Wireless Communication Network Design in IC Factory

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***Abstract*—A wireless local area network (WLAN) is designed for an IC factory in Hong Kong using the hierarchical genetic algorithm (HGA). The HGA is capable of handling multiobjective functions and discrete constraints. Because of this uniqueness, together with the adopting of a Pareto ranking scheme, a solution can be reached even when skewed multiobjective functions and constraints confinements are being imposed. It has been found from this study that a precise number of base stations can be identified for the WLAN network, while it can satisfy a number of objectives and constraints. This added feature provides a further design tradeoff between cost and performance at no extra effort.**

***Index Terms*—Hierarchical genetic algorithm, multiobjective, wireless LAN.**

I. Introduction

THE use of a wireless local area network (WLAN) in telecommunications can be found in offices, factories, mobile robots and/or environments where physical wiring may be problematic. As the cost of advanced technology continues to drop and various standards have been established, the future trend of wireless communications appears to be very promising [18].

The benefit of high data rate communication for computer-controlled manufacturing on the factory floor is now well recognized by manufacturers. The WLAN can provide the required high data rate links and flexible network topologies between the mobile industrial robots, automated machinery, personnel, and remote computer terminals in the factory, all without the cost of installing a wired data network. With the incentive of cost reduction of wireless devices, it is now a trend to develop the WLAN in factories for increasing productivity and quality of goods.

In order to provide adequate radio coverage quality for a specified power level, a set of base stations should be strategically located. To facilitate efficient and low-cost WLAN design, the layout of base stations and the associated terminals' allocation have aroused a great deal of research interest [16], [18]. These are also coupled with other engineering considerations such as the distribution of nodes, traffic intensity, and the radio characteristics of the coverage area, in order to achieve the required degree of acceptable service.

By and large, minimization of the path losses of the terminals and optimization of the number of the base stations would lower the WLAN's cost and increase the quality of its performance. These usually require an accurate prediction of the path losses with a minimum power in order to permit a reduction in the co-channel interference as well as the frequency reuse capability [11].

A very sophisticated formulation and solution using heuristic approaches for this problem is reported in [16]. The optimization procedure involves two specified sets of parameters: 1) the threshold values which ensure good coverage quality at each terminal and 2) the locations of the terminals within a subset of the design space.

The main difficulty here involves the procedure of optimizing a convex combination of minisum and minimax objective functions. Furthermore, the tendency of improving the overall coverage involves sacrificing the coverage of a few terminals.

Although this procedure of optimizing a convex combination of minisum and minimax objective functions works well, the process of selecting suitable weightings and the determination of the number of base stations are not easy.

In this paper, we present an approach based on the hierarchical genetic algorithm (HGA) [9] to optimally locate the base stations over a specified area. Within the design area, the signal strength is guaranteed to meet the design specifications. For realistic modeling, the chosen path loss model is a specified type and the density of the obstructions is also taken into account [16]. This HGA approach is different and has the following aspects.

1) A preferential Pareto ranking is adopted for optimizing the multiple objective functions including the constraints. No penalty functions as in [16] are required.
2) A minimum number of required base stations and their corresponding locations can be precisely identified, so that the cost of the WLAN is considerably reduced.
3) A tradeoff between the number of required base stations with the obtained minisum and minimax objective functions is possible.

Based on the assumption that the capacity of the base station is much larger than the traffic intensity of the allocated terminals, the HGA approach provides the coverage area for each base station, while the location of mobile terminals can be moved anywhere within the design space.

This paper is organized as follows. Section II gives a brief introduction to the path loss model. The constraints and the objectives for the design are also defined. The formulation of the HGA is described in Section III. The application of the HGA to a WLAN design within an IC factory is presented in Section IV. Conclusions are given in Section V.

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II. Problem Formulation

A. Necessity of WLAN in IC Factory

An efficient IC factory should handle a large volume of IC production with a high production yield. It is not only required to have a closed monitoring on each production process, but also provide a close link between the processes. It involves a large amount of data communication among the various production departments, management, and personnel.

As the standards emerge, and both data rates and handheld computers are in great demand, the WLAN is now more than a niche of technical advancement; it is, indeed, a practical proposition for an integrated automation system for factories.

This technology can offer a number of advantages which become the essential facilities that are desperately in demand.

1) With the handheld barcode scanners, the new inventory system provides accurate information on the incoming and outgoing shipments. Without entering the data into a terminal on a traditional wired computer network, the WLAN together with the barcode system can form an automatic system with high efficiency, accuracy, and mobility.
2) The demand of a high production yield with cost control is paramount for the IC manufacturer. Therefore, statistical testing data from the probers, testers, and the die bonders are required for analysis. With the WLAN, engineers (including the production engineers, test engineers, and the QA engineers) and production supervisors can easily access the information at their fingertips on palmtop computers. They can solve the production problems online and, hence, increase their efficiency. The data will also be logged in the server as a report for further product improvement.
3) As handheld computers are easily accessible, the WLAN enables the managers to monitor the manufacturing needs during a factory inspection.
4) The process of laying cables requires a long period of construction work. As a result, the production schedules are disrupted due to the shutdown of the production line. The clean room for the bonding process would also be badly affected.
5) With the use of the WLAN, which is more feasible and reconfigurable, it allows a development on site without the limitation of floor area mobility.

Therefore, within the capability of technology, the WLAN can offer the benefits of being relatively simple, cableless, with quick installation and affordable costs for the production of the IC factory.

B. WLAN Design

To formulate a WLAN design, the terminal locations of a WLAN which distribute over a designated region in a three–dimensional (3-D) Euclidean space must be carefully considered. It is also desirable to be able to determine the required number of base stations, as well as their precise locations so that the best quality of service of the network is obtained. To achieve this objective, a number of technical problems must to be overcome.

C. Path Loss Model

The quality of the network is highly related to the path loss function of the terminals. This is generally governed by a mean path loss function in terms of distance with respect to the nth power [12], [14]

$$S(d) \propto \left(\frac{d}{d_0}\right)^n \tag{1}$$

where

- S mean path loss;
- d_0 reference distance chosen as 1 m;
- d distance between the terminal and base station;
- n mean path loss exponent, indicating how rapidly the path loss is being dissipated as the distance increases.

A number of studies have been carried out in determining the values of n [13], [15], [17]. It is subject to factors such as building type, layout, and the number of floors between the base station and terminals.

Hence, the absolute mean path loss g_i for a particular terminal i in decibels can be computed as

$$g_i = S_0 + 10.0 \cdot n \log(d) \tag{2}$$

where S_0 is due to free space propagation from the base station to a 1-m reference distance or $S_0 = 10 \cdot n_0 \log(4\pi \cdot 1 \text{ m}/\lambda)$ with $n_0 = 2$ and λ is the wavelength of the frequency in used, e.g., $S_0 = 37.55$ dB at 1.8 GHz.

To take into account the physical obstructions that lie directly between the base station and the terminal, g_i can be modified as

$$\begin{aligned} g_i &= S_0 + 10.0 \cdot n_0 \log(d) + \sum_{w=1}^{M} N_w L_w \\ &= 20.0 \log\left(\frac{4\pi d}{\lambda}\right) + \sum_{w=1}^{M} N_w L_w \end{aligned} \tag{3}$$

where N_w is the number of obstructing objects (for example, walls) with type w separating the terminal and the base station; L_w is the penetration loss due to an obstructing object of type w, and there is a total of M types of objects. The free space exponent used in (3) assumes that free space propagation applies for all distances [15].

D. Allocation Subproblem

For the multiple base stations problem, a subproblem of allocation has to be addressed. Let $p_i(X, Y, Z)$ be the path loss function at the ith terminal location, for $i = 1, 2, \ldots, a$ where a is the total number of terminals, then

$$p_i(X, Y, Z) = \min_{j=1, \ldots, b} [g_{i,j}(x_j, y_j, z_j)] \tag{4}$$

where

- X $\equiv (x_1, \ldots, x_b)$;
- Y $\equiv (y_1, \ldots, y_b)$;
- Z $\equiv (z_1, \ldots, z_b)$;
- b total number of base-stations;
- $g_{i,j}(x_j, y_j, z_j)$ path loss at the ith terminal location for the base-station located at (x_j, y_j, z_j), computed as (3).

In such a case, each terminal i is allocated to base station $\arg\min_j\{g_{i,j}(x_j, y_j, z_j)\}$. A set R_j is, hence, defined for the set of terminals allocated to the base station j, where $\cup_{j=1}^{b} R_j = \{1, \ldots, b\}$ and $R_{j_1} \cap R_{j_2} = \emptyset,\ \forall\ j_1 \neq j_2$.

E. Constraints

The above formulation constitutes two basic constraint problems: 1) the locations of the base-stations are restricted to certain acceptable subsets of the design space and 2) the power loss at each terminal location over the design space must not exceed a given threshold value.

F. Objectives

Given a set of terminal layouts, the design objectives of the WLAN are listed as follows:

1) to minimize the required number of base-stations in order to minimize the cost of the overall system;
2) *minisum*—to minimize the sum of the path loss predictions over the design space with respect to the base station location;
3) *minimax*—to minimize the maximum of the path loss predictions over the design space; this function concentrates on the worst case scenario to ensure the quality of service.

III. Multiobjective HGA Approach

In conventional design methodology, it is not only necessary to have a predefined number of base stations, but the conflicting multiobjective functions cannot be solved without the aggregation of the objective functions [16], according to a certain utility function. In many cases, however, the utility function is not well understood prior to the optimization process. In this paper, instead of using the conventional heuristic approaches for solving this highly constrained, multiobjective problem, an HGA approach is proposed.

A. HGA

The operational cycle of the HGA [9] is the same as the basic GA [4], [6], [10], as shown in Fig. 1.

```
Genetic Algorithm ()
{
   // start with an initial time
   t := 0;
   // initialize a usually random population of individuals
   init_population P (t);
   // evaluate fitness of all initial individuals of population
   evaluate P (t);
   // evolution cycle
   while not terminated do
         // increase the time counter
         t := t + 1;
         // select a sub-population for offspring production
         P' := select_parents P (t);
         // recombine the "genes" of selected parents
         recombine P' (t);
         // perturb the mated population stochastically
         mutate P' (t);
         // evaluate its new fitness
         evaluate P' (t);
         // select the survivors from actual fitness
         P := survive P,P' (t);
   od
}
```

Fig. 1. Genetic algorithm.

The major difference between the HGA and basic GA is its hierarchical chromosome structure. Each chromosome consists of a multilevel of genes, as demonstrated in Fig. 2 which shows the chromosome representation of the HGA for the base station location problem.

The control genes in the form of bits decide the activation or deactivation of the corresponding base-station which is analogous to the control effect of the transacting factor on regulatory sequences [2], [7]. The parameter genes define the x, y, z coordinates of the base station locations. For example, in Fig. 2, the base station location (x_1, y_1, z_1), with the control gene signified as "0" in the corresponding site, is not activated. It should be noted that the inactive genes always exist within the chromosome as they are in the deoxyribonucleic acid (DNA) [3], [8]. This hierarchical architecture implies that the chromosome contains more information than that of the conventional GA structure.

The use of the HGA is particularly important for system structure or topology as well as parametric optimization. Unlike the setup of the conventional GA optimization, where the chromosome and the phenotype structure are assumed to be fixed or predefined, the HGA operates without these constraints. The HGA will search over the suitable number of base stations and their appropriated locations throughout the genetic evolution.

B. Multiobjective Approach

Based on the constraints and the objectives in the design stated in Sections II-E and II-F, it is possible to construct four different objective functions as follows:

1) the number of terminals with their path loss greater than the corresponding threshold

$$f_1 = \sum_{i=1}^{a} q_i \tag{5}$$

where a is the total number of terminals, and

$$q_i = \begin{cases} 1 & \text{if } p_i(X, Y, Z) > s_i \\ 0 & \text{else} \end{cases}$$

and s_i is the specified threshold for the maximum path loss of ith terminal;

2) the number of base stations required

$$f_2 = \sum_{i=1}^{T} c_i \tag{6}$$

where c_i is ith bit value in the control genes, and T is the maximum allowable number of base stations;

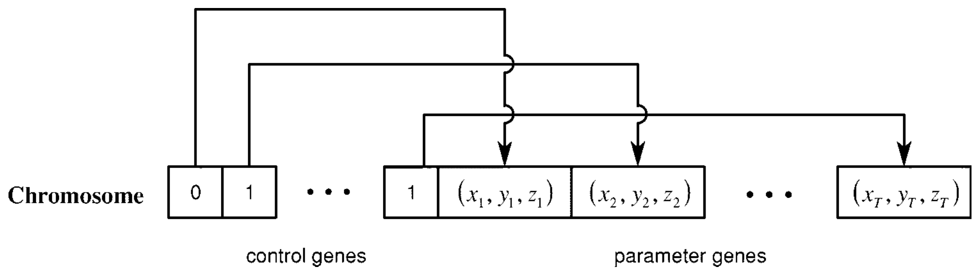

Fig. 2. Hierarchical genetic chromosome structure.

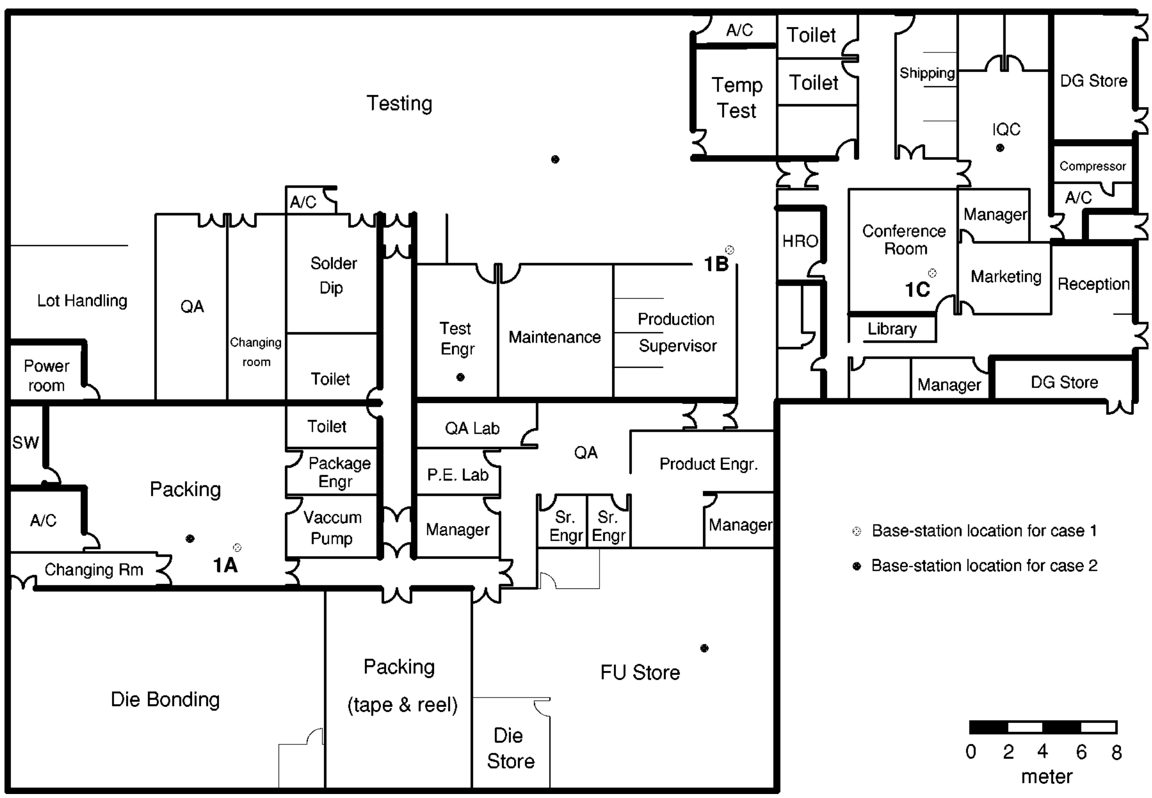

Fig. 3. Floor plan of the IC factory.

3) the mean of the path loss predictions of the terminals in the design space

$$f_3 = \frac{1}{a} \sum_{i=1}^{a} p_i(X, Y, Z) \tag{7}$$

where $p_i(X, Y, Z)$ is computed as in (4);

4) the mean of the maximum path loss predictions of the terminals in each set R_j

$$f_4 = \frac{1}{f_2} \sum_{j=1}^{T} \max_{i \in R_j, c_j = 1} [p_i(X, Y, Z)]. \tag{8}$$

1) Preferential Ranking: Whether a chromosome is able to meet the above four individual objective functions is a matter of controversy. To quantify the available chromosomes, some ranking schemes are required. Consider the following two individual chromosomes I_1 and I_2 with objective values

TABLE I
WALL TYPE AND ITS PENETRATION LOSS

No	Material	Penetration Loss L_w
1	thin partition	2.0
2	cement wall	3.3
3	thickened cement wall	6.5

TABLE II
ACHIEVABLE PERFORMANCE

Case	f_1	f_2	f_3	f_4
1	0	3	66.38dB	87.37dB
2	0	5	60.61dB	75.64dB

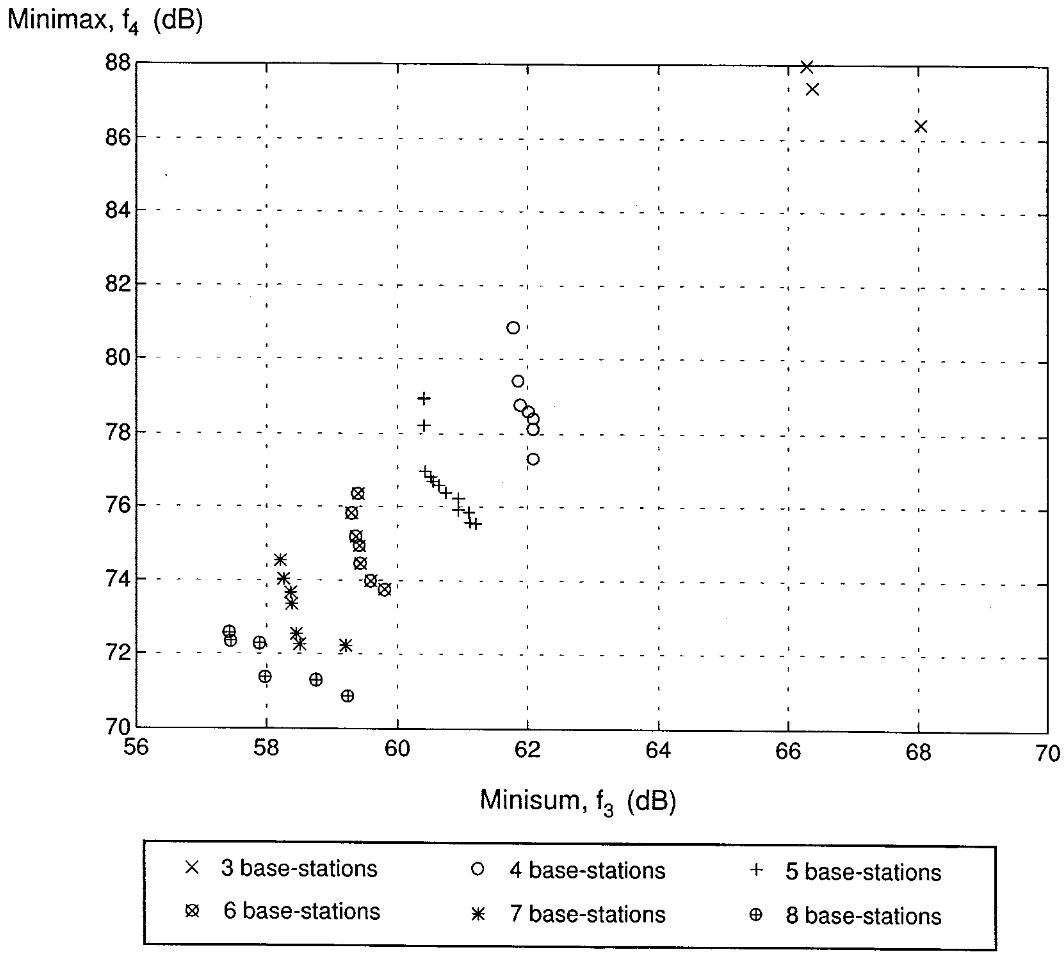

Fig. 4. Final population for case 1.

f_1, f_2, f_3, f_4 and f_1', f_2', f_3', f_4', respectively; I_1 is preferable to I_2 if and only if

$Condition\ I$:

$$f_1 < f_1'$$

$Condition\ II$:

$$\begin{aligned} & f_1 = f_1' \quad \text{and} \\ \forall\, i = 2, 3, 4, \quad & f_i \le f_i' \quad \text{and} \\ \exists\, j = 2, 3, 4, \quad & f_j < f_j'. \end{aligned}$$

The ranking can, thus, be made on the fitness assignment of the chromosome and the procedure is described as follows.

1) Sort the population according to the above ranking scheme.
2) Assign the fitnesses of the chromosomes by interpolating the rank from the highest to the worst, using a function

$$h(I) = h_1 + (h_2 - h_1) \cdot \frac{\text{rank}(I) - 1}{N_{\text{pop}} - 1}$$

where $\text{rank}(I)$ is the rank position of chromosome I in the ordered population, $h(I)$ is the fitness assigned to chromosome I, h_1 and h_2 are the lower and upper limits of fitness respectively, and N_{pop} is the population size.
3) Average the fitnesses of the chromosomes in the same rank, so that all of them will be selected at an equal rate of probability.

The advantage of this multiobjective approach is multifold. First, there is no need to determine the penalty factor, which may affect the searching process. Secondly, no combination of objective functions is required. The designer will obtain a Pareto set of solutions in which any single set of solution can be freely chosen according to the fulfillment of system requirements. Furthermore, the primary interest, that none of the terminals is higher than the power loss threshold, is also reflected.

2) Niche Size: Pareto-based ranking can correctly assign all nondominated chromosomes with the same fitness. However, the Pareto set may not be uniformly sampled. Usually, the finite populations will converge to only one or some of these, due to stochastic errors in the selection process. Such phenomenon is known as genetic drift. Therefore, the additional use of fitness sharing [5] and mating restriction [1] can be used to prevent the drift and promote the sampling of the whole Pareto set by the population.

a) Mating Restriction: Mating restriction has been implemented based on the distance between individuals in the objective domain. The distance between chromosome I and I' is defined as

$$\sigma_{\text{mate}}(I, I') = \sum_{j=1}^{M \cdot T} |I_j - I_j'|. \tag{9}$$

Based on experimental study, if $\sigma_{\text{mate}} \le 0.1 \cdot M \cdot T$, mating is restricted.

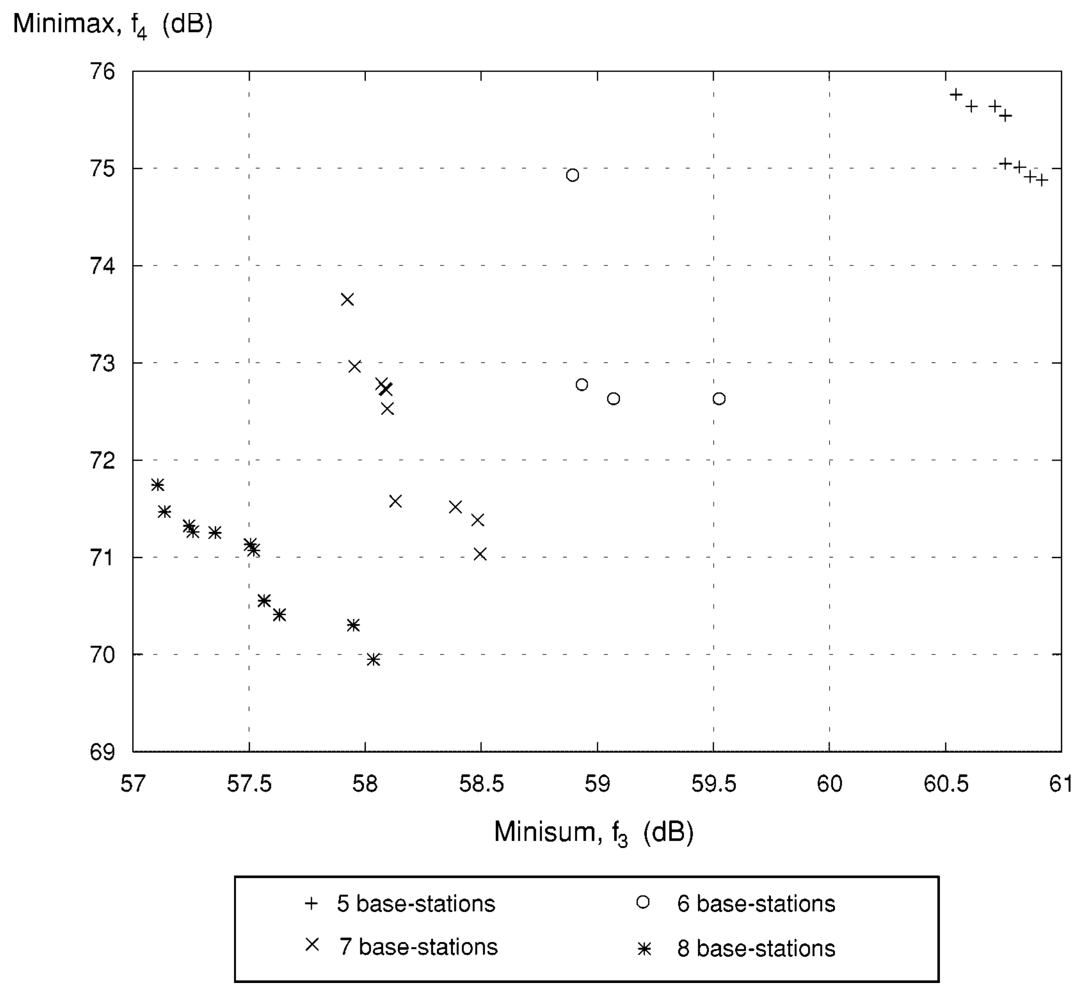

Fig. 5. Final population for case 2.

b) Fitness Sharing: Fitness sharing is introduced to counteract genetic drift. This method penalizes an individual due to the presence of other individuals in its neighborhood. The number of neighbors governed by their mutual distance in objective spaces (in our experiment, the mutual distances are set to 2.0 and 0.1 for O_1 and O_2, respectively) is counted and the raw fitness value of the individual is then weighted by the this niche count. Eventually, the total fitness in the population is redistributed, favoring those regions where fewer chromosomes are located.

C. Genetic Operations

Although different phenotype lengths may exist in the same population, no extra effort is required for reconfiguring the usual genetic operations. Therefore, the standard methods of mutation and crossover may apply independently to each level of genes or even for the whole chromosome if this is homogenous.

Since there are two different types of genes, represented in binary and real numbers, in our design, the genetic operations can be modified appropriately. For a binary-coded control gene, the conventional one-point crossover and bit mutation described in the previous section are used. For a real-number-coded parameter gene, the specialized genetic operations as developed in GENOCOP [10] are adopted. A recovery process is used to ensure that the locations of the base stations are within the ranges and not placed in the restricted areas, for example, inside a wall.

The genetic operations that affect the high-level genes can result in changes within the active genes which eventually lead to a multiple change in the lower level genes. This is the precise reason why the HGA is not only able to obtain a good set of system parameters, but can also reach a minimized system topology.

IV. COMPUTATIONAL RESULTS

Because of the nature of its working environment, the need to install a 1.9-GHz microwave wireless communication system within an IC factory was essential. Without complicating the calculation and obscuring the essence of the proposed design approach, the design networking is based on a two–dimensional (2-D) floor plan, as depicted in Fig. 3.

The measurement in the indoor environment is reported in [12] and [17], and the following simulation is based on (3) with the consideration of the obstructing objects. The studies on the attenuation factor for different materials are also reported [13], [15]. In the IC factory, there are three different types of walls, shown by the lines of different thickness. Table I summarizes the type of walls and their estimated mean path loss exponent (n).

To represent the entire area, a grid of pertinent terminals having a defined density was constructed, such that every 1.5 m $\times$1.5 m section contained a possible terminal location.

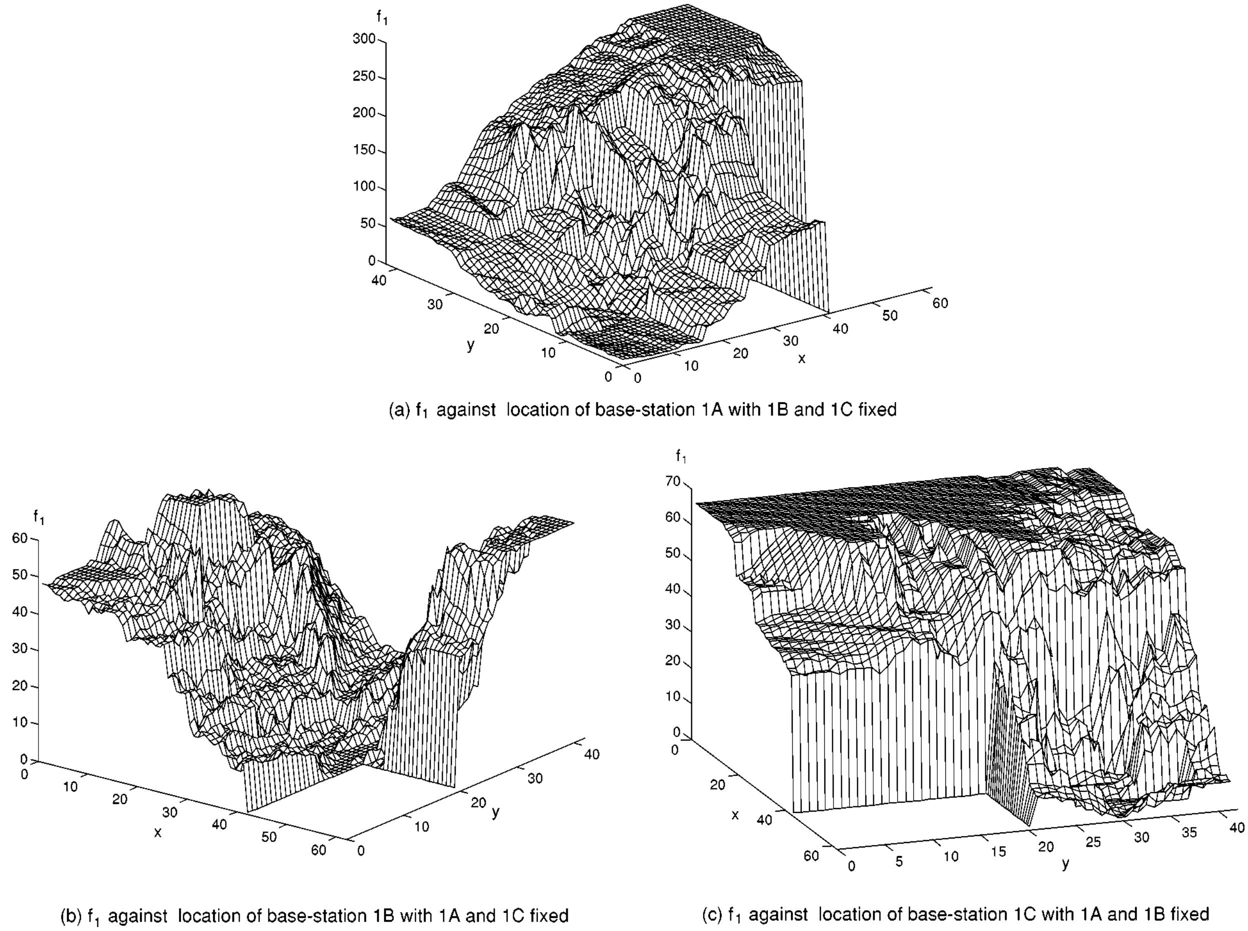

Fig. 6. Number of receivers that exceed the threshold when altering one base station.

Using the loss model described in (3), the propagation prediction procedure counts the number of walls between the base stations and the terminals.

In this arrangement, the chromosome in the form depicted in Fig. 2 is applied with the initial arbitrarily chosen maximum number of base stations $T = 8$. The population size of the GA is limited to 100. In each cycle, 30 offspring are generated through the genetic operations as described in Section III-C.

To demonstrate the effectiveness of this design approach, the power loss threshold requirements are set to 90 and 80 dB for all terminals in cases 1 and 2, respectively. After 1000 cycles, the HGA operation is terminated for a direct comparison. The results are shown in Fig. 3. The derived locations of the base stations from the HGA are identified and denoted by the case number. Table II summarizes the achievable objective values of each case.

From the table, it is clearly demonstrated that the HGA is capable of identifying the required number of base stations as well as their corresponding locations simultaneously. If the power loss threshold requirement s_i is changed, as in the change from case 1 to case 2, the HGA is capable of identifying the larger number (five) of required base stations. It should be emphasized that this is achieved without any changes to the basic structure of the chromosome.

An added feature of this design approach is the tradeoff between cost (number of base stations) and performance on the basis of minimum and minimax objective functions, f_3 and f_4. It should be noted that this is only possible when the condition of $f_1 = 0$ is reached. A complete range of power loss against the number of base stations for each case is identified and these are shown in Figs. 4 and 5. This set of results allows the tradeoff between cost and performance.

Fig. 6 depicts the number of receivers that exceed the threshold in case 1 (f_1) while modifying the solution in Table II. By keeping the locations of two base stations, the location of the last base station is searched along the area. It can be seen that the objective f_1 is discrete and multimodal. Similar observations are also found for other objectives.

To illustrate the globalization of the obtained solution, an exhaustive search with step 0.5 and 2 m are carried out for locating the best locations of two and three base stations for case 1, respectively. It turns out that no feasible solution can be found for both cases.

V. Conclusions

An indoor UHF communication system has been successfully designed for an IC factory by HGA design methodology. It is demonstrated that this approach is capable of identifying the minimum required number of base stations, as well as their corresponding locations, ad well as meeting the power loss specifications.

Due to the Pareto ranking treatment of the objective functions, the simultaneous demands on the minimum and the minimax are traded off with the number of base stations. This is considered a value-added feature which allows design flexibility, with the designer making the choice between cost and performance.

To confirm with the design and the path loss model for the IC factory, on-site testing is under way.

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