

MOEA/D-GO FOR FRAGMENTED ANTENNA DESIGN

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Abstract—In this paper, a hybrid multiobjective evolutionary algorithm, MOEA/D-GO (Multiobjective Evolutionary Algorithm Based on Decomposition combined with Enhanced Genetic Operators), is proposed for fragment-type antenna design. It combines the ability and efficiency of MOEA/D to deal with multiobjective optimization problems with the specific character of two-dimensional chromosome coding of genetic algorithm. And enhanced genetic operators are also introduced to generate new individuals. Numerical results of a set of six multiobjective 0/1 knapsack problems show that MOEA/D-GO with weighted sum decomposition approach outperforms original MOEA/D and MOEA/D-PR (MOEA/D combined with Path-Relinking operator). Then it's applied to optimize a CPW-fed monopole antenna to achieve band-notch characteristic. Both numerical and test results show that MOEA/D-GO is promising for solving multiobjective optimization problems about fragmented antenna.

1. INTRODUCTION

Nowadays, antenna design is more than a simple optimization problem because there are usually several antenna characteristics or specifications to be synthesized. Generally, such a design optimization can be stated as a multiobjective optimization problem (MOP)

$$\begin{aligned} & \text{minimize} \quad F(x) = (f_1(x), f_2(x), \dots, f_m(x)) \\ & \text{subject to} \quad x \in \Omega \end{aligned} \quad (1)$$

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where objective functions $f_i(x)$ ($i = 1, 2, \dots, m$) may represent different antenna characteristics. m is the number of objective functions, Ω a decision space, and x a decision variable which defines the antenna structure. For such a MOP, best trade-off for all m objectives can be achieved by optimal vectors distributed in PF (Pareto Front) [1].

In this paper, rather than considering continuous variables, we focus on a kind of special problems where variable is a 0/1 character string. As known in fragmented antennas, the physical shape can be described by a matrix where the cells “1” and “0” indicate metal and non-metal respectively. This kind of antenna is of great popularity due to flexible impedance matching for different integrated circuit chips and broad bandwidth characteristic in Radio Frequency IDentification (RFID) tag antenna [2, 3] and broadband characteristic in microstrip patch antenna and array element applications [4–6]. Meanwhile, this concept is employed to design reconfigurable aperture antenna and unit cell of fractal structure as a frequency selective surface [7, 8]. It’s also promising in terms of decreasing size of antenna, the design of new type antenna, and the design of anti-breakdown antenna by decreasing its radiation area [9–11].

Genetic algorithm (GA) is the most familiar method to optimize this kind of antenna [2–11] because of its coding representation for both discrete and continuous parameters. In addition, it can also search across a wide sampling of the solution space, and handle a large number of variables [12]. However, most researchers focus on single objective optimization problems (SOPs) rather than MOPs like (1). Though MOPs are considered [4, 13], few multiobjective optimization techniques are employed. In [4, 13], a MOP is aggregated into a SOP using a weight vector which corresponds to one search direction, which leads to much computation cost.

In 2007, Multiobjective Evolutionary Algorithm Based on Decomposition (MOEA/D) [14], was proposed for MOP. In MOEA/D, a MOP is decomposed into several scalar subproblems which can be optimized simultaneously. By utilizing the information of solutions of neighborhood subproblems, MOEA/D has less computational cost, which has been proved by several numerical tests [14–17].

MOEA/D-based optimization techniques have found successful applications in antenna and array design [18–21]. In [18, 19], MOEA/D was applied to a tri-band and a quad-band antenna design by optimizing structure parameters of a double-sided bow-tie antenna. In [20], MOEA/D was introduced to design broadband Yagi-Uda antennas to achieve maximum directivity, minimum voltage standing wave ratio, and maximum front-to-back ratio. In [21], MOEA/D was

used in linear antenna array optimization for minimum average side lobe level and null control in specific directions by optimizing the element spacing of the array.

This paper explores a highly-efficient multiobjective optimization technique based on MOEA/D-GO (multiobjective evolutionary algorithm based on decomposition combined with enhanced genetic operators) for the multiobjective optimization of fragmented-type antenna, in which enhanced genetic operators are introduced. Due to its relative high computation efficiency (in terms of diversity maintenance and evolution speed), MOEA/D-GO is very promising in the optimization design of fragmented antennas.

This paper is organized as follows. In Section 2, we propose MOEA/D-GO, and outline its features and its differences from original MOEA/D. Section 3 compares MOEA/D-GO with original MOEA/D and MOEA/D-PR (MOEA/D combined with Path-Relinking operator) [17]. In Section 4, a fragmented antenna design is performed by using our developed MOEA/D-GO.

2. MOEA/D-GO

2.1. MOEA/D-GO Implementation

The aggregated decomposition and the simultaneous optimization give the core idea of MOEA/D [14]. In MOEA/D implementation, a MOP is first decomposed into several scalar subproblems using weight vectors, where each scalar subproblem is a weighted aggregation of all individual objectives in (1). After decomposition, all scalar subproblems are optimized simultaneously. By taking the information from its neighboring subproblems, simultaneous optimization of those decomposed subproblems results in a low computational cost. MOEA/D-GO is based on the MOEA/D framework, as well as introducing our enhanced genetic operators.

Flowchart of MOEA/D-GO is shown in Fig. 1. During MOEA/D-GO implementation, enhanced genetic operators are utilized to generate a new solution as shown in Fig. 2.

An enhanced crossover operator, which simulates the simplest one-point crossover operator, in MOEA/D-GO operates as:

- (1) select two parents from neighborhood as a and c in Fig. 2 where a is the best individual in neighborhood and c is randomly selected, then crossover is performed among these two individuals and the individual b in the current subproblem;

- (2) randomly pick a matrix row/column number, and intercept the contents above/over and below/under this row/column with equal probability to form a new individual d .

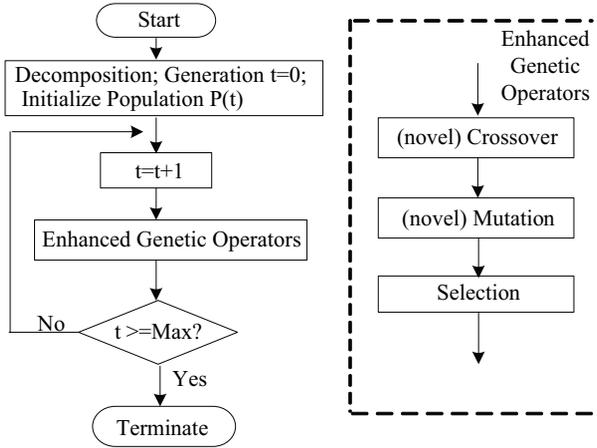


Figure 1. Flowchart of MOEA/D-GO.

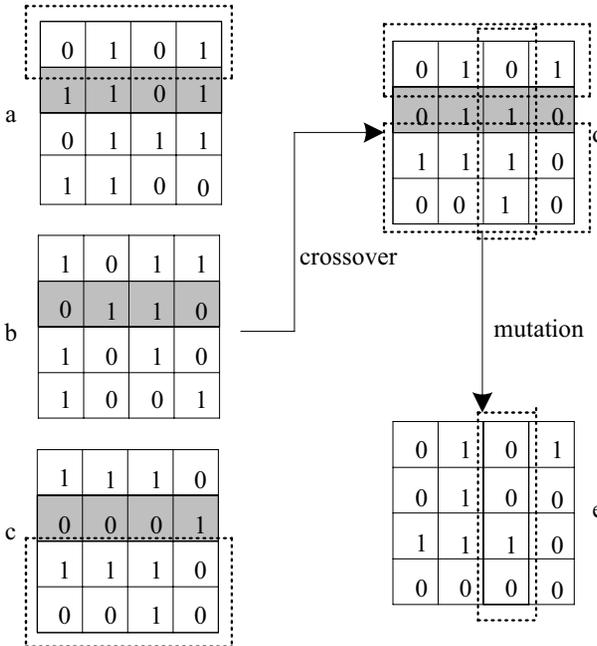


Figure 2. a: the best chromosome matrix in neighborhood; b: the chromosome matrix in current subproblem; c: a chromosome matrix from neighborhood; d: new chromosome matrix by novel crossover; e: new chromosome matrix by novel mutation.

Mutation operator operates as:

- (1) determine mutation times and mutation is performed on the newly-generated individual through the above crossover;
- (2) for each mutation, randomly select a row/column number, and vary gene value between “1” and “0” in this row/column with given probability to obtain individual e in Fig. 2.

2.2. Differences from Original MOEA/D

There are four differences between our proposed MOEA/D-GO and original MOEA/D in [14]:

- (1) coding representation: original MOEA/D and MOEA/D-GO operate on 1-D and 2-D 0/1 character string, respectively;
- (2) selection strategy: original MOEA/D randomly selects two parents from neighborhood, while MOEA/D-GO selects three parents from neighborhood, one of which is the best in its neighborhood, one is the individual belongs to corresponding subproblem, and another is selected randomly;
- (3) crossover operator: one-point crossover operator is applied to the two solutions in original MOEA/D, while one-point crossover operator is simulated among three parents in MOEA/D-GO;
- (4) mutation operator: the mutation mutates each position of the child solution in original MOEA/D, while the mutation mutates some rows and columns in MOEA/D-GO.

2.3. Features of MOEA/D-GO

In MOEA/D-GO, the best individual in neighborhood can be utilized to guide the global-search, which leads to faster convergence. And the crossover among three individuals reinforces the diversity. Therefore, MOEA/D-GO is expected to generate global optimum with better convergence and diversity than original MOEA/D in [14].

MOEA/D-GO introduces the ability and efficiency of MOEA/D for dealing with multiobjective optimization problems. Thus, it has all of the attractive features of MOEA/D framework as follows:

- (1) after decomposition, MOEA/D allows the use of selection operators, local search, fitness assignment, and diversity maintenance proposed for scalar optimization;
- (2) MOEA/D may directly control the movement of each individual in its population, and the distribution of its computation effort over different ranges of the PF along different search directions;
- (3) for certain MOPs with many objectives and large population, MOEA/D provides satisfactory search ability for complicated Pareto set shapes;

(4) objective normalization techniques can be incorporated into MOEA/D for solving disparately scaled objectives.

3. COMPARISON WITH ORIGINAL MOEA/D AND MOEA/D-PR

We compare the performances among MOEA/D-GO, original MOEA/D, and MOEA/D-PR on six test instances of the multiobjective 0/1 knapsack problem.

3.1. Multiobjective 0/1 Knapsack Problem

Given a set of n items and a set of m knapsacks, the multiobjective 0/1 knapsack problem (*MOKP_{n-m}*) can be stated as

$$\text{maximize } f_i(x) = \sum_{j=1}^n p_{ij} \cdot x_j \quad (i = 1, 2, \dots, m) \quad (2)$$

$$\text{subject to } \sum_{j=1}^n \omega_{ij} \cdot x_j \leq c_i \quad (i = 1, 2, \dots, m)$$

$$x = (x_1, x_2, \dots, x_n)^T \in \{0, 1\}^n$$

where $p_{ij} \geq 0$ is the profit of item j in knapsack i . $\omega_{ij} \geq 0$ is the weight of item j in knapsack i , and c_i is the capacity of knapsack i . $x_i = 1$ means that item i is selected and put in all the knapsacks. In this paper, six widely used test instances of the above problem [22] have been used in testing MOEA/D-GO.

3.2. Test Setting

Population and neighborhood size (N , T in [14]) of these three algorithms, minimal hammming distance ε , and ratio to apply path relink γ in MOEA/D-PR [17] are listed in Table 1. In this paper, both weighted sum and Tchebycheff decomposition approaches are used. Each of them is run 20 times for each test instance. In addition, initial population is produced randomly and greedy repair method [23] is employed to deal with constrain in (2). Transformation from 1-D to 2-D 0/1 character string is made.

3.3. Test Results

To make comparison with original MOEA/D and MOEA/D-PR, inverted generation distance (IGD) metric is used [14]. Let P^* be

Table 1. Common parameters.

n	m	$N(H)$	T	ε	γ
250	2	150 (149)	10	6	0.8
500	2	200 (199)	10	6	0.8
750	2	250 (249)	10	6	0.8
250	3	351 (25)	10	6	0.8
500	3	351 (25)	10	6	0.8
750	3	150 (149)	10	6	0.8

a set of uniformly distributed points in the objective space along the PF, and P be an approximation to the PF. The IGD from P^* to P is defined as

$$IGD(P^*, P) = \frac{\sum_{v \in P^*} d(v, P)}{\|P^*\|} \tag{3}$$

where $d(v, P)$ is the Euclidean distance between v and the points in P . If $\|P^*\|$ is large enough to represent the PF very well, IGD metric can measure both the diversity and convergence of P in a clear sense. In order to have a low value of IGD, set P must be very close to the PF and can not miss any part of the whole PF. In this paper, all of the non-dominated solutions generated by the tested algorithms after 20 runs are utilized to approximate P^* . Table 2 presents both the mean and standard deviation of IGD-metric of the final solutions obtained

Table 2. Mean and standard deviation (Std.) of the IGD-metric values of the final populations for different tests.

Instance	Value-Type	MOEA/D-GO	MOEA/D	MOEA/D-PR
<i>MOKP_250_2</i>	Mean	0.0197 (0.0145)	0.0228 (0.014)	0.0233 (0.0093)
	Std.	0.0023 (0.0014)	0.0027 (0.0014)	0.0035 (0.0014)
<i>MOKP_500_2</i>	Mean	0.0127 (0.0187)	0.0196 (0.0217)	0.0181 (0.0064)
	Std.	0.0014 (0.0018)	0.0028 (0.0017)	0.0023 (0.0008)
<i>MOKP_750_2</i>	Mean	0.0125 (0.0278)	0.0208 (0.0331)	0.0171 (0.0055)
	Std.	0.001 (0.0018)	0.0025 (0.0014)	0.0021 (0.0012)
<i>MOKP_250_3</i>	Mean	0.0501 (0.067)	0.0561 (0.0663)	0.0547 (0.0522)
	Std.	0.0012 (0.0021)	0.0023 (0.0024)	0.002 (0.0012)
<i>MOKP_500_3</i>	Mean	0.0421 (0.0699)	0.049 (0.072)	0.043 (0.048)
	Std.	0.0013 (0.0019)	0.0015 (0.0025)	0.0016 (0.0014)
<i>MOKP_750_3</i>	Mean	0.0307 (0.0731)	0.0436 (0.078)	0.0356 (0.0436)
	Std.	0.0009 (0.0029)	0.0015 (0.0026)	0.0014 (0.0014)

by each algorithm with weighted sum approach and with Tchebycheff decomposition approach (in parentheses) for each test instance. Small mean and small standard deviation of IGD-metric reflect good diversity and stability respectively.

From Table 2, it is observed that the diversity of MOEA/D-GO with weighted sum approach is better than original MOEA/D and MOEA/D-PR in all instances, while that with Tchebycheff approach is worse than others in all instances. And the same results on stability happened except *MOKP_250_2*. It's noteworthy that MOEA/D-GO with weighted sum approach works better than MOEA/D-PR with Tchebycheff approach in all 3-objective instances.

Figure 3 presents the evolution of the average IGD-metric value of the current population to P^* with the number of generation in each

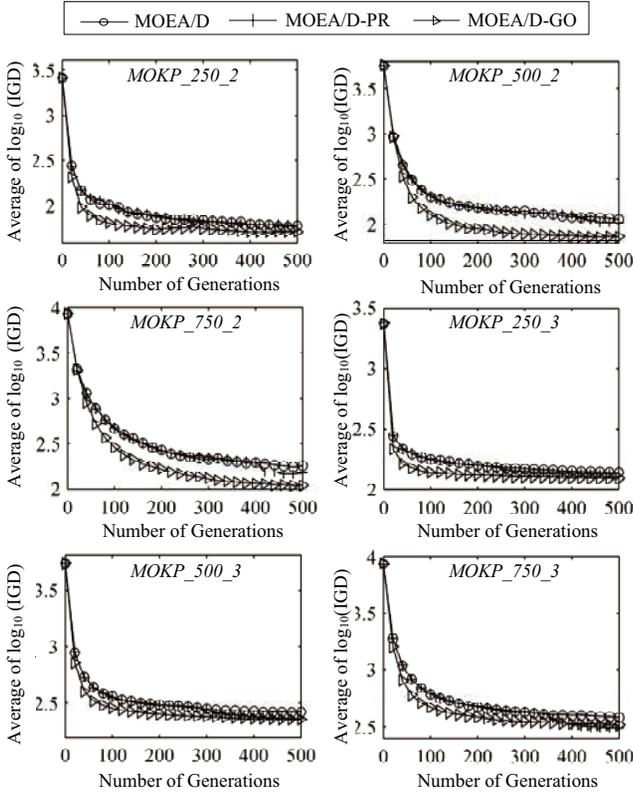


Figure 3. Evolution of IGD-metric values in original MOEA/D, MOEA/D-PR, and MOEA/D-GO with weighted sum approach for each test instance.

algorithm with weighted sum approach for each test instance, which can reflect evolution speed.

From Fig. 3, it is observed that MOEA/D-GO converges faster than original MOEA/D and MOEA/D-PR for all instances.

Therefore, it can be concluded that MOEA/D-GO with weighted sum approach works better in terms of diversity and convergence than original MOEA/D and MOEA/D-PR with weighted sum approach in solving two and three objectives instances. For 3-objective MOKPs, MOEA/D-GO with weighted sum approach performs best among these six algorithms. It is the reason for that MOEA/D-GO with weighted sum approach is only considered in the following.

4. FRAGMENTED ANTENNA DESIGN WITH MOEA/D-GO

A CPW-fed planar circular monopole antenna is proposed for ultra wideband wireless communications in [24]. This kind of antenna is optimized to operate at 3.1 GHz–10.6 GHz with 6.0 GHz–7.2 GHz being notched by discretizing the radiation part using MOEA/D-GO.

Structure of the CPW-fed fragmented antenna is shown in Fig. 4, which is printed on a 2.54 mm thick TP-2 substrate with relative dielectric constant $\epsilon_r = 6.15$. Structure parameters are like those in [24], that is, $(W, L, W_0, L_0, h, g, d) = (42 \text{ mm}, 75.35 \text{ mm}, 20.23 \text{ mm}, 25 \text{ mm}, 0.35 \text{ mm}, 1.04 \text{ mm}, 0.25 \text{ mm})$. We fix $(W_0, L_0) = (21.04 \text{ mm}, 12.2 \text{ mm})$. Therefore, radiation part is sub-

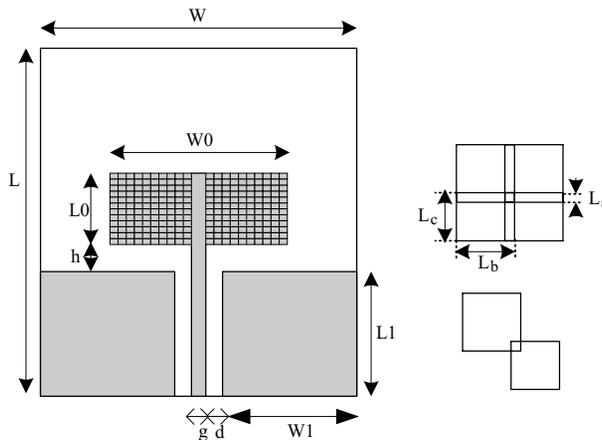


Figure 4. Geometry of a CPW fed fragmented antenna.

divided into 12×20 cells ($L_b = L_c = 1.2$ mm), with overlapped length $L_a = 0.2$ mm to ensure electrical contact in such constellations to reduce loss like in [4].

4.1. MOP for Fragmented Antenna Design

In terms of the conventional 10 dB return loss requirement, the MOP objective functions in (1) can be specified as

$$f_i(x) = \max \left(10 - \min_{f \in [f_{i1}, f_{i2}]} S_{11}, 0 \right) \quad (i = 1, 2) \quad (4)$$

$$f_3(x) = \max \left(\max_{f \in [f_{31}, f_{32}]} S_{11} - 10, 0 \right) \quad (5)$$

where $[f_{i1}, f_{i2}]$ ($i = 1, 2$) in (4) characterizes operation bands, and $[f_{31}, f_{32}]$ in (5) characterizes notched band. S_{11} (dB) is the corresponding return loss of the antenna.

4.2. Optimization Results

In this paper, each function evaluation in (4) and (5) is realized by means of the simulation of Ansoft HFSS 13.0. It takes about eight days for a PC with Intel Core 2@2.99 GHz to solve this MOP after 42 generations with MOEA/D-GO-based optimization for the fragmented antenna design. Optimal design and its prototype have been fabricated as shown in Fig. 5. The dashed line in Fig. 5 shows the original circular radiation patch with $R = 10$ mm in [24].

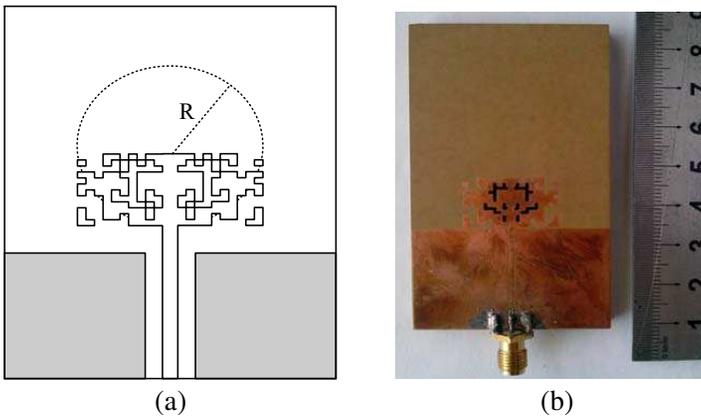


Figure 5. (a) Optimal design, (b) photograph of the fabricated antenna.

The simulated and measured return losses of the prototype antenna are shown in Fig. 6. The return loss was measured by using Agilent E8362B network analyzer. In Fig. 6, points ‘a’ to ‘d’ mark frequencies of 2.92 GHz, 5.98 GHz, 7.29 GHz, and 11.05 GHz, respectively, which characterize the four frequencies in the simulated return loss, while points ‘A’ to ‘D’ mark frequencies of 3.06 GHz, 6.0 GHz, 7.36 GHz, and 11.14 GHz, respectively, which characterize

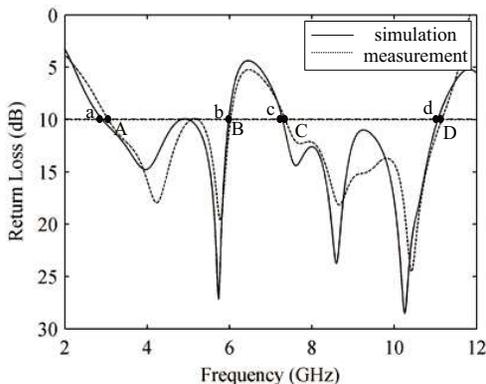
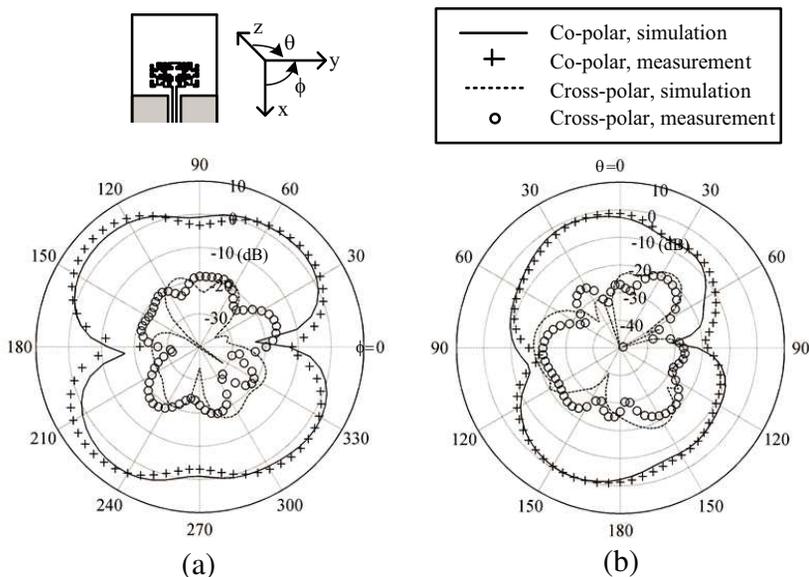


Figure 6. Simulated and measured return loss of the antenna.



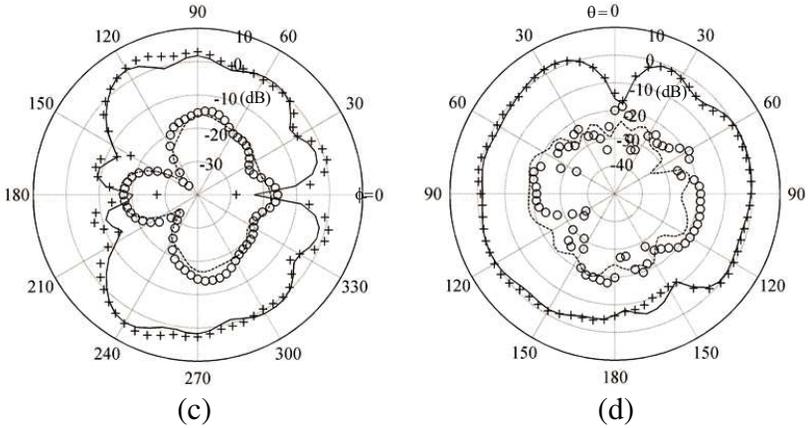


Figure 7. (a) 4.4 GHz, E -plane (xoy), (b) 4.4 GHz, H -plane (xoz); (c) 9.1 GHz, E -plane (xoy), (d) 9.1 GHz, H -plane (xoz).

the four frequencies in the measured return loss. The simulated and measured gain patterns are shown in Fig. 7. And the simulated and measured gain at 4.4 GHz are 4.32 dB and 4.46 dB respectively. The simulated and measured gain at 9.1 GHz are 3.06 dB and 3.57 dB.

From Figs. 6 and 7, it's found that the measurement results agree well with the simulation results of the optimized fragmented antenna. A little offset occurs probably due to fabrication and measurement error. Therefore, MOEA/D-GO works well for this kind of fragmented antenna design.

5. CONCLUSION

A hybrid multiobjective evolutionary optimization algorithm, MOEA/D-GO, for the synthesis of the fragmented aperture antennas is demonstrated. Enhanced genetic operators are introduced to generate new individuals. Numerical results on test instances show that MOEA/D-GO with weighted sum decomposition approach works better in terms of diversity and convergence than original MOEA/D and MOEA/D-PR with weighted sum approach in solving two and three objectives instances. For 3-objective MOKPs, MOEA/D-GO with weighted sum approach performs best among these six algorithms. Then it is applied to optimize CPW-fed fragmented monopole antenna to achieve band-notched characteristic. Simulated and measured results show the potential of MOEA/D-GO for this kind of antenna.

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