

Optimising Motif Models for Indoor Radio Propagation Prediction using Evolutionary Computation

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Abstract – Current developments in wireless communications see a shift from low bit-rate wireless wide area networks to high performance local wireless networks using picocells and high data rates. In order to facilitate proper design of such networks appropriate simulation tools based on accurate signal propagation prediction are required. A semi-deterministic approach called Motif Model was developed to provide an accurate and computationally efficient way for indoor radio propagation prediction. Up to now model parameter have been based on heuristic values derived from propagation measurements. In order to increase the accuracy of the model, an approach for parameter optimisation using evolutionary computation techniques is presented in this paper and the improved accuracy is assessed.

Keywords – Optimisation, Evolution Strategies, Indoor Propagation, Motif Model, WLAN

I INTRODUCTION

The boom of wireless personal communication over the last few years has brought about an increasing demand for sufficient signal coverage also inside buildings. If a signal penetration from outdoor cells into buildings is not sufficient then, in the case of cellular systems such GSM and UMTS, the design of an indoor picocell system is required. Additionally, the popularity of Wireless Local Area Networks (WLAN) as a means of providing an IP based wireless indoor network is rapidly increasing. Such progress brings about the necessity for an appropriate design of wireless systems, which requires accurate signal propagation prediction.

The ideas behind the proposed Motif Model will be briefly mentioned and issues associated with the indoor propagation environment description will be highlighted. We will then discuss how the new model addresses those issues. Afterwards the models performance is assessed with optimisation of stochastic model parameters and a comparison of results will be presented.

Motif Model

The Motif Model was first presented in [1] as a combination of advantages of empirical and deterministic approaches: wide-band channel measures, high site-specific accuracy, short computation time and easy-to-obtain input data. The main idea behind the model is based on a ray

launching technique, the Monte Carlo method and general statistics. When a new “motif concept” is used by employing a stochastic description of the environment, all the electromagnetic effects, including diffuse scattering, are taken into account while complicated calculations of reflection and diffraction can be avoided.

II OPTIMISATION OF MOTIF MODEL PARAMETERS

The accuracy of the Motif model is directly proportional to appropriate shapes of probability radiation patterns and ray absorption of motifs (motif behaviour). If the motif behaviour could be characterised by a straightforward calculation using for example Unified Theory of Diffraction (UTD) and parameters of real obstacles, the accuracy of the Motif Model reaches only the accuracy of deterministic models, which rapidly decreases if some significant obstacle cannot be included in the input database. However in indoor scenarios it is often not possible to describe every obstacle, which has a non-negligible influence on signal distribution inside a building. That is why the use of UTD or other deterministic approaches is not the best way to predict indoor signal strength distribution.

For example, assume a common wall inside a building (Figure 1), which is illuminated by the incident wave. We usually do not just find a bare

wall, but we also typically find furniture or moving persons close to the wall. All of those have a significant influence on electromagnetic wave propagation.

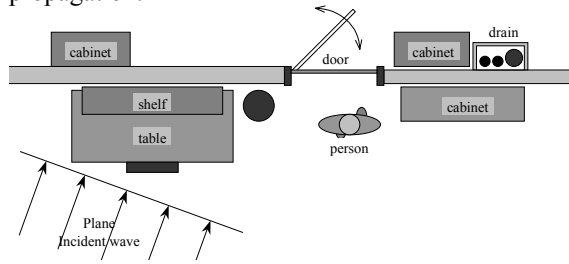


Figure 1: Common situation - a wall surrounded by many other undefined obstacles

Precise prediction of incident wave scattering using deterministic models requires every obstacle (at least those bigger than the wavelength) and their electrical parameters included in the database. The approach presented here describes walls and other vague obstacles by a semi-deterministic approach, which considers walls together with other nearby smaller obstacles as a cluster of obstacles. Such a general clusters can then be described by stochastic scattering parameters, which are used in the Motif Model to increase the prediction accuracy. For accurate prediction using stochastic scattering parameters, the parameters need to be optimized for a particular environment.

a) Gathering of Stochastic Scattering Parameters

The stochastic scattering parameters could be gathered either from a measurement campaign or by calculation of incident wave scattering on randomly distributed obstacles surrounding a wall (Figure 2). The input parameters of the latter approach should be real parameters of obstacles, however their definition is often unknown. The output is an overall stochastic radiation pattern, which is obtained after a sufficient number of randomly generated clusters is analyzed. Here, we use the first method, gathering stochastic scattering parameters from measurements to define radiation pattern.

As is obvious from the description, the Motif Model can be based on the probability of ray absorption in clusters and on the stochastic probability radiation pattern of clusters. Their shapes are typically influenced by many parameters, however, the dominant parameter is the incident angle of incoming wave. All other parameters are constant for a static scenario.

From the observation of different patterns it is evident that their shapes are approximated by easily defined mathematics functions. For example the Motif Model uses the cosine function to power of n to approximate main lobes. Diffraction and diffusion can also be easily described by means of other mathematical functions.

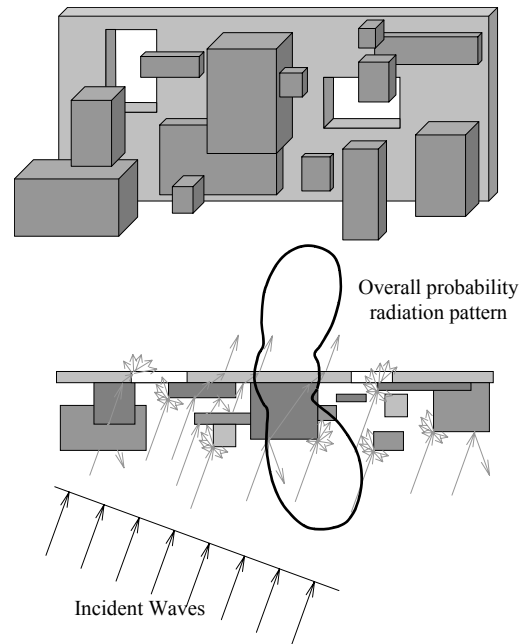


Figure 2: Wall fraction with randomly distributed obstacles and the overall stochastic probability radiation pattern from the incident wave

The Motif Model prediction algorithm [1] uses five basic coefficients to define the probability radiation patterns. These coefficients are unique for different walls and to achieve a better approximation could also be unique for different motifs. If four different kinds of walls are assumed, 20 parameters are necessary to define them. If six different basic motifs are required the overall number of parameters will rise to 120. The best way to identify the appropriate values for such an amount of parameters from measured signal strength distributions is by means of optimisation.

b) Optimisation Technique

The application of the stochastic cluster description presents many advantages. On the other hand it is necessary to carry out many measurement campaigns with different settings and environments to produce a table of stochastic parameters that represent a wide range of buildings. A similar calibration process is often used in other models, where exact calculations are also infeasible because exact data is missing.

A stochastic approach avoids the virtually impossible characterization of all obstacles, but the optimization of 20 or 120 parameters (in the Motif Model) is also quite intricate and an appropriate selection of an optimization technique is crucial. The standard deviation σ and mean error μ of the difference between measurement and prediction is commonly used as an indicator of the signal strength prediction accuracy. However these indicators slightly fluctuate due to a Monte Carlo principle of the Motif Model. Nevertheless alterations of Motif parameters result in a change of the σ and μ of prediction to produce a

fitness landscape containing many sub-optimal solutions with similar accuracy as the optimal solution. In such cases conventional optimization approaches such as the basic Down Hill Simplex method or the exact Conjugate Gradient method are incapable of finding the optimal solution. The optimization problem is in fact such that evolutionary computation techniques are best suited to finding the optimal parameter setting for the Motif Model.

c) Description of Evolution Strategies and Genetic Algorithm Testing

The two best-known evolutionary computation methods are Genetic Algorithms (GA) [2] and Evolution Strategies (ES) [3]. To compare both and their large volume of variants a software tool called Evolutionary Computation Tester (ECT) was developed (Figure 3).

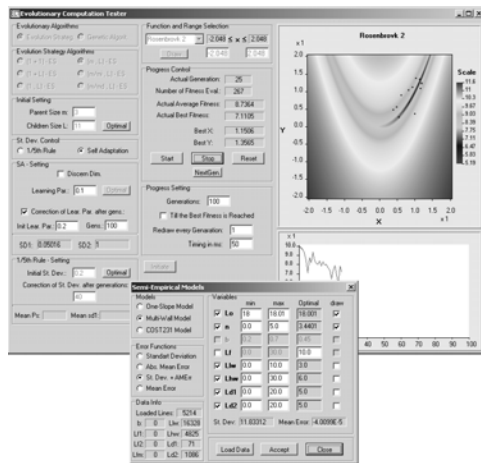


Figure 3: Evolutionary Computation Tester

The optimisation of semi-empirical models (i.e. Multi Wall Model) for indoor propagation prediction was also implemented in the ECT with additive noise to simulate a similar behaviour of fitness landscape as is expected from the Motif Model optimisation.

The following summarises the main points relating to ES and GA application in the semi-empirical or Motif Model optimisation

- The fitness function (cost function) is given by the sum of standard deviation and scaled mean value of a difference between prediction and measurement.
- Vectors of real numbers are used as chromosomes.
- Both crossover and mutation techniques are used in different forms.
- Different techniques to control mutation strength and noise disturbance reduction in case of ES were tested.

We found that ES were better suited than GA to accelerate the convergence towards and to find an optimal solution. An in depth description and comparison of ES and GA performance is not object

of this paper, therefore we will only focus on Evolution Strategies in the following.

III EVOLUTION STRATEGIES

The emphasis of application of ES will be on those variants, which proved most useful for the Motif Model optimisation problem. A method for estimating the optimisation limit will be described and the final optimal parameters discussed. Finally, ways of effective reduction of noise in the fitness are debated.

In the following we comply with conventions and symbols that are used in [3]. The most important conventions in ES are as follows:

λ Number of children (offspring)

μ number of parents

A tilde “ \sim ” above a symbol represents an ES disturbed by noise. An asterisks “*” above a symbol represents parameters normalised by N/R , where N is number of optimised parameters and R is an absolute distance to optimum. Such normalisation becomes crucial if a spherical landscape model is used as in [3].

a) Basic ES with Disturbed Fitness Value

ES can be roughly divided into four groups according to the number of individuals and selection technique.

- $(\tilde{1} + \tilde{1})$ – ES The ES with one child replacing a parent in case it has better fitness.
- $(\tilde{1} + \tilde{\lambda})$ – ES The same selection technique as the previous ES, but with higher number of children.
- $(\tilde{1}, \tilde{\lambda})$ – ES The parent does not take part in the selection as in the previous ES.
- $(\tilde{\mu}, \tilde{\lambda})$ – ES The same as previous ES, but with higher number of parents. This ES is less efficient than previous one. Modifications of this ES, the intermediate $(\mu/\mu_i, \lambda)$ – ES and dominant $(\mu/\mu_d, \lambda)$ – ES, were also implemented and tested.

b) Control Mechanisms of Mutation Strength

In contrast to GA, it is important for ES to control the mutation strength σ such that σ is driven to zero as the optimum is approached in order to achieve a maximal progress rate.

Two mechanisms have been suggested for this [3]

▪ 1/5th Rule

This control mechanism keeps the Success Probability P_s (~ 0.2) of the optimisation process constant by directly altering σ . For noisy landscape the rule can be modified to 1/10th.

▪ σ -Self-Adaptation

The principal idea lies in coupling individuals with their set of strategy parameters. This means that when an offspring is selected its strategy parameter vector also survives. During the optimisation process not

only individuals are mutated but also their mutation strengths. Of the many different mutation operators that have been proposed [3], the Log-Normal operator ξ , was implemented as follows:

$$\tilde{\sigma} = \xi\sigma \quad \xi = e^{\tau N(0,1)} \quad (1)$$

where $\tau N(1,0)$ is a normally distributed learning parameter.

c) Evolution Strategy used for Motif Model

We carefully selected appropriate ES with respect to their computational efficiency (number of necessary fitness evolutions) and reliability to find global optimum in a noisy fitness landscape. We evaluated many variants of ES with appropriate parameters and σ -control that were able to find a global minimum in many test landscape. The ES that was eventually selected despite its lower efficiency compared to the $(\tilde{1} + \tilde{1})$ -ES, was:

$(\tilde{1}, \tilde{5})$ -ES with:

- σ -Self-Adaptation mechanism
- coordinate-dependent strengths σ_n
- learning parameter τ from interval [0.1, 0.15]

To make a distinction of N independent mutation strengths was significant in that each parameter has a different influence on the fitness landscape. Figure 4 shows an example of a fitness landscape on which two parameters have a different influence. The position of individuals in the figure reflects different σ for the two dimensions. Such behaviour is highly desirable as it provides protection against pre-maturity of an optimisation process. The $(\tilde{1}, \tilde{5})$ -ES is the most efficient variant of $(1, \lambda)$ -ES.

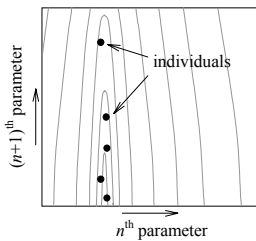


Figure 4: Example of a fitness landscape with individuals lay out

Some comments on other methods:

- The $(\tilde{1} + \tilde{1})$ and $(\tilde{1} + \tilde{\lambda})$ - ES showed poor behaviour with σ -Self-Adaptation.
- The $(\tilde{\mu}, \tilde{\lambda})$ - ES and its variants yield a high stability of the global optimum location, but their computational efficiency is reduced by high number of offspring.
- The ESs with 1/5th Rule tended to pre-maturity in our particular case despite many modifications and parameters combinations. The ECT contains many other recommended test fitness functions for which 1/5th Rule had similar or better performance then the σ -Self-Adaptation.

d) Finite Limit of ES Convergence

Due to the intrinsic noise of all Monte Carlo based methods such as the Motif Model the convergence of parameter optimisation is reduced. If the fitness landscape $Q(R)$ within the vicinity of the optimum is approximated by a power function of the distance R from the optimum (2),

$$Q(R) = cR^\alpha \quad (2)$$

the finite limit of convergence for infinite number of generations can be estimated by the following equation [3].

$$R_\infty = \sqrt[\alpha]{\frac{\sigma_{eq} N}{c\alpha} \frac{1}{\sqrt{4c_{1,\lambda}^2 - \sigma^{*2}}}} \quad (3)$$

Where: σ_{eq} noise level
 σ^* normalised mutation strength
 N number of dimensions
 $c_{1,\lambda}$ progress coefficient

e) Implementation of ES in the Motif Model Software Tool

We added a new optimisation window to the existing Motif Model software tool (Figure 5) to allow smart setting of the optimisation algorithm in conjunction with an actual floor plan. The optimisation kernel of the ECT tool was implemented into the Motif Model tool in order to test different combinations of ESs.

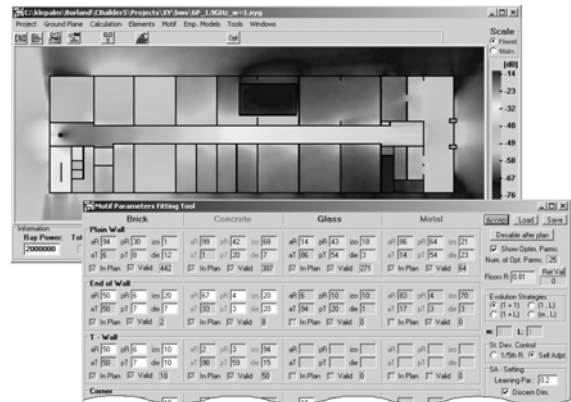


Figure 5: Motif Model software tool together with the implemented parameters in the optimisation window

IV OPTIMISATION OF MOTIF MODEL PARAMETERS BY ES

Initially all parameters of motifs within a particular floor plan were optimised together to find the limit of convergence for each of them. To estimate the finite limits of convergence of each parameter it is necessary to first compute the noise level σ_{eq} and then to approximate the fitness function as described above. The noise level was estimated as a standard deviation of a sufficiently large set of fitness values calculated by the Motif Model with constant optimal motif parameters. Due to the Monte Carlo behaviour of Motif Model the noise level is reduced with the number of launched rays as shown in Figure 6.

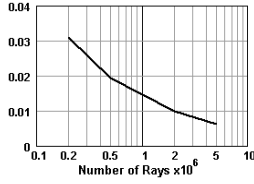


Figure 6: Noise Level of Fitness Function

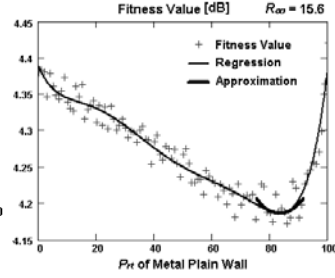


Figure 7: Example of the approx. process for one parameter

For the approximation of the fitness landscape by equation (2) it is essential to estimate an optimum within the noisy fitness landscape. For this purpose the fitness values of particular continuously changing parameters were calculated with other fixed parameters. Then by regression the optimum was estimated and the approximation (2) carried out. An example of such process shows Figure 7.

To evaluate the optimisation process from the aspect of convergence the standard deviation σ_{par} of parameter values during the n last iterations can be compared with the standard deviation calculated from R_∞ according to equation (4). The convergence of σ_{par} towards σ_∞ indicates the level of available accuracy of the optimisation process, which cannot be exceeded. Therefore σ_{par} can serve as a good progress indicator.

$$\sigma_\infty = R_\infty \cdot 0.56 \quad (4)$$

The constant 0.56 represent a standard deviation of uniformly distributed samples in the interval $[-1,1]$.

An example of some optimised parameter values and their associated quality measures obtained through ES are shown in Table 1.

	Light Plain Wall				
	Prt	Pa	Dr	Dt	Ds
Optimal Value	91	5	45	33	16
R_∞	3.8	1.85	26.0	47.6	3.15
σ_{par}	1.98	3.38	10.3	24.4	3.77
σ_∞	2.13	1.04	14.6	26.7	1.77

Heavy Plain Wall					Prf
Prt	Pa	Dr	Dt	Ds	
97	8	29	18	20	72
9.76	5.23	34.7	25.5	13.1	3.5
5.15	4.87	24.4	24.6	0.85	4.8
5.47	2.93	19.4	14.3	7.35	2.0

Table 1: Example of motif parameters with their values obtained with the $(\tilde{1}, \tilde{5})$ -ES- σ -SA

Notation of Motif Parameters:

(Range of each is normalised to range from 0 to 100)

Prt Probability of Ray Reflection over Ray Transition [-]

Pa Probability of Ray Absorption [-]
 Dr Directivity of Reflected Rays [-]
 Dt Directivity of Transmitted Ray [-]
 Ds Degree of Diffuse Scattering [-]

Floor Parameter:

Prf Probability of Ray Reflection from Floor and Ceiling [-]

The obtained values for motif parameters satisfy physical rules. Nevertheless their deeper assessment is not aim of this paper. By comparison of σ_{par} with σ_∞ one can notice slightly different values of σ_{par} to σ_∞ . The reason for this is that the behaviour of the σ -SA process, which tries to reach an optimum of σ , but due to a noisy fitness and evolution strategy itself the actual mutation strength is altered only in the vicinity of the optimum mutation strength.

a) Improving the Convergence Property at Noisy Fitness

If more accurate values are demanded, the reduction of R_∞ is essential. From (3) one can see that R_∞ is influenced by different factors. R_∞ increases with N , σ_{eq} , and σ^* and decreases only with $c_{1,\lambda}$ i.e. by increasing the number of offspring. (c , α and N are problem specific and therefore cannot be altered). The two methods of R_∞ reduction are

▪ Fitness averaging

Fitness averaging aims at reducing σ_{eq} . The m independent fitness measurements per offspring are carried out and their mean values entered into the original $(\tilde{1}, \tilde{\lambda})$ -ES. Because the measurements are statistically independent, the σ_{eq} is reduced by the square root of m .

The m times averaged $(\tilde{1}, \tilde{\lambda})$ -ES should be preferred to the $(\tilde{1}, \tilde{\lambda}_m)$ -ES as m fulfils the next criterion:

$$\sqrt{m}c_{1,\lambda} < c_{1,\lambda m} \quad (5)$$

for $\lambda > 3$ it is not possible to satisfy this criterion for any m . Therefore the $(\tilde{1}, \tilde{5})$ -ES with m measurement repetitions and subsequent fitness averaging is better than $(\tilde{1}, \tilde{5}m)$ -ES.

▪ Inheriting Scaled Mutations

This technique imaginarily decreases σ_{eq} by a factor κ , because the best offspring does not become the parent of the next generation, but rather the mutation, which produced it, is inherited after downscaling by κ . The necessary conditions for that are described in [3]. To theoretically realise the same progress rate, the mutation strength can be multiplied by the factor κ , if the following holds: $\sigma^{*2}/N \ll 1$.

b) Comparison of Signal Strength Prediction

Original motif parameters of the Motif Model were defined from real parameters of bare walls. As was mentioned above, an indoor signal strength distribution is strongly influenced by other

unspecified obstacles and therefore parameter adaptation to real requirements of indoor propagation is essential. The series of Figures 8 to 13 compare Motif Model predictions with measurements and Multi-Wall model prediction, which was optimised based on the same measurement data. The gauges of predictions difference from measurement indicate standard deviation σ and mean error μ .

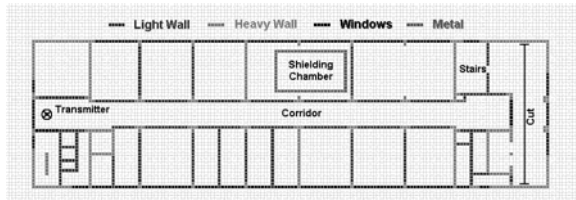


Figure 8: Floor plan with a transmitter

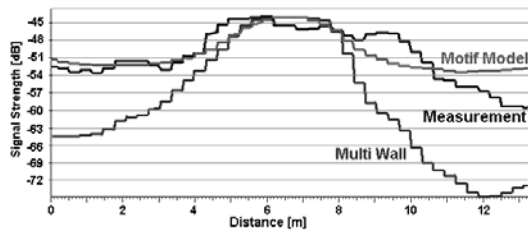


Figure 9: Signal strength in the cut, which position indicates Figure 8

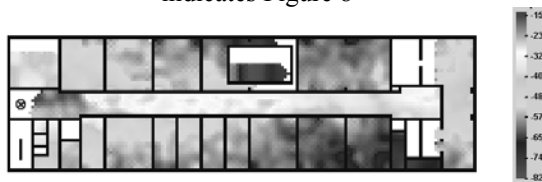


Figure 10: Measured signal strength

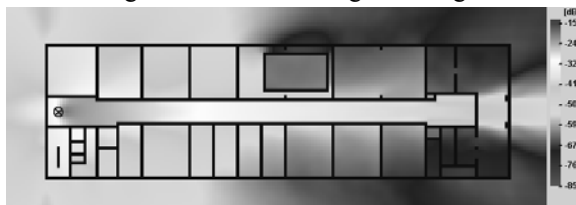


Figure 11: Motif Model - original prediction
 $\sigma = 6.25$ dB, $\mu = -1.82$ dB

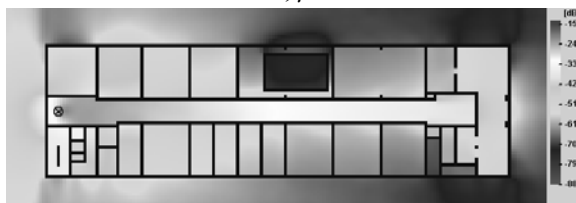


Figure 12: Motif Model - optimised prediction
 $\sigma = 3.94$ dB, $\mu = 0.0$ dB

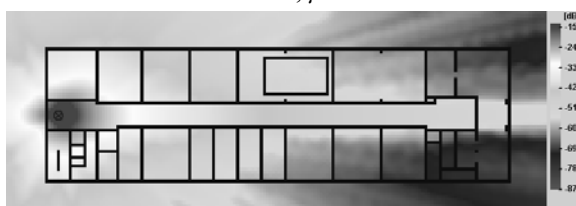


Figure 13: Multi Wall model - optimised prediction
 $\sigma = 9.94$ dB, $\mu = 0.0$ dB

This example floor presents difficulties for common prediction models, because it contains a long corridor with a strong wave guiding effect and a shielding metal chamber. Moreover, on the opposite site of the corridor from the transmitter is a vestibule where surprisingly high signal strength was measured.

The Motif Model with original parameters behaves similarly to models based on ray-tracing techniques. The newly optimised parameters successfully incorporate influence of all obstacles and rough features of this floor plan to predict signal strength with very high accuracy within the whole floor.

V CONCLUSION

The Motif Model can predict the radio signal strength and other parameters of communication channels such as impulse response and angle of arrival at high speed and with simple input data (a prediction took 2.25 seconds for floor plan at figure 8). None of the electromagnetic wave propagation phenomena is neglected. From this point of view the Motif Model can be considering more deterministic than optical models.

The key aspect of prediction accuracy inside buildings is the incorporation of all significant obstacles to the model input. Reasons for preferring the stochastic description of obstacles instead of the exact description in case of indoors propagation were discussed. Possible ways of stochastic parameter gathering were mentioned.

Motif Model parameter optimisation based on broad measurement data using evolutionary computation techniques to create the table of stochastic parameters were presented. The most suitable ESs were identified and their assessment was discussed.

The improvement of prediction accuracy of the Motif Model by implementing optimisation techniques from $\sigma = 6.25$ to 3.94 dB proves the high performance and robustness of the Motif Model as well the suitability of the implemented ES.

VI ACKNOWLEDGMENTS

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