Classical and Quantum Genetic Optimization Applied to Coverage Optimization for Indoor Access Point Networks

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***Abstract*— The new focus of wireless communication is moving 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 [7,8,9, 10,11]. The fitness function of the optimization problem has numerous local optimum and therefore gradient based methods can not be applied. 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.**

The complexity of the selection procedure of a classical genetic algorithm is $O(N\log N)$ where N is the size of the population. The Quantum Genetic Algorithm (QGA) exploits the power of quantum computation in order to speed up genetic procedures. While the quantum and classical genetic algorithms use the same number of generations, the QGA outperforms the classical one in identifying the high-fitness subpopulation at each generation. In QGA the classical fitness evaluation and selection procedures are replaced by a single quantum procedure.

The article introduces the Quantum inspired Genetic Algorithm (QGA) for indoor access point position optimization to maximal coverage and compares with the Classical Genetic Algorithm (CGA).

***Index Terms*— optimization, radio network, indoor radiowave propagation**

I. 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. [3] 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. [12]

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 [7,8,9,11,15].

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 AP-s are searched globally.

This article presents approaches in optimizing the indoor radio coverage using multiple access points for indoor environments. First the conventional Classical Genetic Algorithm (CGA) and Quantum inspired Genetic Algorithm (QGA) [1,2,16,17] is shortly introduced and applied to determine the optimal access point positions to achieve optimum coverage.

Finally the importance of applying this optimization process is certified by evaluating the indoor coverage area for different AP cardinality.

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II. THE INDOOR PROPAGATION MODEL AND THE BUILDING DATABASE

In our path loss estimation the Motley-Keenan [6] 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_{wi} and k_{fj} 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 [6] 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 I)

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 (Figure 1-2.). 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 (80x5)x(22x5)=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*0.2 m2. The receiver plane was chosen at the height of 1.2 m.

TABLE I
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	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.

Fig. 1.a. Floor view of V2 building at BME

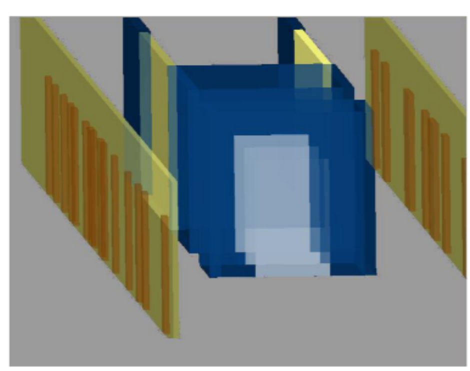

Fig. 1.b. Polygon data base of V2 building at BME

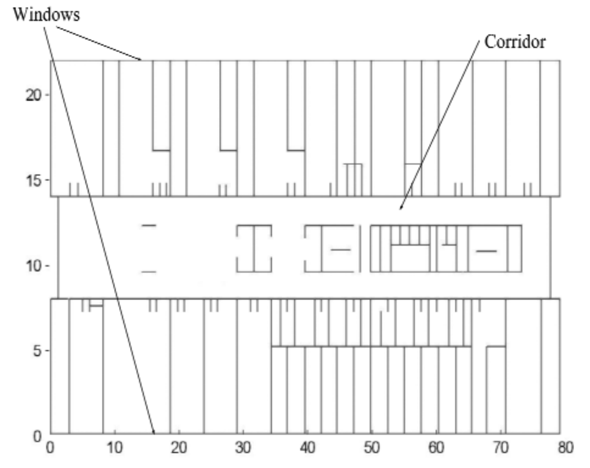

Fig. 2. The building database

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.

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.

III. Optimization Methods

There are already numerous optimization methods published which can be applied to the optimal design of such radio indoor networks [7,8,9,11,15]. The recently published methods use any heuristic technique for finding the optimal AP positions.

In the paper two global optimization methods the Classical Genetic Algorithm (CGA) and Quantum inspired Genetic Algorithm (QGA) global search algorithm are used with wave propagation solver as can be seen in Fig. 3.

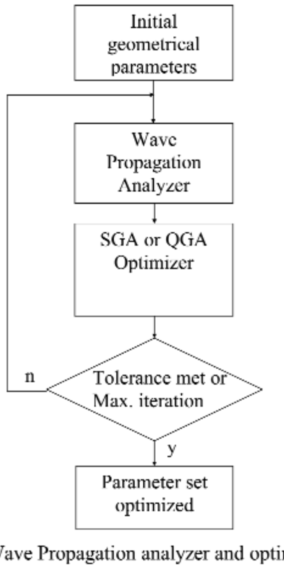

Fig. 3. Diagram of Wave Propagation analyzer and optimizer

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.

A. Optimization Method through Classical Genetic Algorithms (CGA)

Genetic Algorithms are increasingly being applied to complex problems. Genetic Algorithm optimizers are robust, stochastic search methods modeled on the principles and concepts of natural selection. [5,7,10,14] GA are increasingly being applied to difficult optimization problems. GA optimizers are robust, stochastic search methods modeled on the principles and concepts of natural selection. (Fig. 4.)

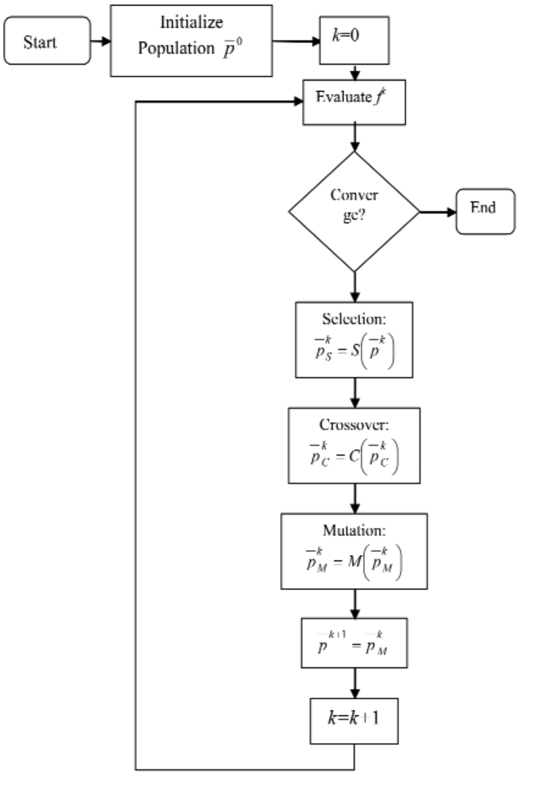

Fig. 4. The flowchart of a simple GA

If a receiver position that is fully described by N_{par} parameters arranged in a vector $x=\{x_i|\ i=1,\dots,N_{par}\}$ 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 $p=\{g_i|\ i=1,...,N\}$ 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_{all}^i 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 classical GA (CGA) simultaneously acts upon a set of candidates or population

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

where N_{pop} is the population size.

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

$$f^k = \{f(x(p^k(i)))|i = 1..N_{pop}\} \tag{4}$$

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 $\bar{p}_S^k = S(\bar{p}^k)$ 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 $\bar{p}_S^k$ by mating its members, thereby creating a new population

$$\bar{p}_C^k = \bigcup_{i=1}^{N_{pop}/2} C\left(ch\left(\bar{p}_S^k\right), ch\left(\bar{p}_S^k\right)\right) \tag{5}$$

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 $\bar{p}_C^k$. The action of M can be represented in operator form as

$$\bar{p}_M^k = \bigcup_{i=1}^{N_{pop}} M\left(\bar{p}_C^k(i)\right) \tag{6}$$

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.

$$f = c(P_{rec}) = \frac{\text{Number of points}\,(P_{thresh} < P_{rec})}{\text{Total number of test points}} \tag{7}$$

B. Optimization Method through Quantum inspired Genetic Algorithm (QGA)

GQA is based on the concepts of qubits and superposition of states of quantum mechanics.[16,17] The smallest unit of information stored in a two-state quantum computer is called a quantum bit or qubit. A qubit may be in the '1' state, in the '0' state, or in any superposition of the two. The state of a qubit can be represented as

$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{8}$$

where α and β are complex numbers that specify the probability amplitudes of the corresponding states. $|\alpha|^2$ and $|\beta|^2$ gives the probability of finding the qubit in logical value '0' or '1' if the state has been measured. Normalization of the state to unity guarantees

$$|\alpha|^2 + |\beta|^2 = 1 \tag{9}$$

It is possible to use a number of different representations to encode the solutions onto chromosomes in evolutionary computation. The classical representations can be broadly classified as: binary, numeric, and symbolic. GQA uses a novel representation that is based on the concept of qubits. One qubit is defined with a pair of complex numbers, (α,β) and for m qubits as

$$\begin{bmatrix} \alpha_1 & \alpha_2 & .. & \alpha_m \\ \beta_1 & \beta_2 & .. & \beta_m \end{bmatrix} \tag{10}$$

This representation has the advantage that it is able to represent any superposition of states.

QGA maintains a population of qubit chromosomes, $Q(t) = \{\mathbf{q}_1^t, \mathbf{q}_2^t, \ldots \mathbf{q}_n^t\}$ at the generation t, where n is the size of population and $\mathbf{q}_j^t$ is a qubit chromosome defined as in (10).

$$\mathbf{q}_j^t = \begin{bmatrix} \alpha_1^t & \alpha_2^t & .. & \alpha_m^t \\ \beta_1^t & \beta_2^t & .. & \beta_m^t \end{bmatrix} \tag{11}$$

The observed values of $Q(t)$ states can be generated taking into account the α_j probabilities. One binary representation of the j-th qubit is $\mathbf{x}_j^t, j = 1,2,\ldots,n$ and the observation of the $Q(t)$ is $P(t) = \{\mathbf{x}_1^t, \mathbf{x}_2^t, \ldots, \mathbf{x}_n^t\}$.

The set of qubit chromosomes $Q(t)$ is updated in each evolution step by applying appropriate quantum gates (Q-Gates) $G(\theta)$, which are evaluated taking into account the best fitness solution and given by the rotational angle selection strategy (Table II) [14]. This step makes the qubit chromosomes converge to the fitter states.

$$G(\theta_i) = \begin{bmatrix} \cos(\theta_i) & -\sin(\theta_i) \\ \sin(\theta_i) & \cos(\theta_i) \end{bmatrix} \tag{12}$$

TABLE II
ROTATIONAL ANGLE SELECTION STRATEGY OF Q-GATE

x_i	b_i	$f(x) \geq f(b)$	$\Delta\theta_i$	$\alpha_i\beta_i>0$	$\alpha_i\beta_i<0$	$\alpha_i=0$	$\beta_i=0$
0	0	0	$10^{-3}\pi$	-	+	±	±
0	0	1	$10^{-3}\pi$	-	+	±	±
0	1	0	0.08π	-	+	±	±
0	1	1	$10^{-3}\pi$	-	+	±	±
1	0	0	0.08π	+	-	±	±
1	0	1	$10^{-3}\pi$	+	-	±	±
1	1	0	$10^{-3}\pi$	+	-	±	±
1	1	1	$10^{-3}\pi$	+	-	±	±

The flowchart of the QGA is showed in the following.

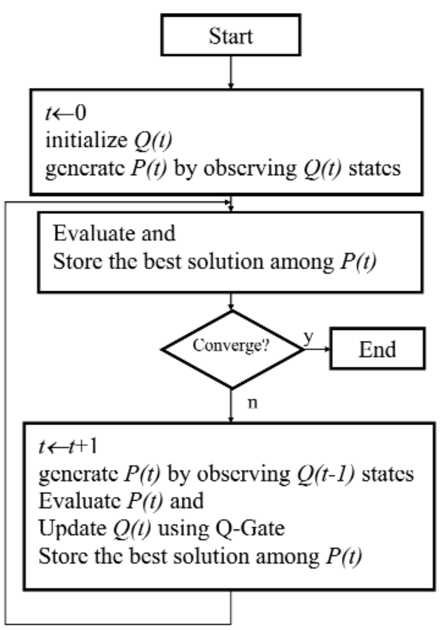

Fig. 5. The flowchart of QGA

Learning the description of the two versions of Genetic algorithms there are two significant differences between a classical and quantum versions or computer and a quantum computer realization.

The first is in storing information, classical bits versus quantum q-bits. Each quantum state represents many possible values of observation therefore the QGA increases the searching space.

The second is the quantum mechanical feature known as entanglement, which allows a measurement on some qubits to effect the value of other qubits.

The last section compares the algorithms and shows results on coverage results.

IV. RESULTS

The optimization procedure characterized as searching space with multiple local optimums and in this first session short investigation will be shown evaluating objective function for one access point in indoor environment.

The Fig. 6 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%. The Fig. 6 illustrate unambiguously the 'good' positions for access points having best coverages.

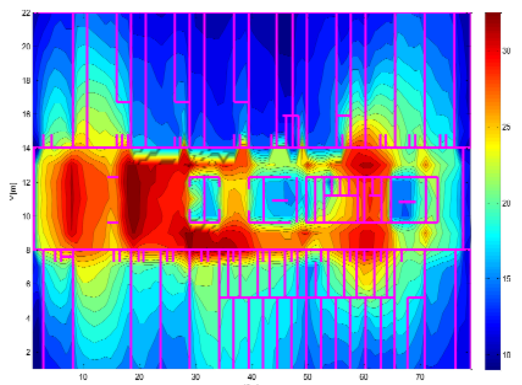

Fig. 6. Objective function for 1 AP

The Fig. 6 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 III)

TABLE III
EXHAUSTIVE (BRUTE FORCE) SEARCH

Number of AP-s	Resolution of search space	Computation 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)	

Next the convergence comparison will be introduced for CGA and QGA for one access point. The testing results of the algorithms are shown in Fig. 7.

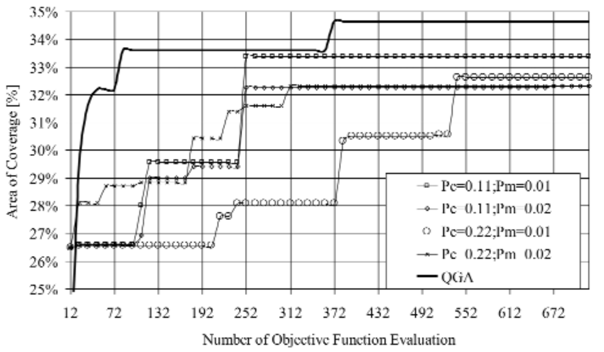

Fig. 7. Comparison of SGA and QGA (best objective function)

For CGA four set of parameters were tested two mutation and two crossover probability sets are evaluated.

Based on the comparison in Fig. 7 and other not detailed evaluations can be stated that for our indoor one access point coverage optimization case the QGA outperforms the classical SGA therefore it worth to investigate and deploy for more complex optimization cases with multiple access points.

In the last part of the results chapter coverage results are shown for 3, 4 and 6 access points.

The first scenario is an optimization on AP positions (circles in Fig. 8) of the half part of the floor. The Fig. 8 shows the original 4 AP positions which were chosen to best coverage in laboratories and the corridor coverage was not an aim.

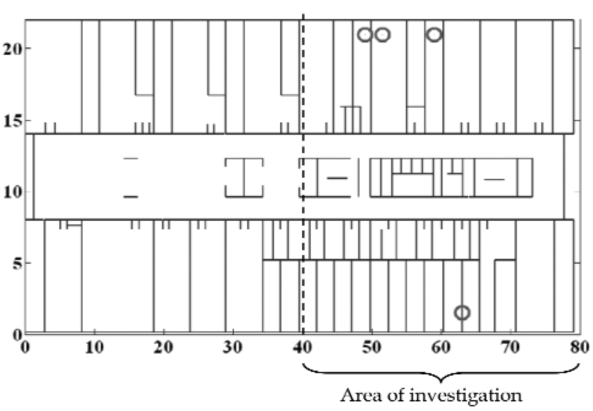

Fig. 8. Original (not optimized) AP positions

The Fig. 9 shows the optimal AP positions using the cost function of (7). The simulated distribution of received power for the optimized geometry is shown in Fig. 10 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 shows a good agreement for the received power distribution.

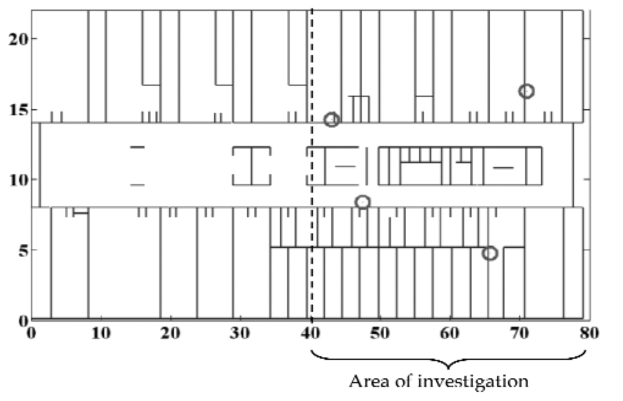

Fig. 9. Optimized AP positions

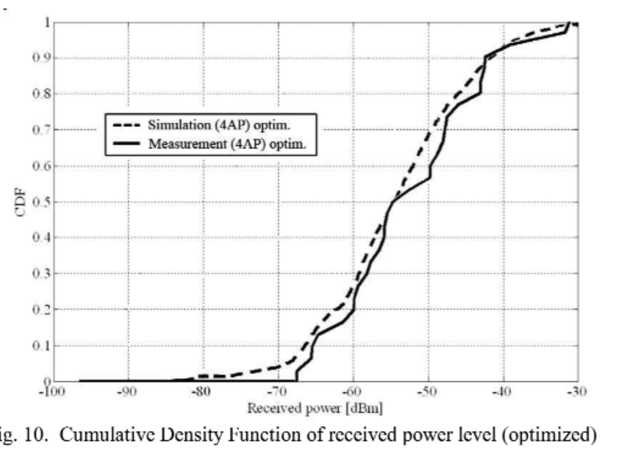

Fig. 10. Cumulative Density Function of received power level (optimized)

The most important change in the distributions of optimized and not optimized cases is increased number of points with proper coverage. (TABLE IV.)

TABLE IV
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 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.

The Fig. 11 shows plausible positions of APs and the Fig. 12 the optimized ones.

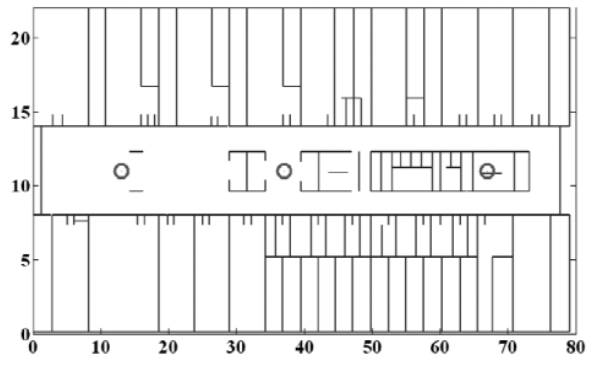

Fig. 11. Plausible AP positions

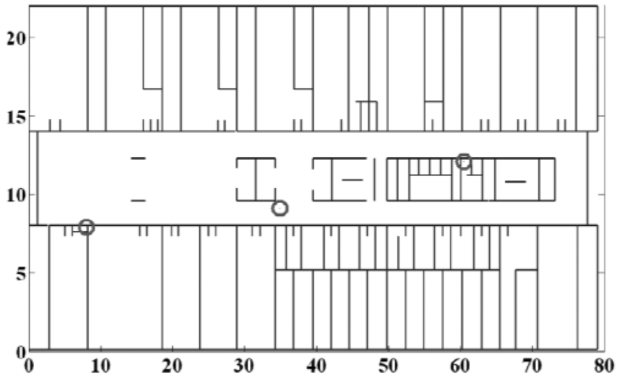

Fig. 12. Optimized AP positions

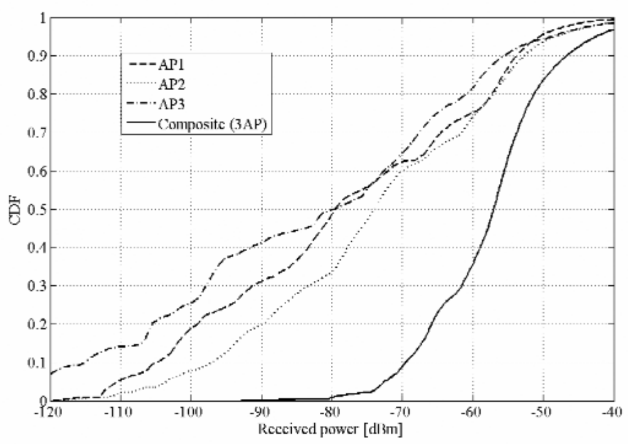

Fig. 13. Independent and composite CDF (optimized AP positions)

The Fig. 14 and TABLE V summarize the importance of APs 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.

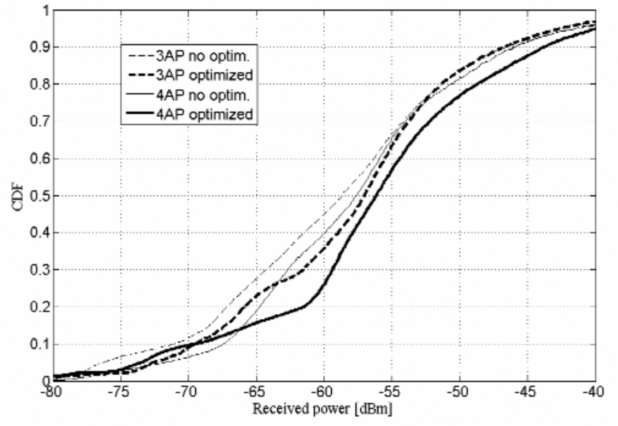

Fig. 14. Optimized and not optimized CDF using 3 and 4 APs

TABLE V
AREA COVERAGE FOR OPTIMIZED AND NOT OPTIMIZED CASE

Configuration	3AP	4AP	6AP
Coverage (not optimized)	40%	60%	66%
Coverage (optimized)	65%	75%	87%

These results (TABLE V) illustrate and justify well the importance of Access Point installation positions in radio networks in order to maximize the wireless coverage. Using the mentioned optimization procedure the network cost can be significantly reduced and the optical distribution network also can be simplified.

V. CONCLUSION

The optimal Access Point position of radio network is investigated for indoor environment. The article illustrates the possibility of optimization of radio network using Genetic Algorithm and Quantum inspired Genetic Algorithm in order to determine positions of APs. The QGA as new approach is introduced to solve the global optimization problem. 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, the algorithms are compared for the one AP case 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 WLANs.

The results clearly justify the advantage of the method we used but further investigations are necessary for convergence comparison for multiple AP case. 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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