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Lajos Nagy

Global Optimization of Indoor Radio Coverage

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Original scientific paper

The new focus of wireless communication is shifting from voice to multimedia services. There is a growing interest in providing and improving radio coverage for mobile phones, short range radios and WLANs inside buildings. The need of such coverage appears mainly in office buildings, shopping malls, train stations where the subscriber density is very high. The cost of cellular systems and also the one of indoor wireless systems depend highly on the number of base stations required to achieve the desired coverage for a given level of field strength. There are already numerous optimization methods published which can be applied to the optimal design of such indoor networks [2,3,4,5]. The recently published methods use any heuristic technique for finding the optimal Access Point (AP) positions. Common drawbacks of the methods are the slow convergence in a complex environment like the indoor one.

Key words: Coverage indoor propagation, Optimization, Radiowave propagation

Globalne optimizacijske metode za određivanje pokrivanja u zatvorenom prostoru. Zadnjih godina fokus bežičnih komunikacija usmjerio se iz glasovnih na multimedijske usluge. Postoji povećani interes u pružanju i poboljšanju pokrivenosti radio signala za mobilnu telefoniju, za radio sustave kratkog dometa i WLAN unutar zatvorenog prostora. Potreba za takvom pokrivenošću pojavljuje se uglavnom u uredskim zgradama, trgovačkim centrima, željezničkim stanicama, gdje je gustoća pretplatnika vrlo visoka. Cijena mobilnih sustava i bežičnih sustava za zatvorene prostore bitno ovisi o broju baznih stanica potrebnih za postizanje željene pokrivenosti za određenu razinu jakosti polja. Postoje brojne optimizacijske metode koje se mogu primijeniti za postizanje optimalnog dizajna takvih mreža za zatvorene prostore [2,3,4,5]. Nedavno razmatrane metode koriste neku od heurističkih tehnika za pronalaženje optimalnih pozicija za pristupne točke (AP). Najčešći nedostatak razmatranih metoda je spora konvergencija rješenju u složenom okruženju kao što je zatvoreni unutrašnji prostor.

Ključne riječi: pokrivenost radio signala u zatvorenom prostoru, optimizacija, propagacija

1 INTRODUCTION

The new focus of wireless communication is shifting from voice to multimedia services. User requirements are moving from underlying technology to the simply need reliable and cost effective communication systems that can support anytime, anywhere, any device. While a significant amount of traffic will migrate from mobile to fixed networks, a much greater amount of traffic will migrate from fixed to mobile networks. In many countries mobile operators are offering mobile broadband services at prices and speeds comparable to fixed broadband. Though there are often data caps on mobile broadband services that are lower than those of fixed broadband, some consumers are opting to forgo their fixed lines in favor of mobile [1]. There is a growing interest in providing and improving radio coverage for mobile phones, short range radios and WLANs inside buildings. The need of such coverage appears mainly in office buildings, shopping malls, train stations where the subscriber density is very high. The cost of cellular systems and also the one of indoor wireless systems depend highly on the number of base stations required to achieve the desired coverage for a given level of field strength [10].

The design objectives can list in the priority order as RF performance, cost, specific customer requests, ease of installation and ease of maintenance. The first two of them are close related to the optimization procedure introduced and can take into account at the design phase of the radio network. There are already numerous optimization methods published which can be applied to the optimal design of such indoor networks [6,7,9,13]. The recently published methods use any heuristic technique for finding the optimal Access Point (AP) or Remote Unit (RU) positions. Common drawback of the methods are the slow convergence in a complex environment like the indoor one because all of the methods are using the global search space i.e. the places for APs are searched globally.

This article presents approaches in optimizing the indoor radio coverage using multiple access points for indoor environments. First the conventional Simple Genetic Algorithm (SGA) and Simulated Annealing (SA) is shortly introduced and applied to determine the optimal access point positions to achieve optimum coverage. Next to overcome the disadvantage of SGA two optimization methods are applied Divided Rectangles (DIRECT) global optimization technique and Kriging based interpolator is used as Surrogate function for optimization is introduced and comparisons are made for the methods deployed.

2 THE INDOOR PROPAGATION MODEL AND THE BUILDING DATABASE

In our article the Motley-Keenan [4] model was used to analyze indoor wave propagation. This empirical type prediction model is based on considering the influence of walls, ceilings and floors on the propagation through disparate terms in the expression of the path loss.

The overall path loss according to this model can be written as

$$L = L_F + L_a, \tag{1}$$

where L_F is the free space path loss and L_a is an additional loss expressed as

$$L_a = L_c + \sum_{i=1}^{I} k_{wi} L_{wi} + \sum_{j=1}^{J} k_{fj} L_{fj}, \tag{2}$$

where L_c is an empirical constant term, k_{wi} is the number of penetrated i type walls, k_{fj} is the number of penetrated floors and ceilings of type j, I is the number of wall types and J is the number of floor and ceiling types.

For the analyzed receiver position, the numbers k_i and k_j have to be determined through the number of floors and walls along the path between the transmitter and the receiver antennas. In the original paper [4] only one type of walls and floors were considered, in order for the model to be more precise a classification of the walls and floors is important. A concrete wall for example could present very varying penetration losses depending on whether it has or not metallic reinforcement.

It is also important to state that the loss expressed in (2) is not a physical one, but rather model coefficients, that were optimized from measurement data. Constant L_c is the result of the linear regression algorithm applied on measured wall and floor losses. This constant is a good indicator of the loss, because it includes other effects also, for example the effect of furniture.

For the considered office type building, the values for the regression parameters have been found (Table 1.).

The Motley-Keenan model regression parameters have been determined using Ray Launching (RL) deterministic radio wave propagation model. These calculations were made for the office-type building floor of the Department of Broadband Infocommunication and Electromagnetic Theory at Budapest University of Technology and Economics (Fig. 1). The frequency was chosen to 2450 MHz with a $\lambda/2$ transmitter dipole antenna mounted on the 2m height ceiling at the center of the floor.

The receiver antenna has been applied to evaluate the signal strength at $(80 \times 5) \times (22 \times 5) = 44000$ different locations in the plane of the receiver. At each location the received signal strength was obtained by RL method using ray emission in a resolution of 10. A ray is followed until a number of 8 reflections are reached and the receiver resolution in pixels has an area of $0.2 \cdot 0.2$ m^2. The receiver plane was chosen at the height of 1.2 m.

Table 1. The regression parameters

Wall type	Nr. of Layers	Layer widths	Regression parameter [dB]
Brick	1	Brick – 6 cm	4.0
Brick	1	Brick – 10 cm	5.58
Brick	1	Brick – 12 cm	6.69
Brick+ Concrete	3	Brick – 6 cm Concrete – 20 cm Brick – 6 cm	11.8
Brick+ Concrete	3	Brick – 10 cm Concrete – 12 cm Brick – 10 cm	14.8
Brick+ Concrete	3	Brick – 6 cm Concrete – 10 cm Brick – 6 cm	9.3
Brick	1	Brick – 15 cm	8.47
Concrete	1	Concrete – 15 cm	6.56
Concrete	1	Concrete – 20 cm	8
Concrete	3	Concrete – 15 cm Air – 2 cm Concrete – 15 cm	12.47
Glass	3	Glass – 3 mm Air – 10 cm Glass – 3 mm	0
Plasterboard	1	Plasterboard – 5 cm	4.5
Wood	1	Wood – 6 cm	0.92
Wood	1	Wood – 10 cm	0.17

The wall construction is shown on Fig. 1 made of primarily brick and concrete with concrete ceiling and floor, the doors are made of wood. The coefficients of the model have been optimized on the data gathered by the RL simulation session described above.

The geometrical description of the indoor scenario is based on the concept that the walls has to be partitioned to surrounding closed polygons and every such polygons are characterized by its electric material parameters.

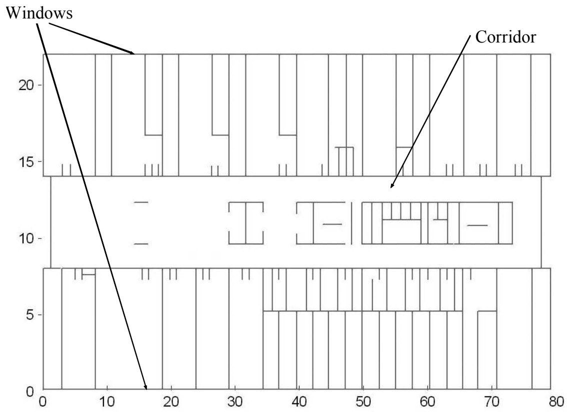

Fig. 1. The building database

The data base for the ray tracing method in our applications can not contain cut-out surfaces directly, such as windows, doors. Therefore the cut-out surface description is based on surface partitioning of the geometry as can be seen in Fig. 2.

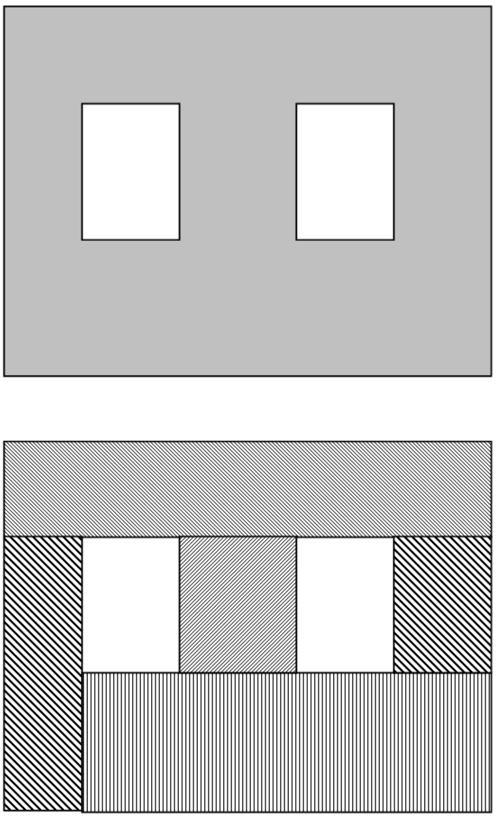

Fig. 2. A possible polygonal partitioning of windowed walls for ray tracing method

3 OPTIMIZATION METHODS

There are already numerous optimization methods published which can be applied to the optimal design of such Hybrid Fiber Radio indoor networks [6,7,9,13]. The recently published methods use any heuristic technique for finding the optimal AP or RU positions. Common drawback of the methods are the slow convergence in a complex environment like the indoor one because all of the methods are using the global search space i.e. the places for APs are searched globally.

Heuristic search and optimization is an approach for solving complex and large problems that overcomes many shortcomings of traditional (gradient type) optimization techniques. Heuristic optimization techniques are general purpose methods that are very flexible and can be applied to many types of objective functions and constraints. Another advantage of heuristic methods is their simplicity because of its gradient-free nature. Gradient free optimization methods are primarily based on the objective function values and are suitable for problems either with many parameters or with computationally expensive objective functions.

In the paper two global optimization methods the Simple Genetic Algorithm (SGA) and a method using Divided Rectangles (DIRECT) global search algorithm are used with wave propagation solver as can be seen in Fig. 3.

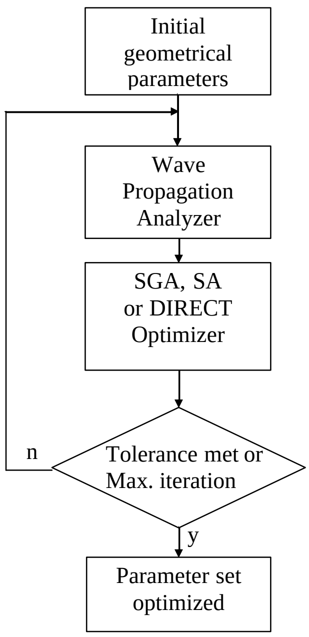

Fig. 3. Diagram of Wave Propagation analyzer and optimizer

3.1 Optimization Method through Simple Genetic Algorithms (SGA)

Genetic Algorithms (GA) are increasingly being applied to complex problems. Genetic Algorithm optimizers are robust, stochastic search methods modeled on the principles and concepts of natural selection [3,5,8,12] (Fig. 4).

If a receiver position that is fully described by N_{par} parameters arranged in a vector $x = \{x_i | i = 1, \ldots, N_{par}\}$ is considered, then the knowledge of x permits the evaluation of the objective function $f(x)$, which indicates the worth of a design (the area coverage percentage). It is assumed that x_i take on either real or discrete values, and that $f(x)$ needs to be maximized.

The GA does not operate on x but on a discrete representation or chromosome $p = \{g_i | i = 1, \ldots, N\}$ of x, each parameter x_i being described by a gene g_i. Each gene g_i in turn consists of a set of N^i_{all} all that are selected from a finite alphabet and that together decode a unique x_i.

The GA does not limit themselves to the iterative refinement of a single coded design candidate; instead the simple GA (SGA) simultaneously acts upon a set of candidates or population

$$\bar{p} = \{ p(i) |\, i = 1, ..., N_{pop} \}, \quad (3)$$

where N_{pop} is the population size.

Starting from an initial population $\bar{p}^0$, the SGA iteratively constructs populations $\bar{p}^k, k = 1..N_{gen}$, with N_{gen} denoting the total number of SGA generations. Subsequent generations are constructed by iteratively acting upon $\bar{p}^0$ with a set of genetic operators. The operators that induce the transition $\bar{p}^k \to \bar{p}^{k+1}$ are guided solely by knowledge of the vector of objective function values

$$f^k = \left\{ f\left(x\left(p^k(i)\right)\right) \middle|\, i = 1..N_{pop} \right\}, \quad (4)$$

and induce changes in the genetic makeup of the population leading to a $\bar{p}^{k+1}$ comprising individuals that are, on average better adapted to their environment than those in $\bar{p}^k$, i.e., they are characterized by higher objective function values.

This change is effected by three operators mentioned in the introduction: selection (S), crossover (C), and mutation (M).

The selection operator implements the principle of survival of the fittest. Acting on $\bar{p}^k$, S produces a new population $\bar{p}^k_S = S\left(\bar{p}^k\right)$ again of size N_{pop} that is, on average, populated by the better-fit individuals present in $\bar{p}^k$. Among the many existing schemes tournament selection has been chosen. The crossover operator mimics natural procreation. Specifically, C acts upon the population $\bar{p}^k_S$ by mating its members, thereby creating a new population

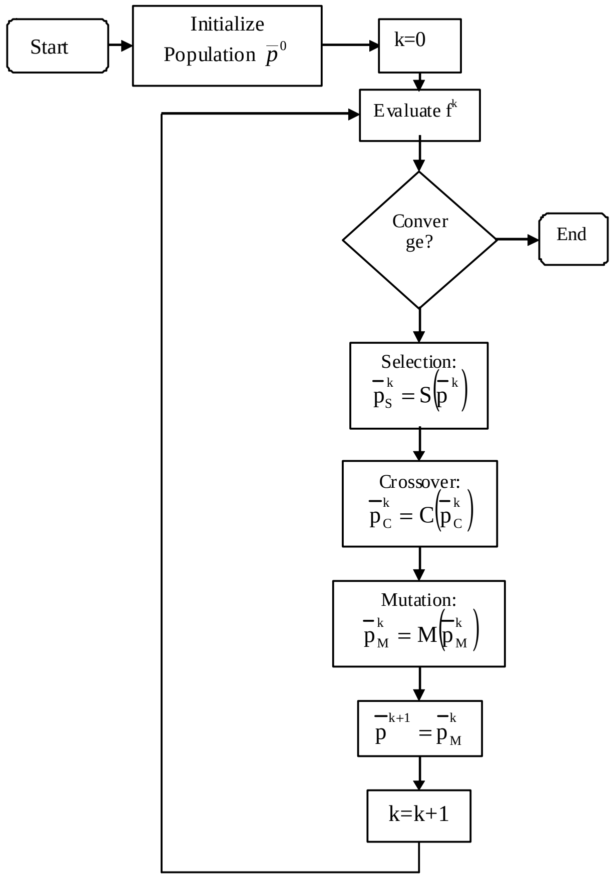

Fig. 4. The flowchart of a simple GA

$$\bar{p}^k_C = \bigcup_{i=1}^{N_{pop}/2} C\left(ch\left(\bar{p}^k_S\right), ch\left(\bar{p}^k_S\right)\right), \quad (5)$$

where the chromosome crossover operator C selects a random crossover allele a_{Ncross} between the two chromosomes to be crossed upon which it acts with probability P_{cross}.

The mutation operator generates a new population of size by introducing small random changes into $\bar{p}^k_C$. The action of M can be represented in operator form as

$$\bar{p}^k_M = \bigcup_{i=1}^{N_{pop}} M\left(\bar{p}^k_C(i)\right). \quad (6)$$

The cost function of the optimization procedure has been the coverage percentage of the points for which the received power is greater than a given level

$$f = c\left(P_{rec}\right) = = \frac{\text{Number of points } (P_{thresh.} < P_{rec})}{\text{Total number of test points}}. \quad (7)$$

3.2 Simulated Annealing

Simulated annealing is a probabilistic method for finding the global minimum of a cost function that may possess several local minima. It works by emulating the physical process whereby a solid is slowly cooled so that when eventually its structure is "frozen", this happens at a minimum energy (minimum cost function) configuration [14].

The Algorithm Simulated Annealing is stated as follows with the basic elements:

1. Finite set S of points on the user defined examination area ($0 \leq x \leq 80$; $0 \leq y \leq 22$).
2. A cost function f defined on examination area.
3. For each $i \in S$, a set $S(i) \subset S - (i)$, called the set of neighbors of i.
4. For every i, a collection of positive coefficients $q_{ij}, j \in S(i)$, such that $\sum_{j \in S(i)} q_{ij} = 1$. It is assumed that $j \in S(i)$ if and only if $i \in S(j)$.
5. A nonincreasing function $T : N \rightarrow (0, \infty)$, called the cooling schedule. Here N is the set of positive integers, and $T(t)$ is called the temperature at time t.

The flowchart and algorithm of Simulated Annealing are the follows.

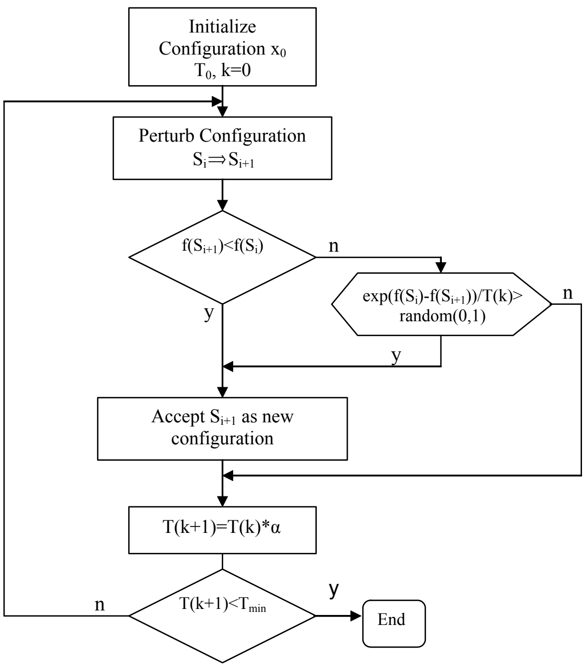

Fig. 5. The flowchart of a SA

Algorithm 1 Simulated Annealing

$x(0) \in S$ initial set
while $f_{objective} > f_{limit}$ and iteration steps $<$ iteration steps_{limit} **do**
  if $f(j) \leq f(i)$ **then**
    $x(t+1) = j$
  else if $f(j) > f(i)$ **then**
    $x(t+1) = j$
     with probability $\exp[-(f(j) - f(i))/T(t)]$
  else
    $x(t+1) = i$
  end if
end while

3.3 DIRECT algorithm

The DIRECT optimization algorithm is a derivative-free global algorithm that yields a deterministic and unique solution [2]. Its attribute of possessing both local and global properties make it ideal for fast convergence. An essential aspect of the DIRECT algorithm is the subdivision of the entire design space into hyper-rectangles or hyper-cubes for multidimensional problems.

The iteration starts by choosing the center of the design space as the starting point. Subsequently, at each iteration step, DIRECT selects and subdivides the set of hypercubes that are most likely to produce the lowest objective function. This estimation is based on Lipschitzian optimization method. Basically for one dimension a function is called Lipschitz continuous on domain R with Lipschitz constant α if

$$|f(x_1) - f(x_2)| \leq \alpha |x_1 - x_2|, \quad x_1, x_2 \in R, \tag{8}$$

where $f(x)$ is the objective function for the optimization problem.

The complementary of the coverage percentage which has to be minimized was chosen as objective function for the DIRECT algorithm

$$f(x) = 1 - c(P_{rec}). \tag{9}$$

The Lipschitzian function finds the global minimum point provided the constant α is specified to be greater than the largest rate of change of the objective function within the design space and that the objective function value is continuous.

As mentioned above, DIRECT divides the domain into multiple rectangles in each iteration. Thus, the convergence process is greatly sped up and the optimization algorithm achieves both local and global searching properties.

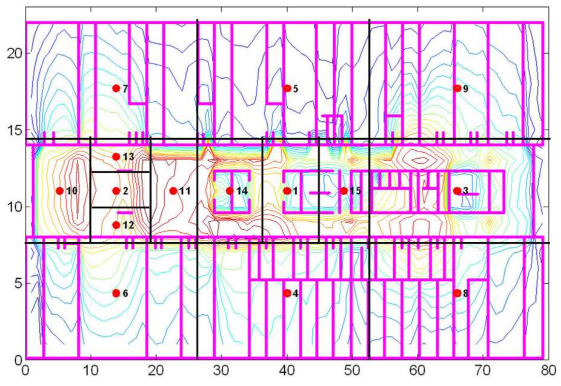

Fig. 6. DIRECT global optimizer search steps

As illustration of subdividing the search region into hyper-rectangles and sampling, two dimensional problem optimization steps are shown in Fig. 6.

The Algorithm DIRECT is stated as follows.

Algorithm 2 DIRECT

Start point at the center of the user defined area ($0 \leq x \leq 80$; $0 \leq y \leq 22$)

while $f_{objective} > f_{limit}$ and iteration steps $<$ iteration steps$_{limit}$ **do**

  Divide the area of investigation space into three rectangles

  Set centers of three rectangles

  Use the Lipschitz constant α to select the rectangle that has to be divided

end while

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4 RESULTS

Figure 7 shows the objective function which is the covered area percentage for the (X,Y) points as AP. If for instance the AP position is at (18,11) than the coverage is more than 30%, but if at (45,19) than the coverage is less than 15%.

Figure 7 clearly shows the multiple local maximums of the objective function and therefore the motivation to apply heuristic optimization methods.

The brute force search which would be a possible optimization search doesn't give the expected result because of the huge computational demand (Table 2.).

The testing of the SGA optimization has been done with two testing cases at the office building in which first optimizing the coverage for part of the floor area and secondly for the whole level.

The results are shown for population size of 14, crossover probability –0.12, mutation probability –0.01, simple roulette wheel selection and simple elitist strategy.

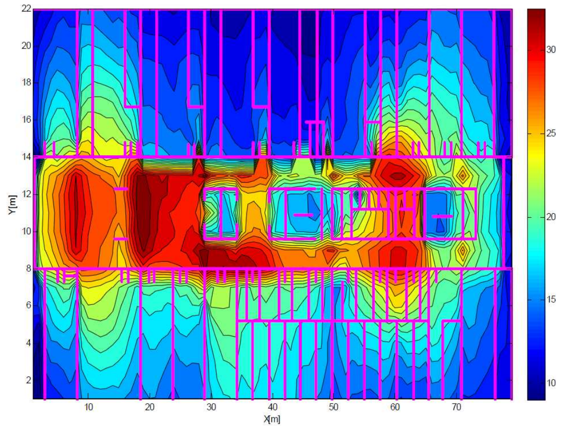

Fig. 7. Objective function for 1 AP

Table 2. Exhaustive (Brute Force) Search

Number of APs	**Resolution of search space**	**Comp. time**	**Result of optimization**
1AP	1m x 1m grid (1738 points)	5.5 min	33.67% (19;12)
2AP	1m x 1m grid	159 hours (estimated)	
1AP	0.5m x 0.5m grid	22 min	34.57% (18.5;12.5)
2AP	0.5m x 0.5m grid	637 hours (estimated)	

The first scenario is an optimization on AP positions (circles in Fig. 8) of the half part of the floor. Figure 8 shows the original 4 AP positions which were chosen to best coverage in laboratories and the corridor coverage was not an aim. The 9 shows the optimal AP positions using the cost function of (7). The simulated distribution of received power for the two geometries is shown in Fig. 10,11 with the measured results.

To make the measurements we have chosen WLAN APs and the power levels were measured using laptops with external wireless adapter moved on the area of investigation. 90 sampling points in distances of 1 m were chosen on the level and the comparison of Fig. 10 and 11 show a good agreement for the received power distribution.

The most important change in the distribution of optimized and not optimized cases is increased number of points with proper coverage (Table 3.).

Table 3. Area Coverage for Optimized and not Optimized Case

Configuration	**Not optimized**	**Optimized**
Coverage for P_{rec}>-60dBm (simulation)	40%	75%
Coverage for P_{rec}>-60dBm (measurement)	50%	80%

The convergence of the Genetic Algorithm can be im-

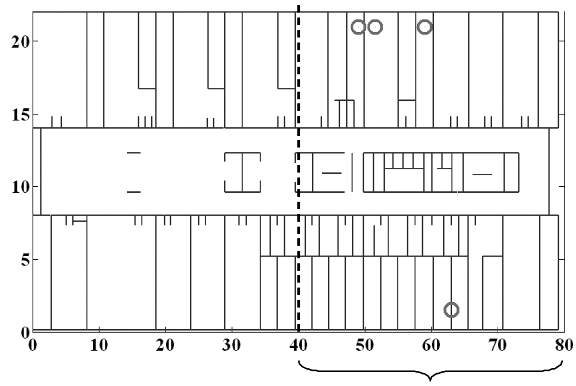

Fig. 8. Original (not optimized) AP positions

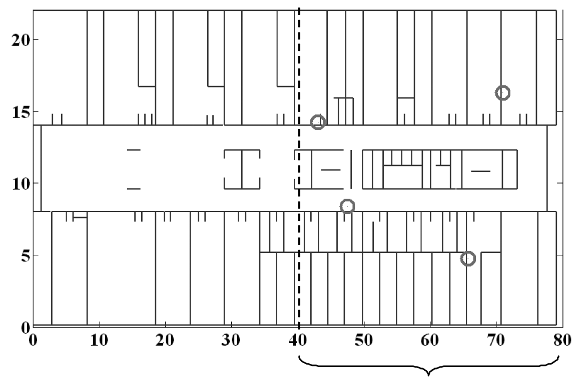

Fig. 9. Optimized AP positions

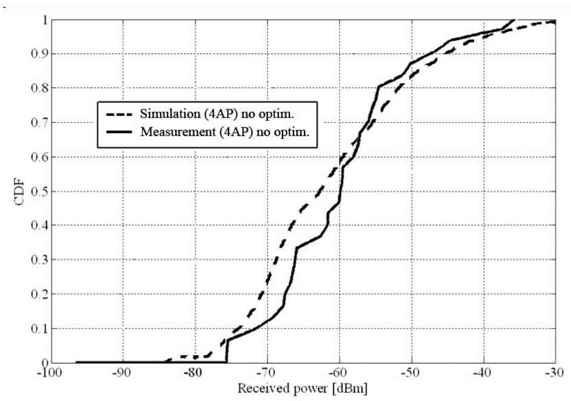

Fig. 10. Cumulative Density Function of received power level (not optimized)

proved by adjusting the crossover and mutation probability. Figure 12 shows the convergence dependence on these parameters for the same generation size.

Figure 12 shows a significant dependence of convergence on GA parameters and this result in a 1 to 10 running time ratio. The iteration step means that the number of necessary objective function evaluation can be calculated by multiplying with the population size.

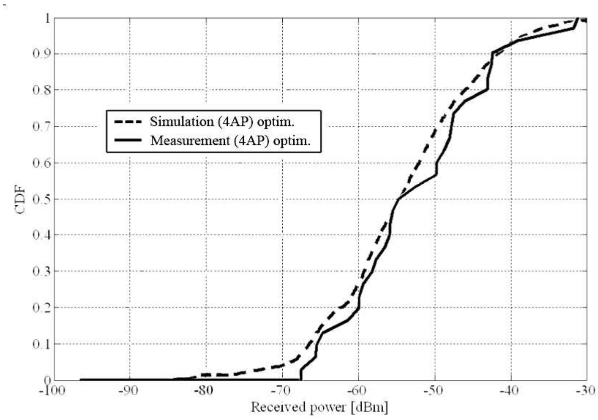

Fig. 11. Cumulative Density Function of received power level (optimized)

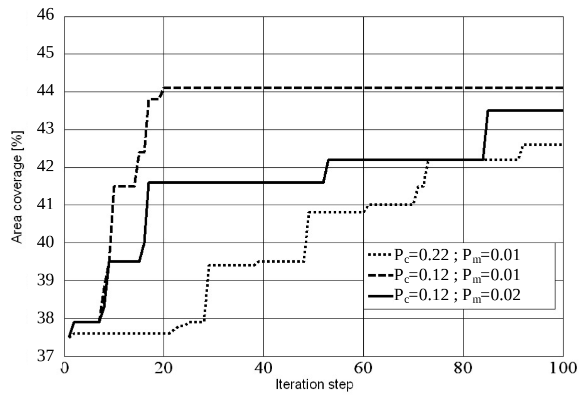

Fig. 12. Genetic Algorithm convergence

The second simulation is on the entire floor level and the aim of the simulation is to compare the necessary number of APs for the same area coverage.

Figure 13 shows plausible positions of APs and the Fig. 14 the optimized ones.

Figure 14 and Table 4 summarizes the importance of AP or RU position of radio network. With the proper choice of the placement the optimized 3 AP network configuration results nearly the same coverage as the configuration 6 AP with APs installed in plausible positions.

Table 4. Area coverage for optimized and not optimized cases

Configuration	**3AP**	**4AP**	**6AP**
Coverage (not optimized)	55%	60%	66%
Coverage (optimized)	65%	75%	87%

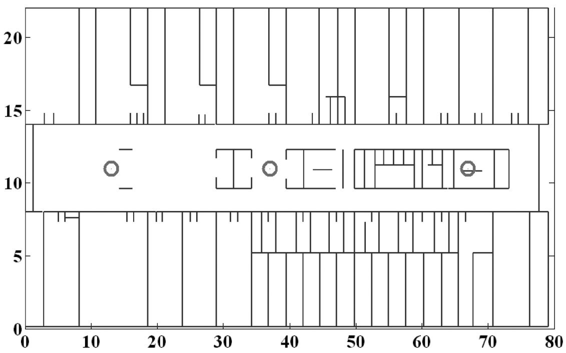

Fig. 13. Plausible AP positions

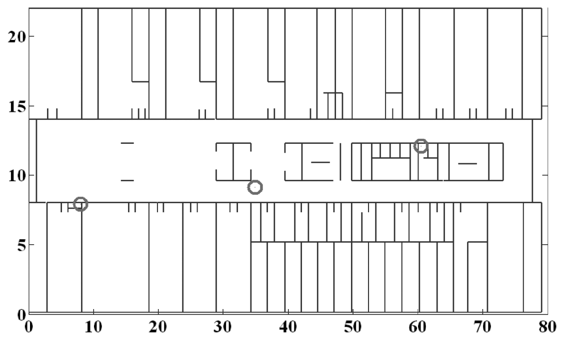

Fig. 14. Optimized AP positions

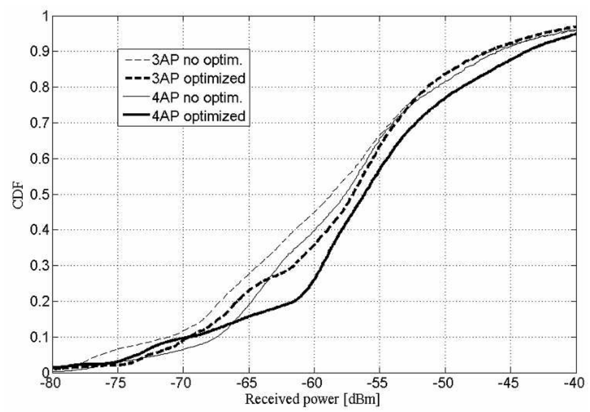

Fig. 15. Optimized and not optimized CDF using 3 and 4 APs

Next we compare the SGA and SA heuristic optimization methods for a 1 AP optimization case. First has to be established that SA (cooling rate - α, population size) has very similar sensitivity to the proper parameter choice like SGA (mutation, crossover probability, population size). Our experience shows a slight advantage for SGA for our optimization task and problem size (Fig. 16).

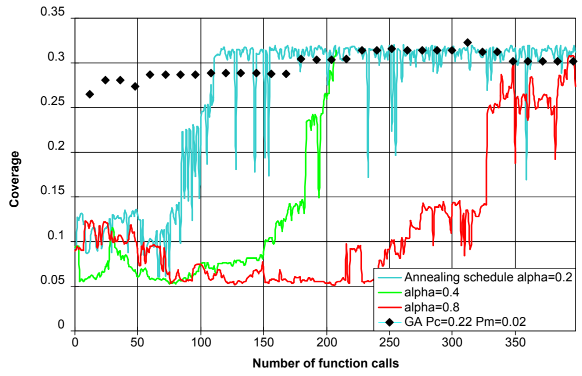

Fig. 16. Convergence rate of SGA and SA for a parameter set

As we have shown the SGA is a powerful global optimization tool to improve the indoor coverage for indoor data mobile radio network and other mobile radio systems [5,8]. The main drawback of the method is the ambiguous convergence and therefore its application needs experience of the user. The DIRECT global optimization algorithm is a derivative-free global algorithm that yields a deterministic and unique solution. In the next simulation results will be shown using DIRECT for the same indoor AP position optimization problem. We are comparing DIRECT to SGA and the main point of comparison is the number of evaluation of objective function.

It is worth to investigate the candidate points for the AP position by the DIRECT algorithm. The simplest case is analyzed for one AP network and the investigated and best candidate points are shown in accordance with the objective function the area of coverage percentage in Fig. 19. The objective function was only evaluated 1 by 1 m resolution. It is well appreciable the testing of the attractive AP positions with high area coverage property.

Next the convergence of SGA and DIRECT will be compared in Fig. 20, 21 and 22. It can be point out that the DIRECT algorithm behaves well for 1 or 2 AP optimization problems (i.e. for 2 and 4 dimensional optimizations) but the convergence rate achieve is far below the SGA for 3 AP problem. Similar behavior can be experienced for higher dimensional optimization problems.

Based on this investigations DIRECT algorithm can be proposed for low dimensional cases till 4 dimensions but the theoretically guaranteed fast and unique solution of global problem has to analyzed further.

The last part shows the comparisons of SGA and the proposed hierarchic two steps optimization method, first the convergence of the simple Genetic Algorithm for different population sizes (Fig. 23). Now we investigate 6 AP optimization cases in order to validate the two step method.

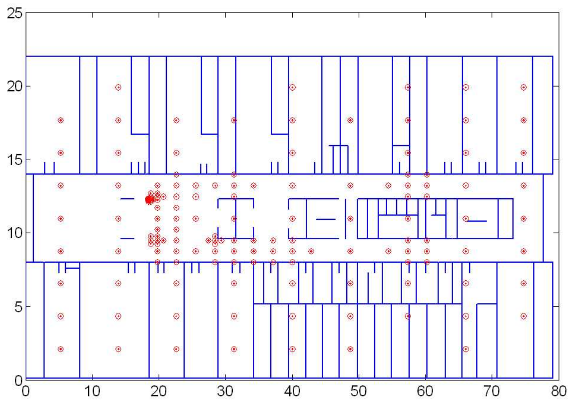

Fig. 17. Candidate points for AP position (after 12, 24, 36... iterations, DIRECT)

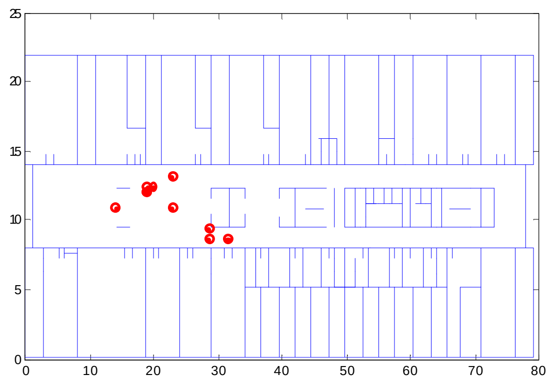

Fig. 18. Best candidate point for AP position (after 12, 24, 36... iterations, DIRECT)

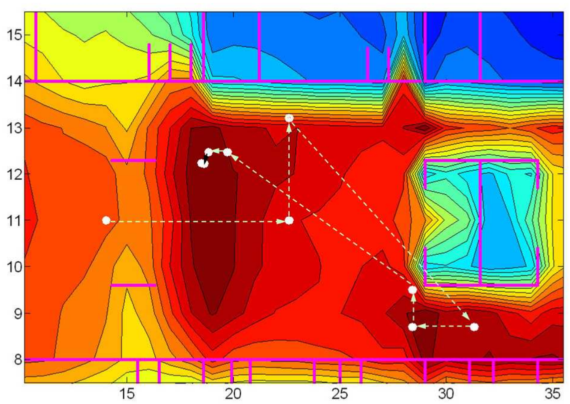

Fig. 19. Best candidate points for AP position (Area of coverage % is also shown for this zoomed area)

As we have seen problems of dimensions above 4 can not be analyzed with DIRECT and therefore for comparison

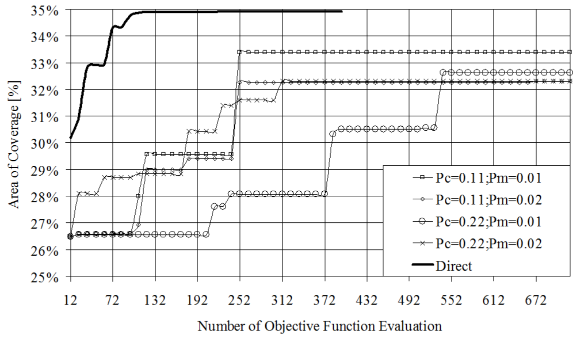

Fig. 20. Convergence of SGA and DIRECT for 1 Access Point

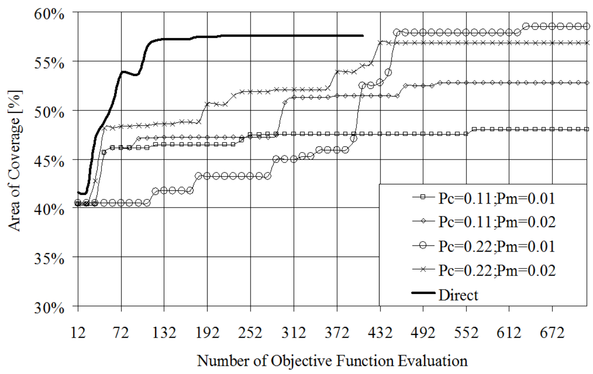

Fig. 21. Convergence of SGA and DIRECT for 2 Access Points

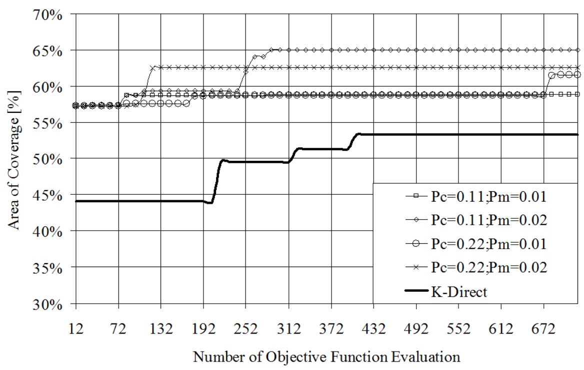

Fig. 22. Convergence of SGA and DIRECT for 3 Access Points

this 12-dimensional problem will be investigated. First the GA optimization is shown after performing the AP search by using power law path loss model i.e. the hierarchic approach. Finally the optimization results are analyzed.

Figure 23 presents effect of values population size, crossover (C) and mutation (M) probability on convergence for 6 APs placement and single GA optimization in our simulations.

The population size extension effect a better convergence (Fig. 23) but the calculation time increase polynomial.

The most important observations are that the crossover and mutation probabilities have optimal values in this case for the geometry investigated these values are $P_C = 0.22$ and $P_M = 0.01$ (Fig. 23,24).

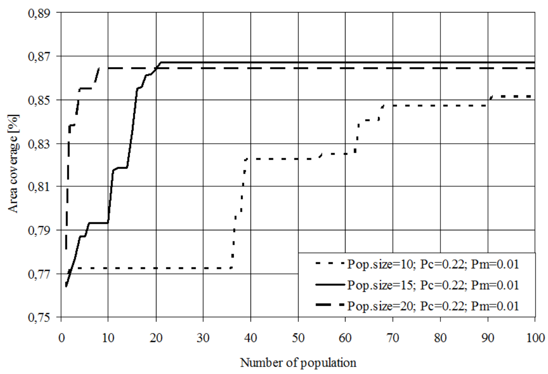

Fig. 23. Genetic Algorithm convergence (6 AP whole floor)

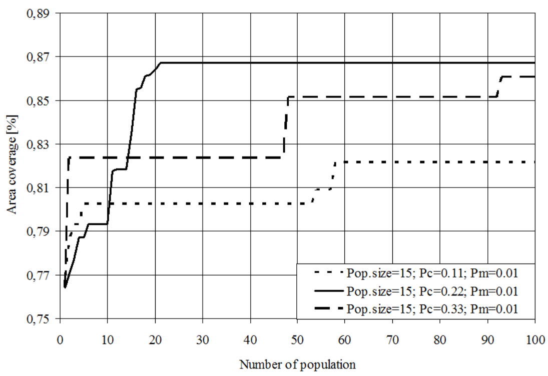

Fig. 24. Genetic Algorithm convergence (6 AP whole floor)

5 CONCLUSION

The optimal Access Point or Remote Unit position of WLAN network or Hybrid Fiber Radio is investigated for indoor environment. The article illustrates the possibility of optimization of radio network using Genetic Algorithm in order to determine positions of APs. Two new approaches are introduced to solve the global optimization problem the SA and DIRECT. The methods are introduced and investigated for 1, 2, 3 and 6 AP cases. The influence of Genetic Algorithm parameters on the convergence has been tested and the optimal radio network is investigated. It has been shown that for finding proper placement the necessary number of APs can be dramatically reduced and therefore saving installation cost of WLAN or HFR.

The results clearly justify the advantage of the method we used but further investigations are necessary to combine and to model other wireless network elements like leaky cables, fiber losses. Other promising direction is the extension of the optimization cost function with interference parameters of the wireless network part and with outer interference.

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Lajos Nagy received the Engineer and PhD degrees, both from the Budapest University of Technology and Economics (BME), Budapest, Hungary, in 1986 and 1995, respectively. He has been the head of Department of Broadband Infocommunications and Electromagnetic Theory in 2007. He is a lecturer at BME on Antennas and radiowave propagation, Radio system design, Signals and systems. His research interests include antenna analysis and computer aided design, electromagnetic theory, radiowave propagation, communication electronics, signal processing and digital antenna array beamforming. Member of Hungarian Telecommunication Association, Hungarian Committee Secretary of URSI and chapter chair of Hungarian IEEE joint chapter MTT, ED, AP, ComSoc.

AUTHORS' ADDRESSES

Assoc. Prof. Lajos Nagy, Ph.D.
Department of Broadband Infocommunications and Electromagnetic Theory,
Faculty of Electrical Engineering and Informatics,
BME Budapest University of Technology and Economics,
Goldmann György ter 3, H-1111 Budapest, Hungary
e-mail: nagy@mht.bme.hu

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