new parameter set originates from the minimization of an error criterion. As defined in [15, 27], the minimization criterion is the squared-sum difference between the predicted and the observed RSRP levels, the definition of which is shown later in Equation (6).

As a general rule when applying this approach, only the first two components of the vector $\vec{\beta}$ are adapted, i.e., β_1 and β_2, whereas the values of β_3 and β_4 are kept constant. Therefore, the analytical method consists in fitting only the linear part of the path-loss definition previously presented in Equation (3), i.e.:

$$\Delta L(x, y, \vec{\beta}) = \beta_1 + \beta_2 \log(d_{(x,y)}). \tag{4}$$

The expression in Equation (4) does not take the terrain height into account, which is feasible when the field measurements are taken at a roughly constant height relative to the base station [8, 27]. However, when these heights fluctuate within the coverage area of a cell, the other two parameters, β_3 and β_4, have a considerable effect on the adaptation of the signal-propagation model, as it will be shown in the following sections.

3.1 Differential ant-stigmergy algorithm

In order to adapt the vector $\vec{\beta}$, including its four components, we turn our attention to metaheuristic algorithms in general [24] and swarm intelligence in particular [16]. From this last family of metaheuristics, we have chosen the differential ant-stigmergy algorithm (DASA) [17].

A standalone metaheuristic, the DASA is based on the well-known Ant-Colony Optimization (ACO) [9]. It provides a specialized extension for solving high-dimensional, numerical-optimization problems, whereas the ACO operates on the discrete domain. The DASA represents the search space in a fine-grained discrete form, producing a graph. This graph is then used as the walking paths for the ants, which iteratively improve the temporary best solution.

There are several reasons for choosing the DASA as the optimization algorithm in the context of this problem. First, the benefits of metaheuristic algorithms for solving optimization problems, particularly in the context of radio networks, was demonstrated by numerous authors [4, 12, 15, 18]. Second, in [17], the authors shown the suitability of the algorithm for solving numerical problems, also exhibiting better performance than other swarm-based metaheuristics. Moreover, it has already been successfully applied for tackling an optimization problem in the area of radio networks [4], obtaining competitive results.

The mapping between the parameter-optimization problem and the DASA is as defined in Equation (5).

$$X_a = \{x_1, x_2, x_3, x_4\}, \tag{5}$$

where X_a is the solution vector of ant a during the minimization process, and x_j represents the j-th component of vector $\vec{\beta}$ for the signal-propagation model of a given cell. At the end of every iteration, and after all the ants have created solutions, they are evaluated to establish if any of them is better than the best solution found so far.

For a more in-depth explanation about this procedure and the DASA itself, we refer the reader to [17].

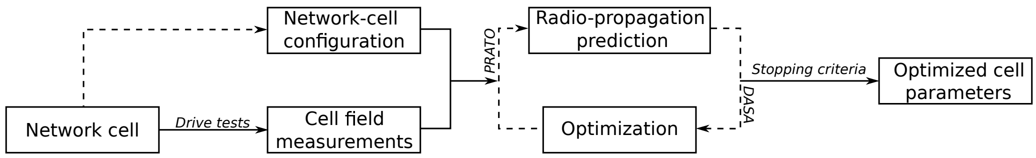


Figure 1: The parameter-optimization system as executed per network cell by a parallel process of PRATO.

3.2 Optimization objective

The optimization objective consists in adjusting the values of components of vector $\vec{\beta}$ according to a set of field measurements of a given cell. Each network cell is independently optimized, so that its radio-propagation prediction minimizes the mean-squared error against the field measurements, as defined in Equation (6).

$$f^*(c) = \min \sum_{m \in M_c} \frac{(p_c - L_c(\mathrm{coord}(m), \vec{\beta}) - m)^2}{|M_c|} \; \forall c \in N, \quad (6)$$

where $f^*(c)$ is the optimization objective to be minimized for cell c, N is one of the test networks, p_c is the transmit power of cell c, m is a field measurement of cell c, M_c is the set of all field measurements of cell c, and $L_c(\mathrm{coord}(m), \vec{\beta})$ represents the path loss of cell c at the same geographical point of the field measurement m, as defined in Equation (3). Note that $f^*(c)$ is independently calculated for each $c \in N$.

4 Simulations

In the parameter-optimization problem, the process starts with a mobile network. Each network cell is optimized by an independent parallel process as shown in Figure 1. The set of field measurements corresponding to the cell under optimization has to be gathered through drive tests before hand. Together with the cell configuration, they provide the input data for the optimization process itself. An iteration begins when the DASA generates a solution vector for each of the ants in the colony. The following step involves the evaluation of the solution vector carried by an ant, i.e., one radio-propagation prediction per iteration of the optimization process. The objective-function value is calculated as defined in Equation (6), and sent back to the DASA for it to generate the next set of solutions. The optimization process involves multiple iterations, which are repeated until some stopping criteria are met. Then, the best solution found represents the optimized values of the tuning parameters for the radio-propagation model of the target network cell.

The optimization process is performed by PRATO in parallel over the worker processes, each of which runs independently of the others while optimizing the parameters of one network cell.

Compared with the analytical approach, the solution of which requires solving a linear system of equations, a large number of evaluations is needed for the metaheuristic optimization to converge to a solution. Therefore, it is essential to exploit the parallel nature of PRATO in order to concurrently optimize the parameter sets of multiple cells within the network. Otherwise, such approach would not be feasible, since the time required to reach a reasonable solution would be excessive.

	Number of cells	Calculation radius [km]	Area [km^2]	Field-measurement proportion [%]
Net$_1$	9	16.00	82.90	4.40
Net$_2$	25	16.00	133.47	6.74

Table 1: Some characteristics of the test networks used for the experimental simulations.

4.1 Test networks

The test networks, Net$_1$ and Net$_2$, are subsets of a real LTE network deployed in Slovenia by Telekom Slovenije, d.d. For the path-loss predictions, we were provided DEM and clutter maps of 25 m^2 resolution. A calculation radius around each network cell limited the path-loss prediction to a distance where it is feasible for an UE to connect to a cell, i.e., when the RSRP is greater or equal to -124 dBm [20]. At the same time, this calculation radius provides enough overlap among neighboring cells to calculate the network coverage over the whole region, for which the receiver height was set to 2 m above ground level. Table 1 provides more information about the test networks used, such as the number of network cells, the area surface, and the covering proportion of the collected field measurements in terms of the total area of each test network.

Net$_1$ represents a network deployed over a dominant agricultural area with almost flat terrain, some forests and waters streams. The other network, Net$_2$, is deployed over a hilly terrain mostly covered by forests.

As the stopping criteria for the optimization runs, we fixed the maximum number of iterations to 250, since the algorithm showed an acceptable convergence profile in all runs. Overall, the framework completed 20,000 objective-function evaluations, i.e., 180,000 radio-coverage predictions for Net$_1$ and 500,000 for Net$_2$.

The simulations were carried out on several computing nodes of the DEGIMA cluster [13] at the Nagasaki Advanced Computing Center (NACC) of the Nagasaki University in Japan. The reason for using a high-end computer cluster as DEGIMA is to exploit the parallel nature of PRATO. To this end, groups of 5 and 13 computing

	Manual		Analytical		DASA	
Test network	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Net_1	5.88496	13.69240	0.00001	12.64708	0.01974	12.13723
Net_2	6.52300	14.35561	0.00007	12.30833	0.01372	10.59590

Table 2: Mean and standard-deviation values of the radio-propagation prediction against the field measurements. The values, expressed in dB, are given when using the manual, analytical and DASA approaches in each test network.

nodes were used for executing the simulations of the different problem instances, i.e., Net_1 and Net_2, respectively.

The computing nodes were connected by a LAN, over a Gigabit Ethernet interconnect. The nodes were equipped with a Linux 64-bit operating system (Fedora distribution). OpenMPI was used as the message passing implementation, version 1.6.1, the binaries of which were manually compiled with the distribution-supplied *gcc* compiler, version 4.4.4.

After some trial-optimization runs, the six parameters that control the way the DASA explores the search space were set to the following values:

- $m = 80$, the number of ants;
- $b = 10$, the discrete base;
- $\rho = 0.2$, the pheromone dispersion factor;
- $s_+ = 0.01$, the global scale-increasing factor;
- $s_- = 0.01$, the global scale-decreasing factor; and
- $\epsilon = 10^{-5}$, the maximum parameter precision.

The trial runs consisted in doubling m from 5 to 640, and verifying the convergence profile and best solution found. The values of the other parameters were left unchanged.

4.2 Result analysis

The mean and standard-deviation values after correlating the field measurements with the radio-propagation prediction of each test network and parameter set are shown in Table 2.

The parameter set used for the "Manual" column of Table 2 was provided by the radio experts of the Radio Network Department at Telekom Slovenije, d.d. These values were calculated based on manual observations and were applied to all the cells in the network. The column labeled as "Analytical" represents the parameter set calculated by the least-squares approach as presented in the related literature [1, 8, 27]. The last column, which is labeled as "DASA", represents the average parameter set calculated by the DASA after 30 independent runs.

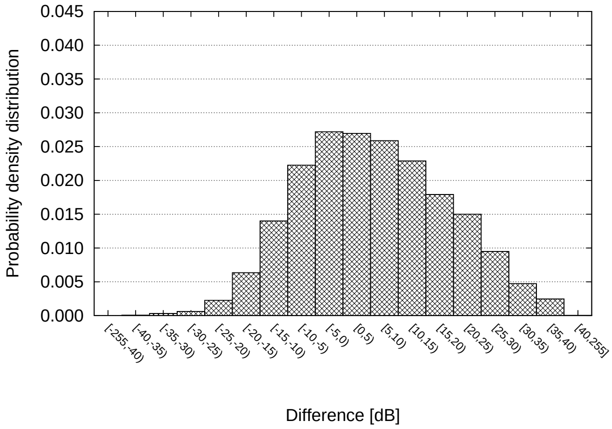
The manual approach clearly shows the biggest discrepancy of the radio-propagation predictions in both the rural (Net_1) and hilly (Net_2) environments. The analytical approach considerably improves the results achieved by the manual method, thus showing lower mean and standard-deviation values in both test networks. As for the DASA, it further improved the standard deviation of the analytical approach. Moreover, this correction is significant for in Net_2, thus confirming the influence of the hilly terrain in the accuracy of signal-propagation predictions. This is especially important on the border of the cell coverage, where a 2 dB difference in the received-signal strength could mean predicting sufficient network coverage where there would otherwise be none. Regarding the mean values showed by the DASA solutions, we may observe that they are several orders of magnitude higher than those of the analytical solutions. However, the values are, in all cases, strictly lower than 0.02 dB, which is a negligible difference in terms of the RSRP levels that outline the coverage of a network cell.

These results confirm that the use of the DASA to perform the optimization of parameters of a signal-propagation model is viable, since it is capable of reflecting the physical phenomena appearing in real-world conditions in two geographically-different network instances.

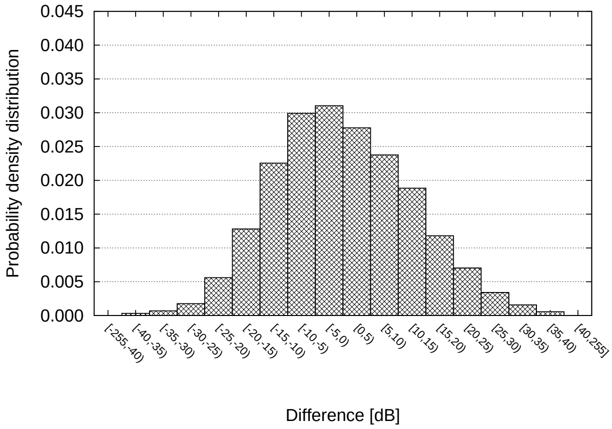
Figures 2 and 3 depict the probability-density distributions of the difference between the signal-propagation predictions and the field measurements. The mean and standard-deviation values of these distributions are listed in Table 2.

Figure 2 (a) depicts the difference distribution of the coverage prediction for test network Net_1 using the manually-calculated parameters, Figure 2 (b) shows the difference distribution for the same test network, but using the analytically-calculated parameters, and Figure 2 (c) shows the difference distribution using the DASA-optimized parameters. Notice how the difference distributions show an improvement when the analytically-calculated parameters are used, lowering the largest (outer) deviations, and raising the lowest (inner) ones. Additionally, the difference is negligible when using the optimized parameters, thus confirming that it is sufficient to only adapt β_0 and β_1 in environments where the height difference between the transmitter and the receiver, i.e., $\log(H_\mathrm{A})$ in Equation (1)), is roughly constant.

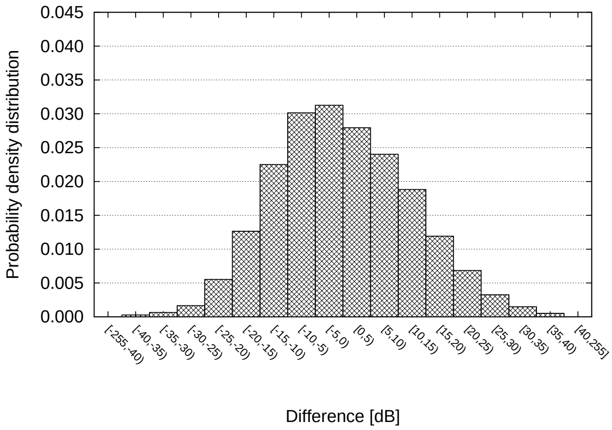
The difference distributions of the radio-propagation predictions for test network Net_2 using the manually-calculated parameters, the analytically-calculated, and the optimized ones are shown in Figures 3 (a), 3 (b), and 3 (c), respectively. Similar to Net_1, the improvement appears in the largest deviations, since their values are lower than when using the manually-calculated parameters. In this case, we may also observe the improvement achieved by the parameter set calculated with the DASA, which included all four components of the vector $\vec{\beta}$, thus better re-



(a)

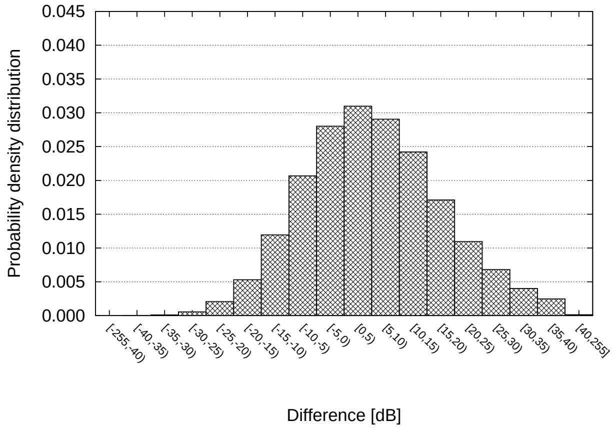


(b)

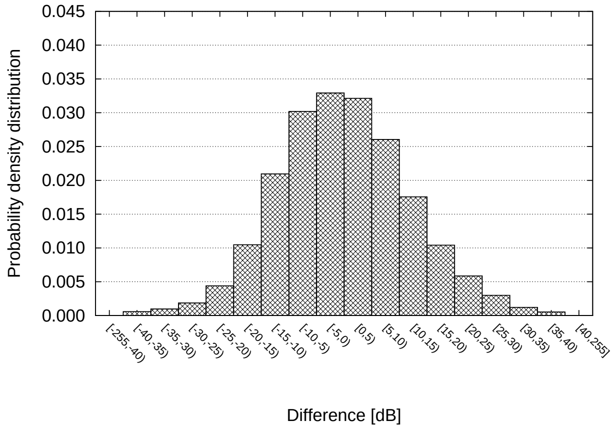


(c)

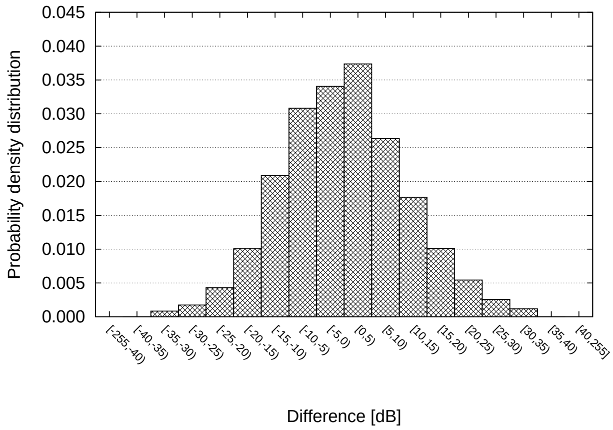
Figure 2: Probability-density distribution of radio predictions against the field measurements of network Net_1 over a rural area using the: (a) manually-calculated parameters, (b) analytically-calculated parameters, and (c) optimized parameters.



(a)



(b)



(c)

Figure 3: Probability-density distribution of radio predictions against the field measurements of network Net_2 over a hilly area using the: (a) manually-calculated parameters, (b) analytically-calculated parameters, and (c) optimized parameters.

flecting the signal propagation over a hilly terrain.

Overall, the parameter optimization of the signal-propagation model with respect to field measurements does improve the quality of the calculated radio-propagation predictions. Considering that the default parameter values were manually calculated by the radio engineers for the whole network, the convenience of the automated optimization procedure is clear. Indeed, these advantages are a consequence of a simpler method that automatically delivers radio-predictions of superior quality and accurately represent the physical properties of a given environment.

4.3 Statistical analysis

Because of the stochastic nature of the DASA optimization algorithm, we have collected the results of 30 independent runs in order to have enough data for them to be statistically relevant. In other words, the robustness of the results presented in the previous section is analyzed here.

To this end, Table 3 shows a statistical analysis of the mean and standard-deviation values of the solutions reached by the DASA for each test network. The analysis includes the minimum, maximum and average values for every quality measure of the radio-propagation predictions, along with their standard deviation.

We may observe that the standard deviation is consistently lower than 0.015 for both quality measures, indicating a consistent convergence of the optimization algorithm and confirming the suitability of the DASA for tackling the parameter-optimization problem.

5 Conclusion

We have presented a metaheuristic-optimization approach for the parameter optimization of signal-propagation models. The open-source framework for coverage-planning and optimization of radio networks (PRATO)[1] was used to concurrently optimize multiple cells of the target network in parallel, exploiting the resources of a computer cluster. Based on extensive experimental simulations, we have shown the suitability of the metaheuristic approach for the automatic adaptation of the parameter values over different regions of a newly deployed LTE network in Slovenia.

By using different sets of field measurements over the target regions, the combination of the afore-mentioned techniques the parameters of the signal-propagation model were adapted to geographical are around each network cell. As a result, the accuracy of the radio-propagation predictions of the whole network was improved. Moreover, the improvement was significant when applying the presented approach to a network deployed over a hilly area, even outperforming the results of a least-squares analytical method commonly used in the related literature. The simulation results suggest that the presented methodology is applicable for LTE networks in general, since it reached very good accuracy of the calculated radio predictions over diverse terrains. Consequently, the applicability of this approach for arbitrary terrain types can be expected.

Further research will include the performance analysis of other metaheuristic approaches [15] and their result comparison with the DASA. Also, the consideration of urban environments, where the signal-propagation conditions differ from those in rural and hilly areas, should also be explored. Furthermore, in the context of the radio-coverage planning activities carried out at the Radio Network Department of Telekom Slovenije, d.d., supplementary testing of the presented approach, as a support methodology for coverage planning, is currently being conducted. So far, the performed analyses yield robust results compared to traditional, manual techniques.

[1]The source code is available for download from the corresponding author's home page, http://cs.ijs.si/benedicic.

Acknowledgment

The authors would like to especially thank the staff at the Nagasaki Advanced Computing Center of the Nagasaki University for their support while making the computer cluster DEGIMA available for the experimental simulations. Additionally, the authors are especially thankful to the radio engineers at Telekom Slovenije, d.d., for supplying the network data sets and sharing their professional expertise throughout the creation of this work. This project was co-financed by the European Union, through the European Social Fund.

References

[1] Erik AarnæS and Stian Holm. Tuning of empirical radio propagation models effect of location accuracy. *Wireless Personal Communications*, 30(2-4):267–281, 2004.

[2] Yassir A. Ahmad, Walid A. Hassan, and Tharek A. Rahman. Studying different propagation models for LTE-A system. In *International Conference on Computer and Communication Engineering (ICCCE)*, pages 848–853. IEEE, 2012.

[3] Pamela Begovic, Narcis Behlilovic, and Elma Avdic. Applicability evaluation of Okumura, Ericsson 9999 and Winner propagation models for coverage planning in 3.5 GHZ WiMAX systems. In *19th International Conference on Systems, Signals and Image Processing (IWSSIP)*, pages 256–260. IEEE, 2012.

[4] Lucas Benedičič, Mitja Štular, and Peter Korošec. Balancing downlink and uplink soft-handover areas in UMTS networks. In *IEEE Congress on Evolutionary Computation (CEC)*, pages 1–8. IEEE, 2012.

[5] Lucas Benedičič, Felipe A. Cruz, Tsuyoshi Hamada, and Peter Korošec. A GRASS GIS parallel module

	Net$_1$				Net$_2$			
Measure	Min	Max	Avg	Std.dev.	Min	Max	Avg	Std.dev.
Mean	0.00276	0.03639	0.01974	0.01300	0.00156	0.03046	0.01372	0.00846
Standard deviation	12.13657	12.13843	12.13723	0.00057	10.59571	10.59628	10.59590	0.00015

Table 3: Statistical-analysis values of the optimization solutions for each test network. All values are expressed in dB.

for radio-propagation predictions. *International Journal of Geographical Information Science*, 28(4):799–823, 2014.

[6] Dieter J. Cichon and Thomas Kürner. *Propagation Prediction Models*, chapter 4, pages 115–208. European Community, 1995. Available from: http://www.lx.it.pt/cost231/final_report.htm.

[7] Yoann Corre and Yves Lostanlen. Three-dimensional urban EM wave propagation model for radio network planning and optimization over large areas. *IEEE Transactions on Vehicular Technology*, 58(7):3112–3123, 2009.

[8] Chhaya Dalela, Marehalli Prasad, and Pankaj Dalela. Tuning of COST-231 Hata model for radio wave propagation predictions. *Computer Science and Information Technology (CS & IT), DOI*, 10:255–267, 2012.

[9] Marco Dorigo, Mauro Birattari, and Thomas Stutzle. Ant colony optimization. *IEEE Computational Intelligence Magazine*, 1(4):28–39, 2006.

[10] Sven Dortmund, Alfred Schmidt, and Ilona Rolfes. Measurement based channel model for large concert halls. In *IEEE International Symposium on Antennas and Propagation Society (APSURSI)*, pages 1–4. IEEE, 2010.

[11] Sonja Filiposka and Dimitar Trajanov. Terrain-aware three-dimensional radio-propagation model extension for NS-2. *Simulation*, 87(1-2):7–23, 2011.

[12] Mario García-Lozano, Maria A. Lema, Silvia Ruiz, and Flaminio Minerva. Metaheuristic procedure to optimize transmission delays in DVB-T single frequency networks. *IEEE Transactions on Broadcasting*, 57(4):876–887, 2011.

[13] Tsuyoshi Hamada and Keigo Nitadori. 190 TFlops astrophysical N-body simulation on a cluster of GPUs. In *Proceedings of the 2010 ACM/IEEE International Conference for High Performance Computing, Networking, Storage and Analysis*, pages 1–9. IEEE Computer Society, 2010.

[14] Masaharu Hata. Empirical formula for propagation loss in land mobile radio services. *IEEE Transactions on Vehicular Technology*, 29(3):317–325, 1980.

[15] Lianfen Huang, Xiaoxin Chen, Zhibin Gao, and Hongxiang Cai. Online propagation model correction based on PSO algorithm in LTE SON system. In *International Conference on Anti-Counterfeiting, Security and Identification (ASID)*, pages 1–4. IEEE, 2012.

[16] James Kennedy. *Swarm intelligence*, pages 187–219. Springer, 2006.

[17] Peter Korošec, Jurij Šilc, and Bogdan Filipič. The differential ant-stigmergy algorithm. *Information Sciences*, 192:82–97, 2012.

[18] Samip Malla, Birendra Ghimire, Mark C. Reed, and Harald Haas. Energy efficient resource allocation in OFDMA networks using ant-colony optimization. In *International Symposium on Communications and Information Technologies (ISCIT)*, pages 889–894. IEEE, 2012.

[19] Aleksandar Neskovic and Natasa Neskovic. Microcell electric field strength prediction model based upon artificial neural networks. *AEU-International Journal of Electronics and Communications*, 64(8):733–738, 2010.

[20] Michaela Neuland, Thomas Kürner, and Mehdi Amirijoo. Influence of Different Factors on X-Map Estimation in LTE. In *73rd Vehicular Technology Conference (VTC Spring)*, pages 1–5. IEEE, 2011.

[21] Noman Shabbir, Muhammad T. Sadiq, Hasnain Kashif, and Rizwan Ullah. Comparison of radio propagation models for Long Term Evolution (LTE) network. *arXiv preprint arXiv:1110.1519*, 2011.

[22] I. Simic, I. Stanic, and B. Zirnic. Minimax LS algorithm for automatic propagation model tuning. In *Proceeding of the 9th Telecommunications Forum (TELFOR 2001)*, 2001.

[23] Lingyang Song and Jia Shen. *Evolved cellular network planning and optimization for UMTS and LTE*. CRC Press, 2010.

[24] El-Ghazali Talbi. *Metaheuristics: from design to implementation*. Wiley, 2009.

[25] Andrej Vilhar, Andrej Hrovat, Igor Ozimek, and Tomaž Javornik. Efficient open-source ray-tracing methods for rural environment. In *Proceedings of the 16th WSEAS International Conference on Computers*, pages 15–17, 2012.

[26] Howard Xia, Henry L. Bertoni, Leandro R. Maciel, Andrew Lindsay-Stewart, and Robert Rowe. Radio propagation characteristics for line-of-sight microcellular and personal communications. *IEEE Transactions on Antennas and Propagation*, 41(10):1439–1447, 1993.

[27] Mingjing Yang and Wenxiao Shi. A linear least square method of propagation model tuning for 3G radio network planning. In *Fourth International Conference on Natural Computation*, volume 5, pages 150–154. IEEE, 2008.