Wireless Heterogeneous Transmitter Placement Using Multiobjective Variable-Length Genetic Algorithm

Chuan-Kang Ting, *Member, IEEE*, Chung-Nan Lee, Hui-Chun Chang, and Jain-Shing Wu

***Abstract*—The problem of placing wireless transmitters to meet particular objectives, such as coverage and cost, has proven to be NP-hard. Furthermore, the heterogeneity of wireless networks makes the problem more intractable to deal with. This paper presents a novel multiobjective variable-length genetic algorithm to solve this problem. One does not need to determine the number of transmitters beforehand; the proposed algorithm simultaneously searches for the optimal number, types, and positions of heterogeneous transmitters by considering coverage, cost, capacity, and overlap. The proposed algorithm can achieve the optimal number of transmitters with coverage exceeding 98% on average for six benchmarks. These preferable experimental results demonstrate the high capability of the proposed algorithm for the wireless heterogeneous transmitter placement problem.**

***Index Terms*—Multiobjective (MO) optimization, variable-length genetic algorithm, wireless heterogeneous transmitter placement.**

I. Introduction

With the advent of heterogeneous networks, such as the integration of Wi-Fi and WiMAX [1]–[3], the infrastructure layout becomes very flexible but thorny. Heterogeneity suggests that many factors must be considered; for example, Wi-Fi and WiMAX networks have different spectrums, coverage ranges, and base station costs. The wireless transmitter (or base station) placement problem is to construct an optimal infrastructure, that is, to identify the optimal placement of transmitters when considering particular factors such as coverage, cost, capacity, interference, and handover. These factors are commonly formulated as objectives, constraints, or both in the problem model, and are subject to the type of wireless networks, e.g., datacom or telecom. The problem is known to be NP-hard.

This paper focuses on datacom networks, specifically, Wi-Fi and WiMAX networks. The wireless transmitter placement problem addressed in this paper is to find the optimal placement of transmitters for four objectives: 1) maximum coverage, 2) minimum cost, 3) maximum capacity satisfaction, and 4) minimum overlap. To solve this wireless transmitter placement problem, three issues are of paramount importance but remain open: the number of transmitters, the heterogeneity of networks, and the multiplicity of objectives.

The first issue is to determine the appropriate number of transmitters. An intuitive method is to manually assign this number prior to optimizing transmitter placement. Nevertheless, the optimal number of transmitters, i.e., the number of transmitters that can achieve full coverage at the lowest cost, is unknown and ordinarily difficult to assess. An inappropriate number of transmitters may cause bad or no results. To prevent such a situation, the problem of how many transmitters to use must be solved before dealing with the placement. Several methods have used an upper bound for the number of transmitters [4]–[7]. However, if additional transmitters are required, then a poor upper bound will restrict the search space and result in a local optimum. Some methods have been developed to overcome drawbacks associated with predefining the number of transmitters or an upper bound. The most successful way is to regard the adopted number of transmitters as an objective to be minimized [8]–[10]. Consequently, the number can optimally be determined along with other objectives. This paper employs this method to determine the optimum number of transmitters.

The second issue is the heterogeneity of wireless networks. Hardware technology has improved, and most laptops and mobile computers now start to support different wireless protocols, such as the 802.11 family (Wi-Fi) and 802.16d (WiMAX) [11]. Restated, a receiver can be covered by transmitters that differ in, for example, power radius, cost, and frequency spectrum. Such heterogeneity in transmitter types makes the placement problem, which is an NP-hard problem, even more intractable.

Fig. 1 illustrates a wireless heterogeneous transmitter placement problem. Two transmitter types exist: the large circle denotes the first transmitter type, which has a large power radius, such as WiMAX base stations, and the small circle signifies the second type, which has a small power radius resembling Wi-Fi access points. The triangle is the area to be covered. Notably, the required number of transmitters of each type is unknown, and here, the heterogeneous transmitters in protocol can correspond to homogeneous transmitters with differing powers. To intuitively solve this problem, one can divide

Manuscript received November 7, 2007; revised March 27, 2008, July 10, 2008, and November 6, 2008. First published April 7, 2009; current version published July 17, 2009. This work was supported by the National Science Council of Taiwan under Contract NSC97-2221-E-194-035. This paper was recommended by Associate Editor H. Ishibuchi.

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Digital Object Identifier 10.1109/TSMCB.2008.2010951

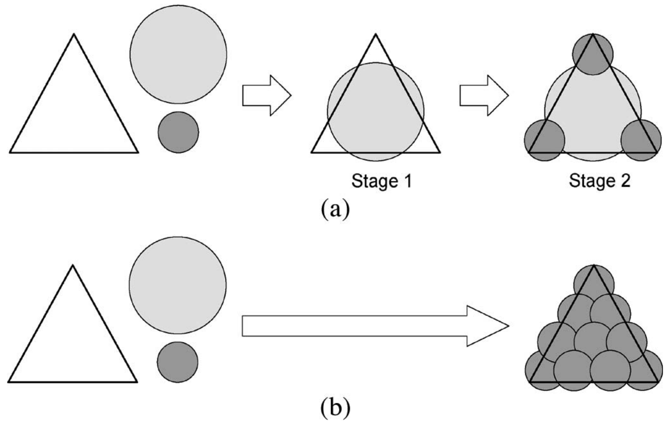

Fig. 1. (a) Two-stage placement. (b) Counterexample of two-stage placement.

the planning into multiple stages. The first stage plans the placement of transmitters with large power, and the second stage plans that for small transmitters [Fig. 1(a)]. The primary drawback of this method is that the resultant placement may not be optimal. For instance, given that the big transmitters cost \$120 and the small ones cost \$10, using only small transmitters [Fig. 1(b)] is better than mixed transmitters [Fig. 1(a)] in terms of cost. A method that simultaneously considers the number and positions of transmitters can overcome this drawback and is relatively more likely to obtain optimal solutions.

The third issue in wireless transmitter placement is the multiplicity of objectives that must be considered for placement optimization. Many existing methods for the placement problem use single-objective (SO) optimization. Wireless transmitter placement, however, frequently considers more than one objective. For instance, one may seek maximal coverage with the minimal number of transmitters. SO schemes solve this problem by combining all the objectives into a weighted objective. Although a possibility exists that SO methods can solve the multiobjective (MO) optimization problem, the performance of SO methods is typically sensitive to the weights, and, even worse, determining appropriate weights is itself another optimization problem. MO methods, on the other hand, do not weight each objective. Instead, they provide a bunch of solutions for each objective on demand. For example, an MO method gives two solutions: one for 98% coverage with four transmitters and another for 88% coverage with three transmitters. A company may choose the second solution based on its budget, rather than the solution with the higher coverage rate.

In consideration of these three issues, this paper presents a novel *multiobjective variable-length genetic algorithm* to solve the wireless heterogeneous transmitter placement problem. This algorithm integrates a variable-length scheme, an MO genetic algorithm, and a new crossover approach to solve the wireless heterogeneous transmitter placement problem without predetermining the number of transmitters or its upper bound.

The rest of this paper is organized as follows. Section II recapitulates related work. Section III gives the definition of the wireless heterogeneous transmitter placement problem. Section IV sheds light on the proposed MO variable-length genetic algorithm. Simulation and results are presented in Section V. Finally, conclusions are drawn in Section VI.

II. Related Work

The infrastructure setup for placement can be categorized into the base station placement problem and the antenna placement problem. The former is concerned with the placement of base stations, whereas the latter is concerned with the allocation of antennas to certain candidate base stations. The wireless transmitter placement problem addressed in this paper is a base station problem. Both the base station placement problem and the antenna placement problem are known to be NP-hard; that is, under the assumption $P \neq NP$, no exact algorithm exists that can solve this problem in polynomial time.

Some heuristic methods have been developed for solving the base station placement problem. Unbehaun and Kamenetsky [12] selected a set of candidate wireless local area network (WLAN) access points using the pruning method and refined these access points via neighborhood search and simulated annealing. Lee and Kang [13] utilized tabu search to increase the capacity of code-division multiple access (CDMA). In focusing on the universal mobile telecommunications system (UMTS) uplink, Amaldi *et al.* [14] developed a randomized greedy method with tabu search to avoid local optima for WLAN coverage planning. In addition, several approaches based on evolutionary computation have shown their power in effectively tackling the transmitter placement problem. Weicker *et al.* [15] proposed the steady-state evolutionary algorithm with Pareto tournaments (stEAPT), which considers frequency assignment and channel interference for base station placement. Zhang *et al.* [7] designed an MO particle swarm optimization on coverage and cost objectives. Park *et al.* [5], [6] applied a genetic algorithm to optimize the total number of transmitters and their positions. Experimental results show the utility of the genetic algorithm on the base station placement problem.

The antenna placement problem is to assign antennas to certain sites selected from a set of predefined candidate sites and determine the parameters of antennas for particular objectives and constraints. Reininger and Caminada [16] formulated the antenna placement problem for cellular networks. Their model has three objectives—minimum cost, maximum traffic capacity, and minimal overlapping criteria—and three constraints—link budget, handover, and connectivity. To address this problem, Vasquez and Hao [17] proposed a three-stage heuristic approach. The preprocess filters out poor solutions, the tabu search optimizes the configuration, and the postprocess improves the results through tabu search. The simulation results for urban and highway networks demonstrated the capability of the heuristic approach. Hurley [18] considered traffic, handover, and transmitter, and proposed an algorithm based on simulated annealing. Zimmermann *et al.* [19] integrated multiple objectives using scalarization; that is, they combined three objectives into one weighted objective. The $(1+1)$ evolution strategy (ES) has been adopted to solve the constrained SO optimization problem. Beyond scalarization, Raisanen and Whitaker [20] addressed the problem using several prominent MO optimization algorithms, including simple evolutionary algorithm for multiobjective optimization (SEAMO), strength Pareto evolutionary algorithm 2 (SPEA2), non-dominated sorting genetic algorithm II (NSGA II), and Pareto envelope-based selection algorithm (PESA). They concluded that NSGA II [21] can achieve the best performance. Raisanen [10] further employed a permutation-coded representation for the problem concerning the objectives of service coverage, cost, traffic capacity, handover, and interference. The experimental results for three realistic simulated environments showed that NSGA II, using the permutation-coded strategy, outperforms that using common binary-coded representation or integer-based representation.

As for the problems that have a changeable number of variables for a solution, a common way to address it is to limit the number with a known upper bound, and then the classic fixed-length representation is applicable. For example, Ripon *et al.* [22] observed the transposon phenomenon [23] and proposed the jumping-gene genetic algorithm (JGGA). Chan *et al.* [24] used additional control genes in JGGA to determine the employment of certain transmitters and received preferable results for optimizing factory WLAN network. However, this manner requires a predefined and assumed upper bound for the length of chromosome. To eliminate this requirement, some variable-length genetic algorithms [25]–[27] have been proposed. Recently, Ripon *et al.* [28] have devised MO evolutionary clustering using a variable-length real-coded JGGA to solve a clustering problem without knowing the number of clusters. In this paper, we propose a new variable-length MO genetic algorithm based on variable-length representation with uniform and one-point crossover.

III. Problem Statement

This section defines the wireless heterogeneous transmitter placement problem. Note that this paper focuses on the placement of transmitters for Wi-Fi and WiMAX networks. First, Section III-A formulates the planning model for the map, transmitters, and receivers based on the model of Park *et al.* [5], [6]. Section III-B introduces the propagation model. The objectives are given in Section III-C, and a formal definition of the problem is presented in Section III-D.

A. Planning Model

The planning model describes the environment of the wireless transmitter placement problem.

1) Map: The map for transmitter placement has two regions: *covered regions* and *placement regions*. The former, which is denoted by CG, represents regions that must be covered (e.g., roads and buildings). The latter, i.e., placement regions PG, are regions where transmitters can be placed when constructing the wireless network. Notably, both covered and placement regions are predefined and can differ. A common method of dealing with these regions is to divide them into several grids with a resolution δ; consequently, for a 2-D map, $CG \subseteq \mathbb{Z}^2$, and $PG \subseteq \mathbb{Z}^2$.

2) Receiver: A receiver gains wireless signals from transmitters. Wireless connectivity is assessed by a signal threshold θ and a data rate demand σ to maintain quality of service. This paper uses a large set R of receivers as test points for coverage: a receiver $r \in R$ has a position $(x_r, y_r) \in CG$ with threshold $\theta_r \in \mathbb{R}_*$ and demand $\sigma_r \in \mathbb{R}_*$.

3) Transmitter: The transmitters are characterized by various parameters. The proposed model takes power, cost, and capacity into account; the transmitter type can, therefore, be represented by a three-tuple $\tau = (p, c, s)$, where $p \in \mathbb{R}_+$ denotes the power, $c \in \mathbb{R}_+$ denotes the cost of transmitters, and $s \in \mathbb{R}_+$ denotes the capacity (bandwidth) provided by the transmitter. Let TP be the set of candidate transmitter types to be placed, and let $|TP|$ be the cardinality of TP. For $|TP| = 1$, only one transmitter type exists, and the planning network is *homogeneous*. For $|TP| > 1$, it turns out to be a wireless *heterogeneous* transmitter network.

The transmitter placement problem is to create a set of transmitters $T = \{t = (\phi_t, \tau_t) | \phi_t \in PG, \tau_t \in TP\}$ and place its elements, namely, transmitters, based on objectives such as coverage and cost. A formal definition of the problem is given in Section III-D.

B. Propagation Model

The signal strength $S_{r,t}$ from a transmitter $t \in T$ to a receiver $r \in R$ can be evaluated using propagation models. This paper adopts the *free space propagation model*, which is widely used in the studies of placement problem [11]. The signal strength in the free space propagation model is computed by

$$S_{r,t} = \frac{p_t G_r G_t \lambda^2}{(4\pi)^2 d_{r,t}^2} \tag{1}$$

where p_t is the power of t, G_r and G_t are the antenna gains of receiver r and transmitter t, respectively, λ is the carrier wavelength, and $d_{r,t}$ is the Euclidean distance from r to t.

Moreover, the path loss due to obstructions is computed using the following formula [24], [29]:

$$L_{r,t} = 20 \log \left(\frac{4\pi d_{r,t}}{\lambda} \right) + \sum_{i=1}^{M} N_i L_i \tag{2}$$

where M denotes the number of obstruction types, N_i is the number of obstructions of type i, and L_i is the penetration loss for an obstruction of type i.

C. Objectives

Many factors affect wireless network planning. This paper focuses on coverage, cost, capacity, and overlap, where coverage and overlap are concerned with the placement of transmitters, cost is associated with the type and number of transmitters, and capacity is subject to the transmitter type.

1) Coverage: A receiver r is said to be *covered* by a transmitter t when the signal strength is greater than the threshold; formally

$$\text{covered}(r) = \begin{cases} 1, & \exists t \in T, S_{r,t} > \theta_r \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where the value 1 indicates that the receiver r is covered by at least one transmitter. Accordingly, the coverage of a set of transmitters can be calculated by

$$\text{coverage}(T) = \frac{1}{|R|} \sum_{r \in R} \text{covered}(r). \tag{4}$$

Note that the objective is to maximize coverage.

2) Cost: Another objective is to minimize cost in placing the set of transmitters T. Here, cost is evaluated by summing the individual costs of all transmitters, i.e.,

$$\text{cost}(T) = \sum_{t \in T} c_t \tag{5}$$

where c_t denotes the cost of transmitter t with type $\tau_t = (p_t, c_t, s_t) \in TP$.

3) Capacity: This paper adopts the notion of data rate to assess the network capacity [30]. An ideal network design should provide sufficient bandwidth (data rate) for users; both oversupply and shortage of bandwidth are not satisfactory. Thus, the objective regarding capacity is formulated to minimize the absolute difference between the transmitter bandwidth and the sum of the data rate demands of its covered receivers, i.e.,

$$\Delta\text{capacity}(T) = \sum_{t \in T} \left| s_t - \sum_{r \in R: S_{r,t} > \theta_r} \sigma_r \right| \tag{6}$$

where s_t is the data rate provided by transmitter t of type $\tau_t = (p_t, c_t, s_t) \in TP$, and σ_r is the data rate demand of receiver r.

4) Overlap: The coverage overlap between transmitters raises the issue of interference [15], [31]. To reduce the interference, we use an additional objective to minimize the overlap. The objective function counts the number of receivers covered by more than one transmitter as

$$\text{overlap}(T) = \sum_{r \in R} \text{overlapped}(r) \tag{7}$$

with

$$\text{overlapped}(r) = \begin{cases} 1, & |AS(r)| > 1 \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

where the active set $AS(r)$ represents the set of transmitters by which receiver r is covered.

D. Problem

The wireless transmitter placement problem in this paper is formally defined as an MO minimization problem

$$\min(f_1, f_2, f_3, f_4) \tag{9a}$$
$$f_1 = 1 - \text{coverage}(T) \tag{9b}$$
$$f_2 = \text{cost}(T) \tag{9c}$$
$$f_3 = \Delta\text{capacity}(T) \tag{9d}$$
$$f_4 = \text{overlap}(T). \tag{9e}$$

To minimize the four objectives, (9b) transforms the objective for maximum coverage into that for the minimum percentage of areas that are not covered, namely, $1 - \text{coverage}(T)$.

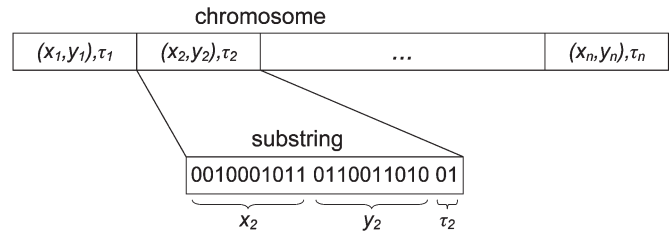

Fig. 2. Representation of chromosome and substring.

IV. Proposed Algorithm

Three issues should be taken into account when solving the wireless heterogeneous transmitter placement problem: the number of transmitters must be flexible, the transmitter infrastructure can be heterogeneous, and the problem solver must consider multiple objectives.

To address these issues, this paper presents a novel variable-length representation and variation operators and integrates them into an MO genetic algorithm based on NSGA II. The algorithm NSGA II [21] is known for its effectiveness in dealing with MO problems; in particular, Raisanen and Whitaker [20] validated that NSGA II performs best in comparison with SEAMO, SPEA2, and PESA on the antenna placement problem. This paper accordingly adopts NSGA II as the scheme for MO optimization. Additionally, the proposed representation and crossover facilitate varying chromosome length and information, i.e., the number, positions, and types of transmitters. Consequently, the proposed algorithm can automatically search for the appropriate number of transmitters and optimize the positions and types of transmitters for maximum coverage, minimum cost, maximum capacity satisfaction, and minimum overlap.

A. Representation

The candidate solution, viz., a set of transmitters T, is encoded into a chromosome. Each transmitter $t \in T$ is represented as a substring that consists of the position $\phi_t = (x_t, y_t)$ and its type τ_t. Fig. 2 presents a chromosome with n substrings, each of which is composed of 22 bits indicating the position (2×10 bits) and type (2 bits). Although the substring length is fixed, the chromosome length is variable since the number of substrings is variable.

B. Initialization

The proposed initialization procedure introduces a temporary upper bound $UB \in \mathbb{N}$, which is randomly generated, to initialize the number of substrings for a particular transmitter type. For instance, suppose two transmitter types exist $TP = \{\tau_1, \tau_2\}$, and their respective UBs are 2 and 3. When initializing a chromosome, the number of substrings (transmitters) for a certain type is randomly picked from $\{0, 1, \ldots, UB\}$, e.g., {0, 1, 2} for the first type τ_1. The corresponding position (x_t, y_t) of the transmitter is randomly generated afterward. Notably, the temporary upper bound UB is used only at population initialization. Section V-A shows that the performance of the proposed algorithm is insensitive to UB.

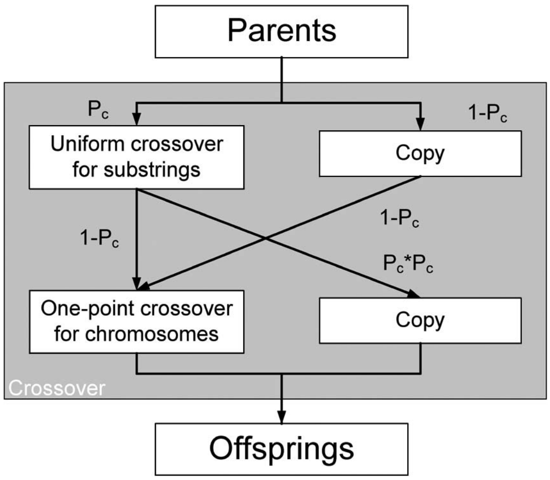

Fig. 3. Hybrid crossover.

C. Fitness Evaluation

The wireless transmitter placement problem is formulated as an MO problem that considers coverage, cost, capacity, and overlap of transmitter placement in this paper. For multiple objectives, this paper adopts the notion of dominance for fitness evaluation. An individual a is said to *dominate* individual b if a is better than b in one objective and not worse than b in all the other objectives. In this case, a is assigned a superior rank. If neither a nor b is dominant, the two individuals are said to *nondominate* each other and are given the same rank.

The proposed MO method is based on NSGA II [21]. Specifically, the proposed algorithm determines whether a chromosome survives or dies according to its rank and crowding distance. In the wireless transmitter placement problem, rank and crowding distance depend on a comparison of the four objectives.

D. Selection

Several methods have been developed for selecting parents in genetic algorithm (GA) [32]. Uniform selection picks chromosomes from the population with equal probability. In roulette wheel selection, the probability that a chromosome will be selected is proportional to its fitness. The tournament selection with tournament size k randomly picks k chromosomes to compete. The winner, i.e., the fittest picked chromosome, is reserved for crossover. This paper uses binary $(k = 2)$ tournament selection in the experiments for its accepted good performance [33].

E. Crossover

This paper devises a hybrid crossover method for the crossover of chromosomes and substrings. Let P_c be the crossover rate. The hybrid crossover has three ways of producing offspring (Fig. 3).

1) Perform only *uniform crossover for substrings* with a probability $P_c \times P_c$.
2) Perform only *one-point crossover for chromosomes* with a probability $1 - P_c$.

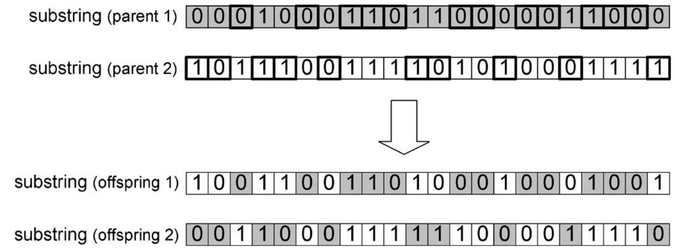

Fig. 4. Example of uniform crossover for substrings.

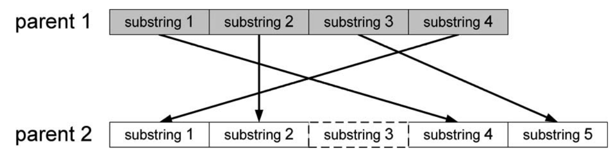

Fig. 5. Scheme of mapping substrings for applying the uniform crossover for substrings.

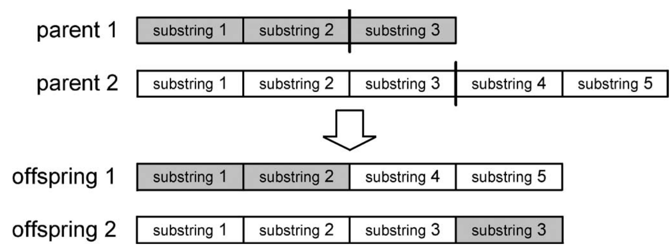

Fig. 6. Example of one-point crossover for chromosomes.

3) Perform both *uniform crossover for substrings* and *one-point crossover for chromosomes* with a probability $P_c \times (1 - P_c)$.

More precisely, a pair of parents has a probability P_c to only exchange the bits inside one substring, a probability $1 - P_c$ to exchange several substrings without modifying the bits in each substring, and a probability $P_c \times (1 - P_c)$ to exchange both bits and substrings. More details about the operation of these crossovers are given below.

1) Uniform Crossover for Substrings: The *uniform crossover for substrings* follows the operation of uniform crossover but limits the scope of the crossover to a substring rather than the whole chromosome. Fig. 4 presents an example of the crossover, where the bits of offspring are equiprobably inherited from parent 1 or parent 2. Notably, the crossover changes transmitter position and type.

A special scheme is developed to perform uniform crossover on chromosomes of different lengths. Fig. 5 illustrates this procedure. First, the lengths of both chromosomes are compared. In the example, parent 1 has four substrings, whereas parent 2 has five substrings. To deal with the unequal chromosome lengths, the shorter chromosome (parent 1) randomly maps its substrings to the longer chromosome (parent 2). The uniform crossover for substrings can then be performed on the four pairs of mapped substrings for parents 1 and 2.

2) One-Point Crossover for Chromosomes: Another crossover to apply is the *one-point crossover for chromosomes*. First, a chromosome is divided into two parts at a random point between substrings. Second, the two parts are exchanged with each other. Fig. 6 shows parent 1 exchanging its part

TABLE I
PARAMETERS OF THE PROPOSED GA IN THE EXPERIMENTS

Parameter	Value
GA-type	generational GA
representation	binary code
substring length	20 (benchmarks 1, 2, 3, 5)
	21 (benchmarks 4, 6)
selection	binary tournament selection
crossover rate P_c	0.9
mutation rate P_m	1/*substring_length*
population size	100
survivor	rank + crowding distance (NSGA II)
termination	500 generations (benchmark 1)
	5000 generations (benchmarks 2, 3, 4)
number of runs	30 runs per experiment

with parent 2. This strategy allows chromosomes to alter their lengths.

F. Mutation

All mutation operators for binary-coded GAs are applicable to the proposed algorithm. This paper adopts the bit-flip mutation with a mutation rate $P_m = (1/substring\_length)$; therefore, each bit has a probability of P_m to be flipped.

V. SIMULATIONS AND RESULTS

A series of simulations is conducted to evaluate the performance of the proposed algorithm. As mentioned, three issues must be resolved: 1) predetermining the number of transmitters or an upper bound is not needed, 2) the transmitters for placement can be homogeneous or heterogeneous, and 3) optimization simultaneously considers coverage, cost, capacity, and overlap.

Six benchmarks are designed for the simulations. Benchmarks 1–5 consider the objectives of coverage and cost, and benchmark 6 additionally takes capacity and overlap into account. The maps in benchmarks 1–4 are defined to have no obstacles; thus, the free space propagation model is used to measure the signal strength. Benchmarks 5 and 6 include obstructions, and the path loss due to obstructions is additionally considered. The grid resolution δ of the map is 0.1 m for benchmarks 1–4, 3 m for benchmark 5, and 1.76 m for benchmark 6. All the transmitters are assumed to be omnidirectional. The gains of transmitters G_t and receivers G_r are set to 1, and wavelength λ is 0.125 m. The threshold θ_r for all receivers is 0. Table I lists the parameters for the proposed algorithm.

A. Benchmark 1

Fig. 7 presents benchmark 1. In a 102.3×102.3 m^2 square, only one transmitter type exists and has a power radius of 37 m. In this benchmark, the optimal number of homogeneous transmitters is 4; Fig. 7 shows their optimal positions.

The proposed algorithm yields a series of nondominated results called *nondominated front* (or *Pareto front*). The nondominated fronts vary among the 30 trials. Hence, the frequency with which a certain cost occurs in the nondominated front and the statistics (average, standard deviation, minimum, and maximum) for the coverage associated with cost are considered.

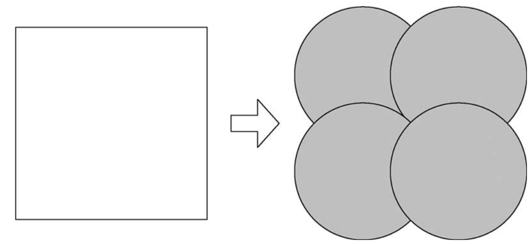

Fig. 7. Map of benchmark 1.

TABLE II
RESULTS OF A NONDOMINATED FRONT FROM 30 TRIALS OF THE PROPOSED ALGORITHM ON BENCHMARK 1 (FREQ: FREQUENCY, AVG: AVERAGE, STD: STANDARD DEVIATION, MIN: MINIMUM, MAX: MAXIMUM)

Cost		Coverage (%)			
#BS	Freq	Avg	Std	Min	Max
1	30/30	41.37	2.26E-14	41.37	41.37
2	30/30	71.07	3.51E-03	71.05	71.07
3	30/30	88.72	0.56	85.89	88.93
4	**30/30**	**99.40**	**1.77**	**93.00**	**100.00**
5	4/30	99.38	1.20	96.50	99.99
6	10/30	99.59	0.76	98.45	99.99

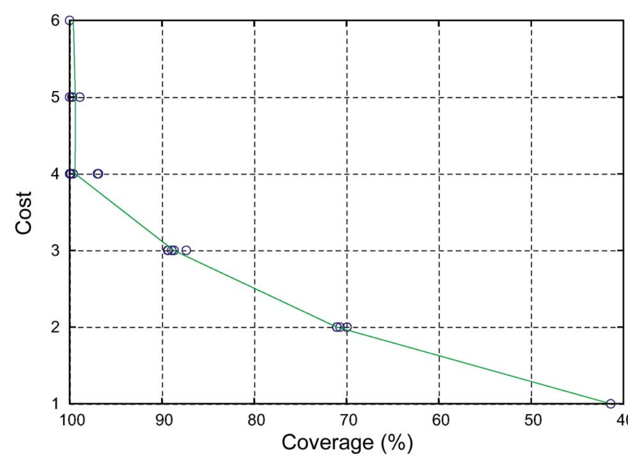

Fig. 8. Results of a nondominated front on benchmark 1. The circles depict the obtained nondominated solutions from a certain trial, and the green line depicts the average coverage for the respective cost.

Table II summarizes the results of nondominated fronts on benchmark 1, where cost is determined by the number of transmitters (#BS). Fig. 8 depicts the nondominated solutions obtained from 30 trials using the proposed algorithm and their averages with respect to each cost. Computational results indicate that the proposed algorithm always finds the optimal number of transmitters in the 30 trials. For the optimum $\#\text{BS} = 4$, the average coverage is 99.40%, and the best coverage is 100%, which is very satisfactory.

Another contribution of the proposed method is that no need exists to preassign the number of transmitters or its upper bound. Although population initialization introduces parameter UB, the computational results in Table III demonstrate that

TABLE III
AVERAGE COVERAGE (%) OVER 30 TRIALS FOR $UB = 3, 10, 50, 100$, AND 1000

#BS	UB=3	UB=10	UB=50	UB=100	UB=1000
1	41.37	41.37	41.37	41.37	41.11
2	70.49	71.07	70.90	70.49	70.87
3	89.27	88.72	89.08	89.27	89.05
4	99.46	99.40	99.97	99.46	99.92
5	99.59	99.38	99.66	99.59	100.00
6	100.00	99.59	100.00	100.00	100.00

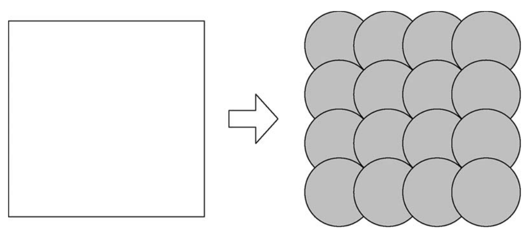

Fig. 9. Map of benchmark 2.

TABLE IV
RESULTS OF A NONDOMINATED FRONT FROM 30 TRIALS OF THE PROPOSED ALGORITHM ON BENCHMARK 2

Cost		Coverage (%)			
#BS	Freq	Avg	Std	Min	Max
10	30/30	89.37	1.58	84.52	90.90
11	28/30	92.26	1.14	89.14	93.21
12	29/30	94.33	1.02	91.21	94.95
13	30/30	95.65	0.78	93.31	96.38
14	12/30	97.04	0.90	95.08	97.82
15	23/30	97.45	0.53	96.69	98.08
16	**29/30**	**98.57**	**0.41**	**97.37**	**99.07**
17	27/30	99.12	0.55	97.96	99.66
18	20/30	99.57	0.54	97.94	99.84
19	11/30	99.71	0.17	99.20	99.80
20	5/30	99.54	0.75	98.20	99.90

the performance of the proposed algorithm is *not sensitive* to a UB: The difference in performance between different UB values (3–1000) is insignificant—the proposed algorithm can always achieve coverage exceeding 99% with four transmitters, regardless of the UB adopted.

B. Benchmark 2

Benchmark 2 uses the map of benchmark 1 but decreases the transmitter power for more transmitters, which renders benchmark 2 more difficult for placement optimization than benchmark 1. Fig. 9 shows that the power radius is reduced to 19 m; the other problem settings are the same as benchmark 1. The optimum is 100% coverage with 16 transmitters.

Table IV and Fig. 10 present the simulation results of a nondominated front in terms of coverage and cost. Generally, coverage increases as cost increases, i.e., the number of transmitters adopted increases. With the optimal number of transmitters at 16, the proposed algorithm achieves 98.57% coverage on average and 99.07% at best. Moreover, the proposed algorithm

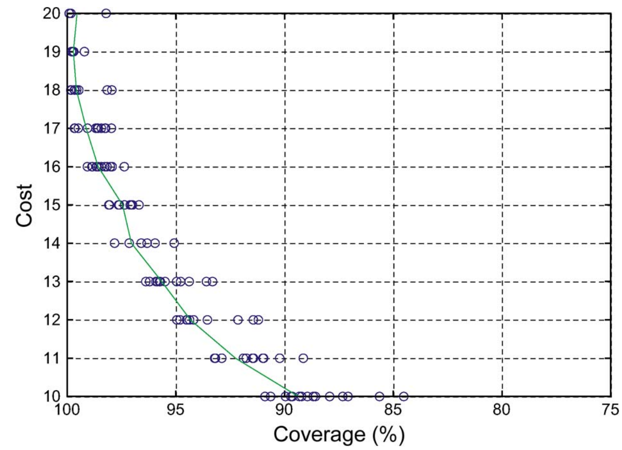

Fig. 10. Results of a nondominated front on benchmark 2. The circles depict the obtained nondominated solutions from a certain trial, and the green line depicts the average coverage for the respective cost.

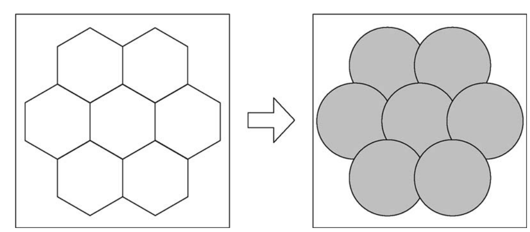

Fig. 11. Map of benchmark 3.

yields the optimal number of transmitters in 29 out of 30 trials, demonstrating its capability in finding the optimal number of transmitters. These simulation results further demonstrate the scalability of the proposed algorithm.

C. Benchmark 3

Benchmark 3 has a more complex geography than benchmarks 1 and 2 and is similar to the benchmark adopted by Park *et al.* [5], [6]. The *placement regions* PG are spread over the entire square $(102.3 \times 102.3\ \mathrm{m}^2)$, whereas the *covered regions* CG are seven identical hexagons with side lengths of 19 m inside the square (Fig. 11). The power radius of each transmitter is 19 m. Transmitters are of only one type with a cost of 1; that is, they are homogeneous. The optimal solution is 100% coverage with seven transmitters located at the centers of seven hexagons.

Table V and Fig. 12 show the simulation results of a nondominated front after 5000 generations. The proposed algorithm achieves 99.05% coverage on average and 99.91% at best with seven transmitters, which is a near-optimal solution. Of the 30 trials, the optimal number of transmitters is covered in the nondominated front 29 times, whereas the others are covered only five or nine times. This shows that the proposed algorithm finds the optimal number of transmitters effectively and robustly.

Compared with the approach of Park *et al.* [5], [6], the proposed algorithm overcomes the difficulty of tuning the weight w_t in the fitness function and the maximal number of transmitters K. Moreover, it produces a set of nondominated solutions

TABLE V
RESULTS OF A NONDOMINATED FRONT FROM 30 TRIALS OF THE PROPOSED ALGORITHM ON BENCHMARK 3

Cost		Coverage (%)			
#BS	Freq	Avg	Std	Min	Max
2	9/30	34.67	0.00	34.67	34.67
3	9/30	52.00	0.00	52.00	52.00
4	9/30	67.22	0.27	66.96	67.70
5	9/30	79.07	0.55	78.41	79.68
6	9/30	89.08	0.78	87.68	89.84
7	**29/30**	**99.08**	**1.26**	**95.25**	**99.91**
8	5/30	99.43	0.81	98.00	99.88
9	5/30	99.40	0.60	98.33	99.72

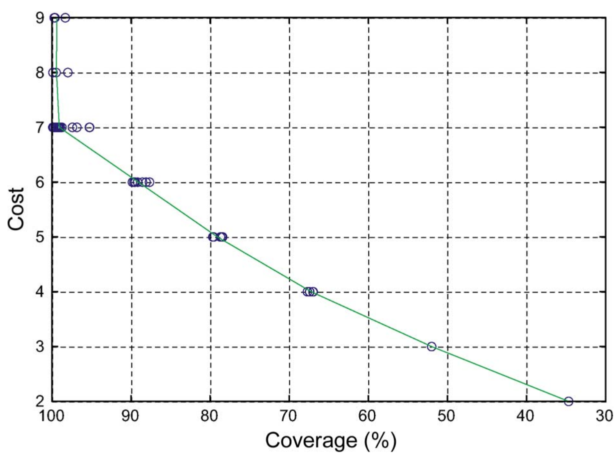

Fig. 12. Results of a nondominated front on benchmark 3. The circles depict the obtained nondominated solutions from a certain trial, and the green line depicts the average coverage for the respective cost.

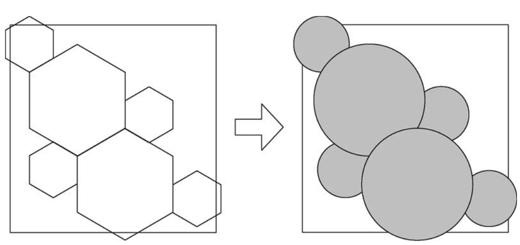

Fig. 13. Map of benchmark 4.

for combinations of coverage and cost rather than merging the two objectives into one via weighting. Hence, the proposed algorithm provides designers with increased flexibility when choosing placement. In terms of solution quality, this approach and that by Park *et al.* [5], [6] achieve coverage exceeding 99%. In summary, the proposed algorithm is flexible and capable of near-optimal solutions.

D. Benchmark 4

Benchmark 4 is a wireless heterogeneous transmitter placement problem. The benchmark has two transmitter types for placement. The first transmitter type has a power radius of 26.5 m and cost of 4. The second type has a power radius of 13.3 m and cost of 1. The map consists of a 102.3×102.3 m^2 square for placement regions and six hexagons for coverage regions, where the two large hexagons have side lengths of 26.5 m and the four small ones have side lengths of 13.3 m. Fig. 13 presents the optimal solution: 100% coverage with cost of 12 (two transmitters of the first type and four transmitters of the

TABLE VI
RESULTS OF A NONDOMINATED FRONT FROM 30 TRIALS OF THE PROPOSED ALGORITHM ON BENCHMARK 4

Cost				Coverage (%)			
Cost	#BS type one	#BS type two	Freq	Avg	Std	Min	Max
10	2	2	30/30	86.01	0.85	84.26	87.07
11	2	3	16/30	92.02	1.52	88.14	93.48
12	**2**	**4**	**29/30**	**98.21**	**2.00**	**93.17**	**99.90**
13	2	5	2/30	97.49	2.45	95.76	99.22
14	3	2	8/30	96.39	0.74	95.29	97.49
15	3	3	12/30	98.75	0.98	97.22	99.90
16	4	0	2/30	99.79	0.19	99.66	99.93
17	4	1	7/30	99.34	0.41	98.63	99.74
18	4	2	11/30	99.90	0.13	99.58	100.00
19	4	3	3/30	99.97	0.03	99.94	100.00
20	4	4	6/30	99.93	0.11	99.78	100.00

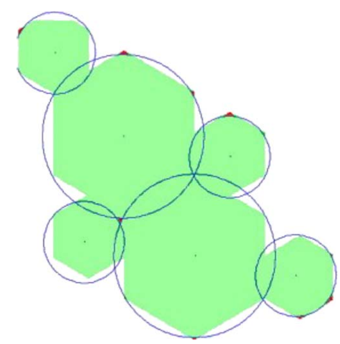

Fig. 14. Best result of transmitter placement for the proposed algorithm (99.90% coverage with cost 12) on benchmark 4, where green marks covered regions and red marks uncovered ones.

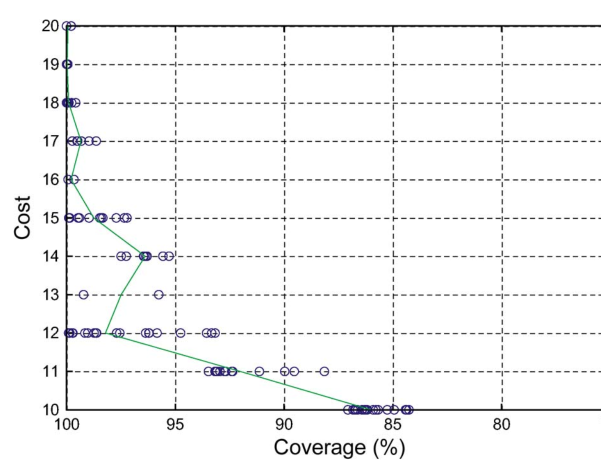

Fig. 15. Results of a nondominated front on benchmark 4. The circles depict the obtained nondominated solutions from a certain trial, and the green line depicts the average coverage for the respective cost.

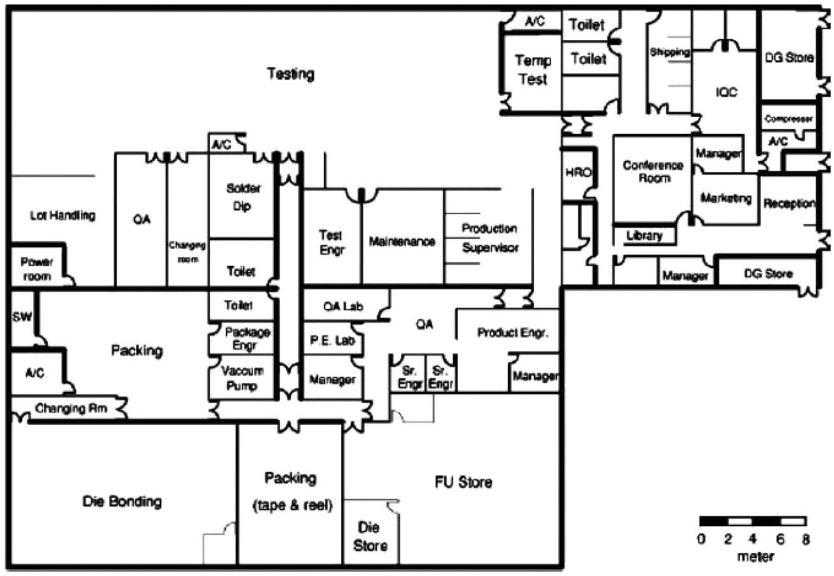

Fig. 16. Factory layout for benchmark 5 [24].

second type). The optimal positions for all the transmitters are at the hexagon centers.

In terms of chromosome representation, a substring has 21 bits owing to an additional bit for the transmitter type. The simulation results for cost and coverage (Table VI) demonstrate that the proposed algorithm achieves 98.21% coverage on average and 99.90% at best, corresponding to the optimal combination of transmitters (four of the first type and two of the second type). Fig. 14 shows the placement of transmitters for 99.90% coverage. These favorable outcomes verify that the proposed algorithm can effectively tackle the heterogeneous transmitter placement problem.

Fig. 15 depicts the nondominated solutions of the 30 trials using the proposed algorithm and their averages with respect to each cost. The irregular profile[1] reveals that high costs (e.g., costs of 13 and 14) do not necessarily achieve high coverage. This irregularity, arising from the heterogeneity of transmitters, complicates the combination of transmitters and makes the placement optimization very difficult. Experimental results show that the proposed algorithm effectively overcomes this difficulty and obtains near-optimal solutions.

E. Benchmark 5

Benchmark 5 is an indoor wireless transmitter placement problem based on the factory WLAN optimization problem [24]. The map contains obstructions with different penetration loss: thin partition, cement, and thickened cement wall (Fig. 16). The parameters and the path loss of these obstructions in our simulation follow those used in [24]. The transmitters are homogeneous, and all have a power radius of 20 m in the 2.4-GHz band.

Table VII summarizes the simulation results of a nondominated front after 5000 generations. The results show the general tendency that coverage increases as the adopted transmitter number increases. With six transmitters, the proposed algorithm always achieves 100% coverage out of the 30 trials. Fig. 17 shows that the resultant placement of the six transmitters is very adequate. These outcomes confirm the effectiveness of the proposed algorithm on this realistic placement problem.

TABLE VII
RESULTS OF A NONDOMINATED FRONT FROM 30 TRIALS OF THE PROPOSED ALGORITHM ON BENCHMARK 5

Cost		Coverage (%)			
#BS	Freq	Avg	Std	Min	Max
1	30/30	37.66	1.12E-14	37.66	37.66
2	30/30	59.74	2.26E-14	59.74	59.74
3	30/30	80.20	1.93E-01	80.09	80.52
4	30/30	93.93	7.85E-02	93.51	93.94
5	30/30	98.93	2.46E-01	98.27	99.13
6	**30/30**	**100.00**	**0.00**	**100.00**	**100.00**

F. Benchmark 6

Benchmark 6 is an outdoor wireless heterogeneous transmitter placement problem. The map of benchmark 6 is a real map (Fig. 18) sampled from Google Earth for a $1.8 \times 1.5\ \mathrm{km}^2$ division of the Kaohsiung city in Taiwan. The map includes a natural barrier (the Shou Mountain) and an artificial barrier (the Kaohsiung harbor). Transmitters cannot be placed in the regions of the mountain and harbor. In addition, the mountain has an altitude of 58 m, and no signal can penetrate the mountain; on the other hand, the harbor allows signals to pass through the region. There are three classes of data rate demands among a total of 3057 receivers: 2478 receivers of 16 kb/s, 420 receivers of 128 kb/s, and 159 receivers of 1024 kb/s. Simulating Wi-Fi and WiMAX networks, the benchmark has two transmitter types for placement. The first transmitter type has a power radius of 1500 m, a cost of 40 000, and a capability

[1]Some actual "dominated" solutions appear in Fig. 15 since the placement with cost 13, for example, may result in higher coverage than that with cost 12 and then become nondominated in some trials.

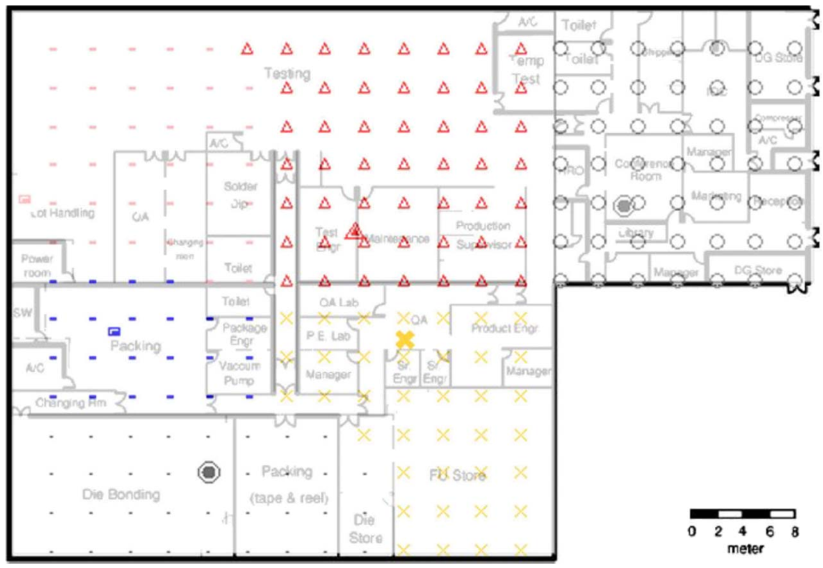

Fig. 17. Resultant placement of six wireless transmitters from the proposed algorithm for benchmark 5. The color symbols denote the coverage range of the respective transmitters.

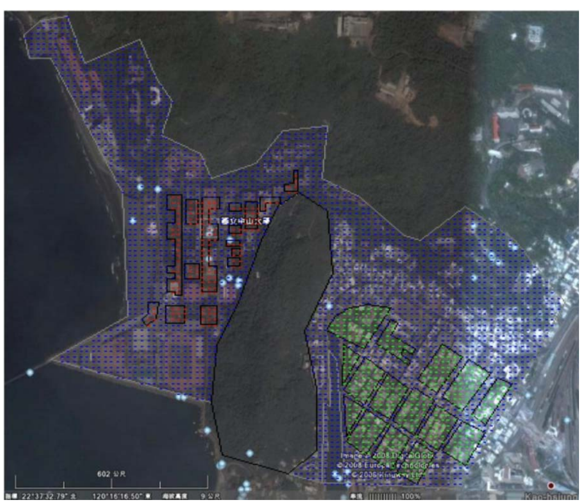

Fig. 18. Map of benchmark 6. The color points mark the receivers in different data rate demands (blue: 16 kb/s, green: 128 kb/s, red: 1024 kb/s).

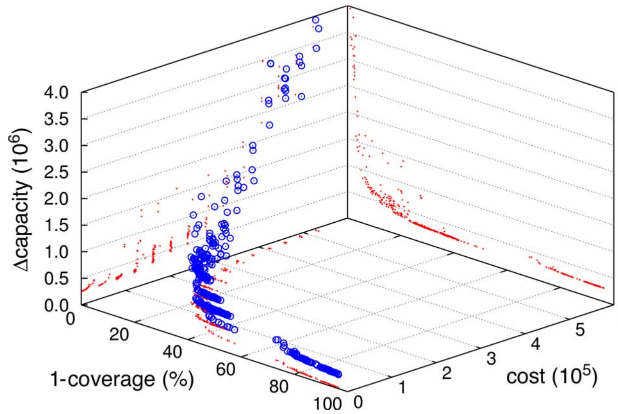

Fig. 19. Results on benchmark 6 in terms of coverage, cost, and capacity objectives. The blue circles denote the nondominated solutions, and the red points represent their projection onto 2-D plane.

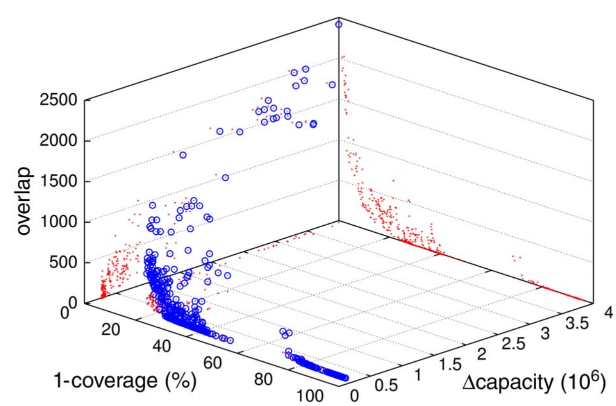

Fig. 20. Results on benchmark 6 in terms of coverage, capacity, and overlap objectives. The blue circles denote the nondominated solutions, and the red points represent their projection onto 2-D plane.

of 75 Mb/s. The second transmitter type has a power radius of 100 m, a cost of 2200, and a capability of 54 Mb/s.

Due to computation complexity, this paper conducts only one trial of the proposed algorithm using a population size of 500 with 2000 generations on benchmark 6. The simulation results in Figs. 19 and 20 demonstrate that the proposed algorithm can generate diverse solutions regarding the four objectives. Moreover, the results reveal the tradeoffs between coverage and the other three objectives (cost, capacity difference, and overlap increase with coverage). The other relationships, e.g., capacity versus overlap, are inconclusive. Fig. 21 plots the distribution and coverage of the solution that achieves 98.69% coverage using 12 first-type and two second-type transmitters. The figure verifies that the proposed algorithm considers the obstruction of signal transmission and the restriction for placement. It also validates that the resultant placement for the transmitters is very satisfactory for coverage, cost, capacity, and overlap.

G. Comparison With SO GA

This paper performed experiments to compare the performance of the SO and MO methods using both the proposed

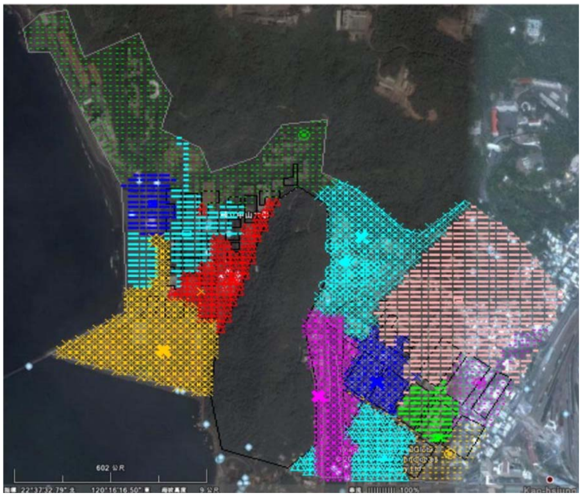

Fig. 21. Resultant placement of wireless transmitters from the proposed algorithm for benchmark 6. The color symbols denote the coverage range of the respective transmitters.

representation and the hybrid crossover. The elements of NSGA II—dominance ranking and crowding distance—are replaced with a weighted sum fitness function. The fitness functions for SO are the following:

- for benchmarks 1–4

$$\begin{aligned} f'(T) &= f_1 + \alpha \cdot f_2 \\ &= 1 - \text{coverage}(T) + \alpha \cdot \text{cost}(T) \end{aligned} \tag{10a}$$

- for benchmark 6

$$f'(T) = \sum_{i=1}^{4} \alpha_i f_i \tag{10b}$$

where α and α_i are the objective weights.

Table VIII(a)–(d) compares the nondominated front for the SO and MO methods on benchmarks 1–4. Since the MO method yields multiple results with different numbers of transmitters and the SO method produces only one result, for fairness, this paper compares the coverage of the MO method corresponding to the number of transmitters that is nearest the resultant number of the SO method. Experimental results indicate that the SO method achieves the optimal number of transmitters with coverage $> 95\%$, which depends upon the setting of α. This result reveals that a serious drawback exists when using SO methods for MO problems: performance is sensitive to the weight α, and identifying a suitable weight value requires an exhaustive effort. The MO method, conversely, overcomes this shortcoming by rendering a set of nondominated solutions for different combinations of coverage and cost. Furthermore, the MO method with comparable number of transmitters outperforms the SO method in terms of coverage in most test cases. In some cases, the coverage achieved by the MO method is less than that attained by the SO method. Such inferiority is partly due to the undervaluation of the compared number of transmitters for the MO method. For example, the SO method in benchmark 3 with $\alpha = 0.06$ has an average coverage of 92.40%, which is higher than the coverage of 89.08% achieved by the MO method using undervalued six transmitters, but lower than the coverage of 99.05% obtained using overvalued seven transmitters.

Moreover, we compare the performance for the SO and MO methods on benchmark 6, which is a four-objective optimization problem. For the SO fitness function, the values of the four objective functions are normalized to [0, 1]; in addition, this paper applies the Taguchi method [34] with four levels, i.e., 0.25, 0.5, 0.75, and 1.0 for each objective weight. Consequently, the experiment for the SO method includes 16 combinations of weights that follow Taguchi L'_{16} orthogonal array. Table VIII(e) presents the results with respect to the 16 settings for four objective weights. To compare the MO results with the SO ones, we adopt the best fitness values of the nondominated solutions obtained from the MO method. The experimental results show that there is no clear winner between the SO and MO methods on all the 16 combinations of weights. The MO method achieves better fitness than the SO method does on six out of eight combinations as $\alpha_1 \leq 0.50$, but worse on all eight combinations as $\alpha_1 > 0.50$. Fig. 22 depicts the nondominated front obtained from the MO method and the 16 solutions obtained from the SO method. The figure demonstrates that the SO method can lead to closer proximity to the true Pareto-optimal set than the MO method does. This outcome confirms that, as the number of objectives increases, the effectiveness of Pareto-ranking methods, like NSGA II, deteriorates due to the augmented likelihood of nondominance [35]–[37]. Although the SO method can keep the search ability for proximity, the limited range of results and the difficulty in choosing weights greatly detract from its utility.

In general, both SO and MO methods using the proposed hybrid crossover effectively deal with the wireless heterogeneous transmitter placement problem. Additionally, the MO method has the advantages of obtaining better results on two-objective benchmarks and broader results on all benchmarks than the SO method. Restated, the proposed MO method can achieve widespread coverage with various numbers of transmitters without suffering from sensitivity to the weights of objectives in the wireless transmitter placement problem.

VI. Conclusion

This paper has presented an MO variable-length genetic algorithm for solving the wireless heterogeneous transmitter placement problem. Specifically, representation and crossover were designed to fit the requirement of variable chromosome length. The representation supports the placement of heterogeneous transmitters. Furthermore, the MO scheme enables simultaneous optimization of coverage, cost, capacity, and overlap.

The proposed algorithm has the following advantages.

1) It automatically determines an appropriate number of transmitters for placement.
2) It deals with transmitter heterogeneity.
3) It simultaneously optimizes placement and considers multiple objectives.

In evaluating the proposed algorithm, simulations were conducted using six benchmarks, including homogeneous and

TABLE VIII
COMPARISON OF A NONDOMINATED FRONT FOR THE SO AND MO METHODS. BOLDFACE MARKS THE SUPERIOR RESULTS. (THE NUMBER #BS FOR THE MO METHOD CORRESPONDS TO THE NUMBER FOR THE SO METHOD). (a) BENCHMARK 1. (b) BENCHMARK 2. (c) BENCHMARK 3. (d) BENCHMARK 4. (e) BENCHMARK 6

(a)

α	Single-Objective				Multi-Objective		
	Cost (#BS)		Coverage (%)		Cost	Coverage (%)	
	Avg	Std	Avg	Std	#BS	Avg	Std
0.1	3.94	0.24	99.37	2.41	4	**99.40**	1.77
0.2	2.00	0.00	**71.99**	0.12	2	71.07	3.51E-03
0.3	1.14	0.57	**44.59**	18.35	1	41.37	2.26E-14
0.4	0.00	0.00	0.00	0.00			

(b)

α	Single-Objective				Multi-Objective		
	Cost (#BS)		Coverage (%)		Cost	Coverage (%)	
	Avg	Std	Avg	Std	#BS	Avg	Std
0.01	17.79	1.53	96.46	1.38	18	**99.57**	0.54
0.02	13.45	1.77	90.79	4.42	13	**95.65**	0.78
0.04	9.14	0.85	79.28	3.52			
0.06	6.97	0.72	68.64	4.74			
0.08	5.19	0.60	55.09	5.10			

(c)

α	Single-Objective				Multi-Objective		
	Cost (#BS)		Coverage (%)		Cost	Coverage (%)	
	Avg	Std	Avg	Std	#BS	Avg	Std
0.02	8.06	3.62	81.55	35.80	8	**99.43**	0.81
0.04	7.59	0.51	95.43	1.87	7	**99.08**	1.26
0.045	7.17	0.43	94.36	2.12	7	**99.08**	1.26
0.05	6.98	0.32	93.80	2.06	7	**99.08**	1.26
0.06	6.66	0.48	**92.40**	3.74	6	89.08	0.78
0.08	5.55	0.64	**84.42**	4.68	5	79.07	0.55

(d)

α	Single-Objective						Multi-Objective			
	#BS (type 1)		#BS (type 2)		Coverage (%)		Cost		Coverage (%)	
	Avg	Std	Avg	Std	Avg	Std	#BS (type 1)	#BS (type 2)	Avg	Std
0.01	3.99	0.10	0.22	0.56	99.13	0.32	4	0	**99.79**	0.19
0.02	3.63	0.56	0.89	1.51	98.16	1.70	4	1	**99.34**	0.41
0.03	2.02	0.14	3.07	0.76	**92.75**	3.77	2	3	92.02	1.52
0.04	1.56	0.83	1.79	1.08	68.92	36.91	2	2	**86.01**	0.85
0.05	2.00	0.00	1.89	0.58	85.15	4.17	2	2	**86.01**	0.85
0.06	1.70	0.46	1.78	1.18	77.03	7.51	2	2	**86.01**	0.85
0.07	1.03	0.17	2.21	1.10	61.61	10.68				
0.08	1.00	0.00	1.19	1.13	51.40	10.58				

(e)

Weights				Single-Objective					Multi-Objective				
α_1	α_2	α_3	α_4	Coverage	Cost	ΔCapacity	Overlap	Fitness	Coverage	Cost	ΔCapacity	Overlap	Fitness
0.25	0.25	0.25	0.25	78.97	120000	246016	18	**0.1302**	68.56	84400	296478	3	0.1397
0.25	0.50	0.50	0.50	67.84	82200	270288	14	0.3794	58.52	48800	268685	0	**0.1861**
0.25	0.75	0.75	0.75	43.54	40000	209904	0	0.2405	58.52	48800	268685	0	**0.2273**
0.25	1.00	1.00	1.00	41.74	40000	190832	0	0.2734	54.76	44400	259897	0	**0.2669**
0.50	0.25	0.50	0.75	67.19	82200	261168	22	0.3829	76.15	122200	319273	10	**0.2240**
0.50	0.50	0.25	1.00	78.05	120000	254256	0	**0.2456**	68.56	84400	296478	3	0.2616
0.50	0.75	1.00	0.25	64.54	80000	202928	46	0.3538	58.52	48800	268685	0	**0.3478**
0.50	1.00	0.75	0.50	67.88	82200	270256	14	0.3792	58.52	48800	268685	0	**0.3554**
0.75	0.25	0.75	1.00	78.38	120000	251296	4	**0.2713**	76.15	122200	319273	10	0.3048
0.75	0.50	1.00	0.75	78.97	120000	246016	18	**0.3460**	76.15	122200	319273	10	0.3846
0.75	0.75	0.25	0.50	79.13	120000	263424	19	**0.3577**	71.84	91000	311148	50	0.3797
0.75	1.00	0.50	0.25	79.46	120000	253952	38	**0.4306**	71.84	91000	311148	50	0.4384
1.00	0.25	1.00	0.50	83.15	160000	235696	55	**0.3211**	76.15	122200	319273	10	0.3819
1.00	0.50	0.75	0.25	85.28	160000	191920	150	**0.3619**	76.15	122200	319273	10	0.4218
1.00	0.75	0.50	1.00	78.93	120000	248064	18	**0.4307**	76.15	122200	319273	10	0.4667
1.00	1.00	0.25	0.75	80.05	122200	313120	19	**0.4706**	71.84	91000	311148	50	0.5018

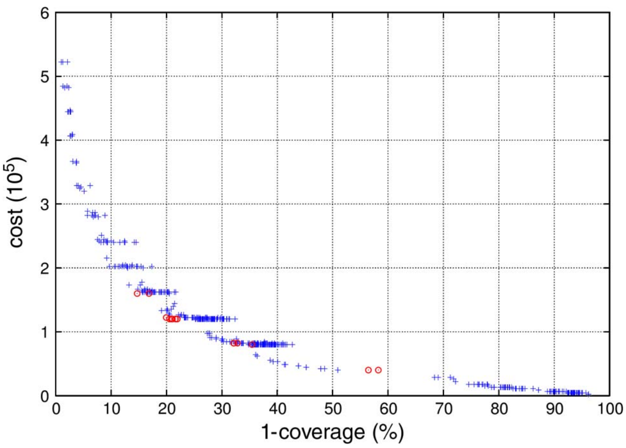

Fig. 22. Comparison of nondominated solutions for the SO and MO methods on benchmark 6 in terms of coverage and cost. The red circles denote the SO results, and the blue crosses denote the MO results.

heterogeneous transmitters. For all the benchmarks, the proposed algorithm yielded nondominated solutions that are very close to the optima in terms of coverage, cost, capacity, and overlap; precisely, it achieves higher than 98% coverage with an optimal number of transmitters on all six benchmarks. These experimental results validate the effectiveness of the proposed algorithm in dealing with the wireless heterogeneous transmitter placement problem.

Future work includes some directions. First, the proposed uniform crossover for substrings operates on a single substring at a time, which may not be efficient enough for large-scale problems that have long chromosomes. A possible way to address this issue is to extend the uniform crossover to operate on multiple substrings. Second, more complicated constraints and objectives should be taken into account in the problem model. Additionally, application to mobile networks is an important direction for future work. Third, the performance evaluation should include a comparison to other MO optimization algorithms, e.g., variable-length real jumping genes genetic algorithm (VRJGGA) [28]. Enhancement in the search ability of MO evolutionary algorithms [38], [39] will also be promising to improve the performance on the wireless heterogeneous transmitter placement problem with more than three objectives.

ACKNOWLEDGMENT

The authors would like to thank the reviewers and the Associate Editor for their valuable comments and suggestions, and C.K. Huang for help with the simulation of the last two benchmarks.

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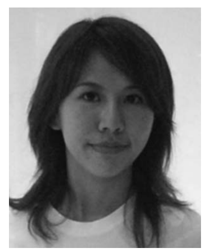

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