

Research Article

A New Jumping Genes Paradigm for an E-Shaped Folded Patch Feed Antenna Design

S. H. Yeung and K. F. Man

Received 14 June 2007; Accepted 3 August 2007

Recommended by K. Yazdandoost

A novel evolutionary computing algorithm, namely, jumping genes evolutionary algorithm (JGEA) is used for the optimization of antenna designs. This scheme incorporates with a multiobjective strategy that enables the gene mobility within the same chromosome, or even to a different chromosome. This type of horizontal gene movement causes the genes to find the suitable locations to achieve the necessary building blocks in such a way that the quality of nondominated solutions and/or the Pareto-optimal solutions can be enhanced. This new scheme is robust and provides outputs in speed and accuracy. It also generates a range of widespread extreme solutions. The design of an E-shaped patch antenna was adopted for the purpose of design demonstration. An antenna structure with 91% impedance bandwidth for a frequency range of 3.6–9.6 GHz was selected amongst the nondominated solutions set for the hardware fabrication. Its measured performances both for impedance bandwidth and frequency range were in good agreement with the simulated solution. The cross-polarized field was found to be small in comparison, and the copolarized field can sustain the broadside radiation pattern over the frequency band. This methodology of optimization can be of an alternative approach for antenna design.

Copyright © 2007 S. H. Yeung and K. F. Man. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

1. INTRODUCTION

Today, radio spectrum congestion and the need for an ever-increasing bandwidth have placed stiffer requirements on antenna designs. Demand for mobile communications, on one hand, and cellular broadcasting, on the other hand, have pushed radio communications, first, into microwave and, later, into millimeter waves region. An effective antenna design is, therefore, gaining its importance for the already limited frequency usage.

Currently, the fabrication of a microwave antenna is conducted manually after computational simulation. Through trial and error, the improved version of a prototype that meets the design requirement will be adopted as the final design [1]. However, this classical method of antenna design is obviously human dependent. It relies on the ability and experience of the design specialists.

As the requirements for antenna design are getting more and more complicated in nature, this way of antenna design has become inefficient and sometime impossible to achieve, particularly when the antenna structure is complex and comprises of abundant number of parameters. To make matters worse, even with the help of some optimization methods, the obtained solution is usually a suboptimal one due to the complexity of the electromagnetic (EM) nature.

Recently, genetic algorithm (GA) [2–7] has been used widely for optimizing RF or microwave designs. GA is now affirmed as a robust, stochastic search method based on the concept of natural selection. As an optimizer, its powerful heuristic characteristic is an effective means for solving complex and correlative problems that could be non-deterministic and probabilistic transitional in nature [8].

The commonly desirable antenna characteristics in terms of gain requirement, cross-polarization, and specific bandwidth are inequitably sought these days. These are stringent requirements. To achieve all the goals from a simple antenna is not easy, but the trend of applying GA with incorporation of multiobjective scheme [4, 5] for searching the right solutions [9] has been very promising.

This paper proposed a new computationally genetic operation named as “jumping gene (JG) transposition” for evolutionary algorithms (EA) and, more importantly, for MOEAs [4] in particular. It comprises a simple operation that mimics the jumping gene phenomenon that was firstly discovered by the Nobel laureate Barbara McClintock from her work on corn plant [10].

The adaptation of gene transposition is a relatively new approach for evolutionary computing. To the best of authors' knowledge, there are very few reports on this topic that can be found. Nonetheless, the analyses for some related work

[11, 12] and some real world applications of JG [13–17] have recently been reported including antenna design [18].

The implementation of JGEA for the optimization of an E-shaped folded patch antenna [19] is presented in this paper. The organization is as follows: Section 2 will show the jumping genes paradigm, including the operational mechanisms for the jumping gene and the use of Pareto-optimal in the multiobjective ranking. Then the design of an E-shaped folded patch antenna using JGEA will be presented in Section 3. An alternative optimization methodology, non-dominated sorting particle swarm optimization (NSPSO) is focused in Section 4, and its performance will be compared to JGEA. Finally, a conclusion will be given in Section 5.

2. JUMPING GENES PARADIGM

JGEA [15–18] is a novel evolutionary algorithm for multiobjective optimization. It introduces a new genetic operator using a horizontal gene transmission mechanism, that is, jumping genes transposition. It enables the genes transfer between the individuals within the same generation. The advantage of using JGEA is its ability in obtaining a set of nondominated solutions that is close to Pareto optimal front. Its capacity for achieving a better performance both in convergence and diversity over the other MOEA has been thoroughly explored and exploited based on some well-defined benchmark both constrained and unconstrained mathematical functions [15], also for real world application in [16, 17].

The important measures for any MOEA are their performance in convergence and diversity. The effects of convergence will safe guide the accuracy of the non-dominated solutions. This can be examined by the measure of closeness in distance between the obtained nondominated solutions and Pareto-optimal front. As for the diversity, it is a measure of the spread of nondominated solutions along the Pareto-optimal front. The wider of the spread, the better would be the diversity of the nondominated solutions. As reported in [15], JGEA has its uniqueness in these two areas of optimization, which is aptly sought by antenna designers. A flowchart of JGEA operation is shown in Figure 1.

The JGEA has two basic JG transposition operations. These are cut-and-paste transposition and copy-and-paste transposition. Figure 2 shows the cut-and-paste transposition among the same and different chromosomes. It is an action that the element in the chromosome is cut from an original position and then pasted into a new position of its own or another chromosome. It emulates the fact that a path is now opened through the landscape of an incomprehensibly large number of chromosome changes [20]. It is a more efficient strategy for creating and trying out new genes than a chromosome that can make random element changes in random places [15].

Figure 3 shows the copy-and-paste transposition among the same and different chromosomes. In this form of transposition, the element will replicate itself and be inserted into a new position of the chromosome while keeping the original position unchanged. It enhances the possibility of merging the various types of genes together that eventually benefit the phenotypic shaping of chromosome. The repeating se-

quences from chromosome provide a more focused strategy for genetic exploration instead of wandering from random changes [20].

The operation of cut-and-paste or copy-and-paste transposition is determined by a certain probability, namely, the jumping rate. Since each transposition selection is opportunistic, jumping process is not streamlined or planned in advance. Therefore, the jumping process is similar to other genetic operations (crossover and mutation) that are operated on the basis of opportunity. A thorough study in this aspect of JGEA is given in [15–17].

To handle the optimization problem with multiple objective functions, the Pareto ranking strategy [3, 4] is applied in JGEA. The obtained solutions are projected in the objective space, and the Pareto dominance principle is applied to rank the solutions. Suppose it is an n -objective minimization problem, a solution u is dominated by another solution v if

$$\begin{aligned} F_i(u) &\geq F_i(v), \quad \forall i = 1, 2, \dots, n, \\ F_j(u) &> F_j(v), \quad \exists j = 1, 2, \dots, n, \end{aligned} \quad (1)$$

where $F_i(u)$ and $F_i(v)$ denote the i th optimization objective of the solution u and v , respectively. A solution is said to be nondominated if there is no feasible solution in the search space that dominates it [4]. Therefore, a solution belonging to the Pareto front is optimal in the sense that there exists no other design that is better with respect to all design goals. In other words, such a solution can be improved with respect to one goal, only, by degrading its performance with respect to another. It should be stated that the computational process in determining the ranking of all chromosomes used in JGEA adopts the fast nondominated sorting [5]. A selected solution from the JGEA nondominated solutions set is implemented into the antenna design as described in the following sections.

3. E-SHAPED PATCH ANTENNA OPTIMIZATION

3.1. Antenna design

Microstrip patch antenna is very popular for wireless communication devices as it comprised the advantages of low profile, lightweight, and low cost. The E-shaped patch antenna is capable of achieving wide impedance bandwidth [19, 21, 22]. However, its bandwidth capacity can be further enhanced if its parameters can be appropriately optimized. The application of JGEA for optimizing the folded patch antenna configuration [19] is an illustrative design that can fulfill the necessary design requirements.

In this section, the optimization of the E-shaped wide-band patch antennas with folded patch feed [19] using JGEA is discussed. Its physical configuration is shown in Figure 4. The antenna is mounted in the middle of a square ground plane. The E-shaped patch is made of a 0.3 mm copper plate. One edge of the patch is connected to the ground by a shorting wall, with a height h from the ground. A portion of the other edge is folded as shown in Figure 4. A coaxial feed with diameter 1 mm is connected to the folded part with a probe offset p_o and a height h_f from the ground plane. All the antenna parameters (including l , l_e , l_f , w , w_e , p_o , h , and h_f)

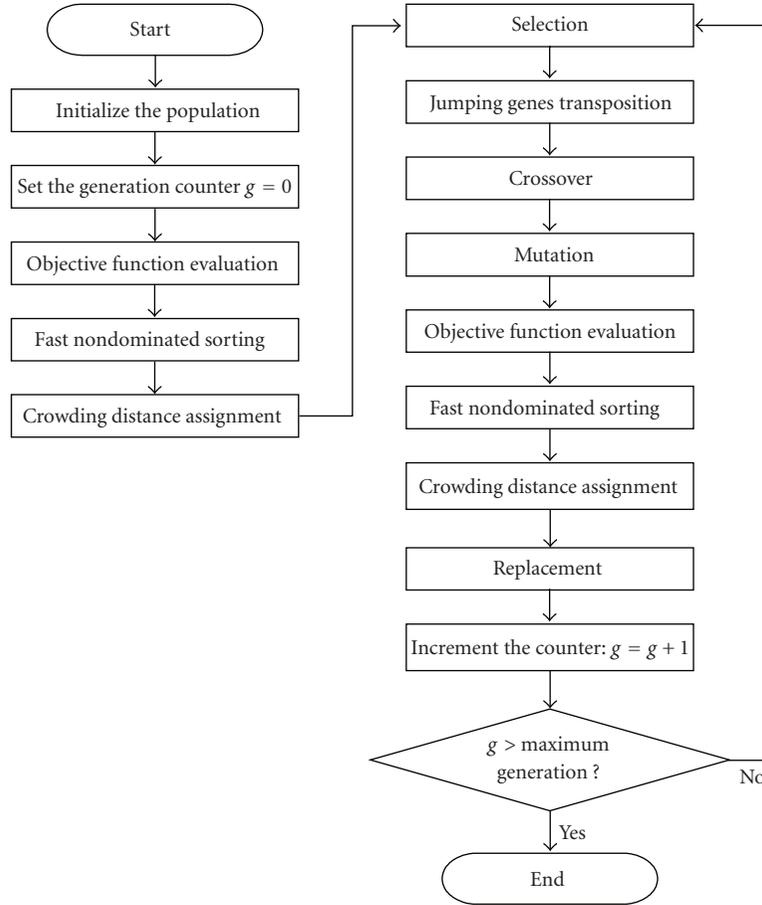


FIGURE 1: Flowchart of jumping gene paradigm.

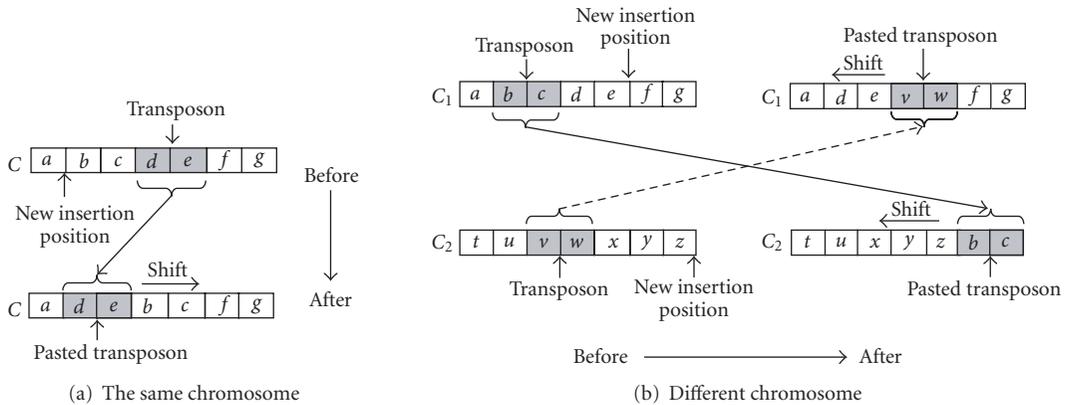


FIGURE 2: Cut-and-paste transposition.

are appropriately labeled in the figure. The profile of the antenna, not including the finite ground plane, is defined by its outer dimensions length $l \times$ width $w \times$ height h (mm^3).

To start the JGEA optimization process, the chromosome gene representation, as well as its association with the real antenna dimensional parameters, is stated in Table 1. All genes are floating points coded in the range between 0 and 1. It

should be mentioned that the antenna profile ($l \times w \times h$) is optimized within the confined range from $(1 \times 1 \times 1)$ to $(20 \times 20 \times 10)$ mm^3 . The maximum values of folded patch lengths l_e and l_f , width w_e , and height h_f of the folded patch part are limited by the outer patch length l , width w , and height h , respectively. These genes are encoded as the function of outer parameters to prevent the constraint violation

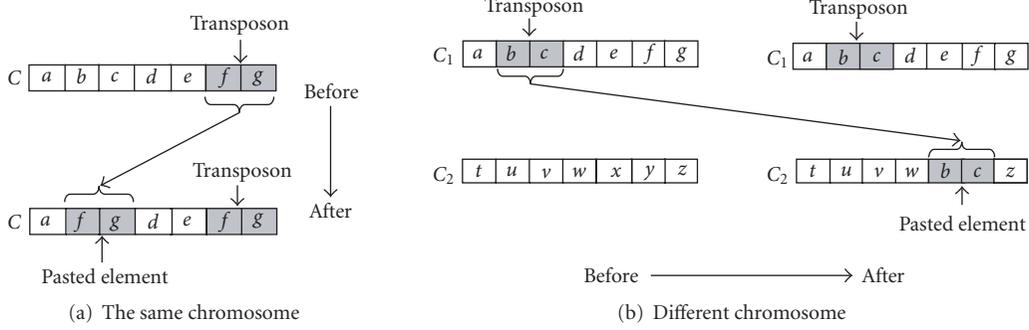


FIGURE 3: Copy-and-paste transposition.

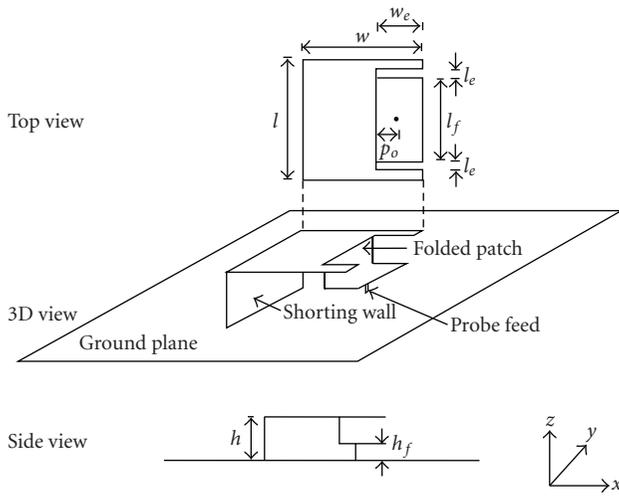


FIGURE 4: Configuration of E-shaped folded patch antenna.

on the physical size. Two optimization objectives are defined in the JGEA optimization:

$$F_1 = \min \left(\frac{\sum_{f=3\text{GHz}}^{9\text{GHz}} \text{VSWR}}{\sum_{f=3\text{GHz}}^{9\text{GHz}} \text{number of frequency points}} \right), \quad (2)$$

$$F_2 = \min (l \times w \times h).$$

The objective function F_1 is to ensure the average VSWR throughout the overall range of frequency band to be optimized, while F_2 is to enforce a patch antenna profile to be a minimum. The multiobjective optimization scheme stated in Section 2 would then be applied.

To calculate the average VSWR in a frequency band, a resolution of 0.1 GHz is used. Hence, totally, there are 61 frequency points considered: 3.0, 3.1, 3.2, ..., 8.8, 8.9, and 9.0 GHz. The objective value F_1 is calculated as the average value of the VSWR in these frequency points. The VSWR is evaluated by the simulation software IE3D [23], and an infinite ground plane model is applied to speed up the antenna evaluation.

There are a number of crucial operational parameters to be defined for the JGEA operations. The jumping rate for both cut-and-paste and copy-and-paste needs to be identi-

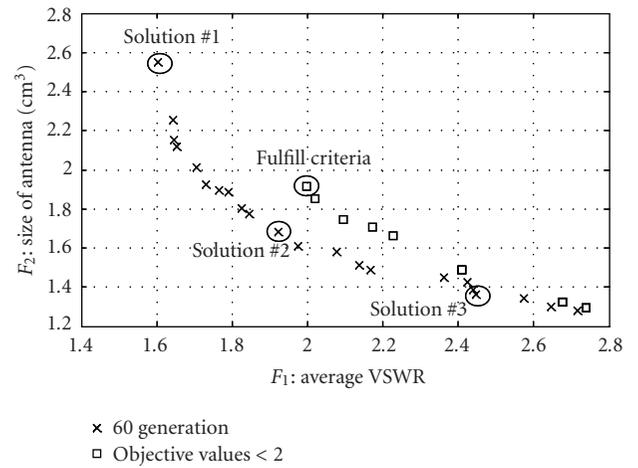


FIGURE 5: JGEA nondominated solutions for E-shaped folded patch antenna.

TABLE 1: Gene representation for the parameters defined in E-shaped folded patch antenna.

Genes representation for antenna parameters (mm)	Searching space
$l = \text{gene}(1) \times 19 + 1$	[1, 20]
$w = \text{gene}(2) \times 19 + 1$	[1, 20]
$w_e = \text{gene}(3) \times w$	[0, w]
$l_e = \text{gene}(4) \times l/4$	[0, l/4]
$l_f = \text{gene}(5) \times l$	[0, l]
$p_o = \text{gene}(6) \times w_e$	[0, w_e]
$h = \text{gene}(7) \times 9 + 1$	[1, 10]
$h_f = \text{gene}(8) \times h$	[0, h]

fied. An extensive study to select the appropriate jumping rates has been reported in [15]. This rate should not be very high in both cases. In general, a probability of 10% (0.1) for the genes to jump is sufficient to achieve the desirable result. As for the classical rates for crossover and mutation, 0.8 for crossover rate [3] and $1/l$ for mutation rate [2], where l is the chromosome length, are widely accepted. A fixed number of generations is used to terminate the optimization process.

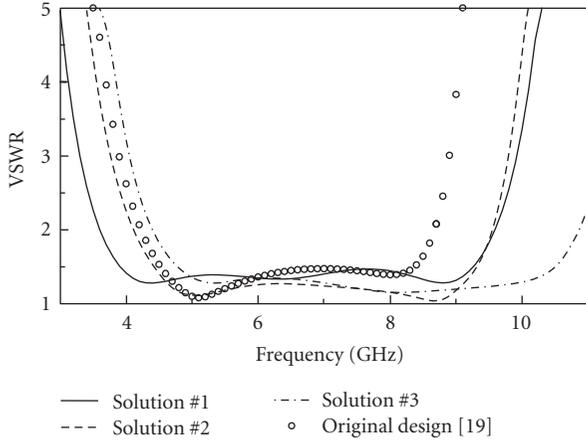


FIGURE 6: VSWR as a function of frequency for 3 solutions extracted from Figure 5 and the original design [19]. Parameters for the 3 optimized solutions are shown in Table 2.

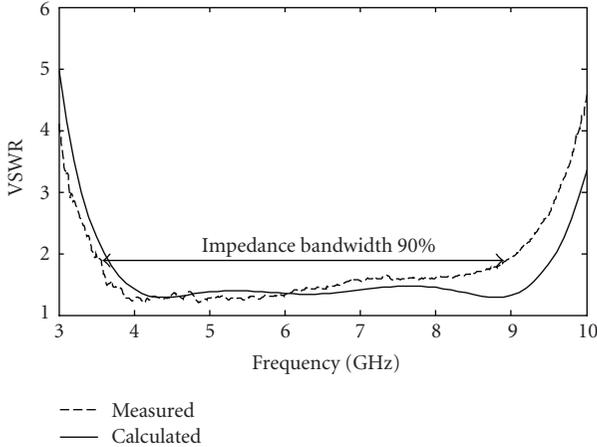


FIGURE 7: Measured and calculated VSWR as a function of frequency for solution #1.

The reasoning and argument will be given in the later part of the paper.

3.2. Result and discussion

For simplicity, an infinite ground plane was adopted for simulation purpose. The nondominated solutions front obtained from the JGEA optimizing process is shown in Figure 5 when 60 generation is used for the stopping criteria. It shows the antenna profile F_2 against the function of the average VSWR F_1 . Within these solutions, only three antenna solutions, named as solution #1, #2, and #3, are singled out from the figure for illustration. Their associated antenna parameters are listed in Table 2.

Solution #1 has the largest profile of $15.4 \times 16.9 \times 9.8 \text{ mm}^3$ but with the lowest average VSWR value. On the other hand, solution #3 has the smallest profile of $13 \times 12.8 \times 8.2 \text{ mm}^3$,

and its VSWR is higher by comparison. Solution #2 is the selected intermediate profile for further overall evaluation. The VSWR versus the frequency function for all three cases are shown in Figure 6.

The simulated impedance bandwidth (VSWR < 2) for antenna solutions can then be determined. Solution #1 was found to have 91% impedance bandwidth in the frequency range of 3.6–9.6 GHz, while 79% impedance bandwidth was for Solution #2 in the frequency range of 4.1–9.5 GHz, and Solution #3 was found to have 85% impedance bandwidth in the frequency range of 4.4–10.9 GHz. All these results seemed to be improved from the original design in which there is only 70% impedance bandwidth in the frequency range of merely 4.2–8.7 GHz [19].

These results demonstrated the power of JGEA for searching a wide range of solutions, as well as gaining appropriate antenna performance. A numerous solutions can be obtained using this approach, and hence provides a wider freedom to choose a suitable solution through the tradeoff process between the antenna profile and the average VSWR.

It should be noted that, the obtained Solution #1 is not an easily obtainable solution other than the use of JGEA. This particular solution can be considered as the extreme solution of all possible solutions from the nondominated solutions front as indicated in Figure 5. It is because of the JG capacity to spread the genes to cause the genes diversity in the chromosome so that a natural building block was formed. Without the JG feature, most of the solutions would mostly be located in the vicinity of solution #2. For the same argument, Solution #3 can also be considered as one of the possible extreme solutions at the other end of the nondominated solutions front. Then, it simply characterizes the antenna to have the smallest profile and yet to meet the maximum possible antenna performance if such a design meets the design criteria.

To verify the simulated and optimized result, solution #1 is selected for hardware fabrication with an antenna feed at the center of an $80 \times 80 \text{ mm}^2$ square ground plane. As for this antenna with lower cut-off frequency (3.6 GHz) and the dimensions ($l \times w \times h$) of $0.18\lambda_0 \times 0.20\lambda_0 \times 0.12\lambda_0$, its measured and simulated VSWR as a function of frequency is shown in Figure 7. The measured VSWR operates from 3.46 to 9.07 GHz, indicating that a 90% impedance bandwidth was achievable, which agrees very well with the simulated value of 91%. The xz -plane and yz -plane radiation patterns at the frequencies 3.5, 6.5 and 9.0 GHz are shown in Figure 8. It can be observed that the E-field component E_ϕ (cross-polarized field) is relatively small compared to E_θ (co-polarized field). The patterns are expected as broadside modes since the antenna has a symmetrical configuration. That is the reason why the optimization in the radiation pattern does not have to be included in our JGEA optimization. Figure 9 shows the measured and simulated antenna gain as a function of frequency. From the measurement result, the peak gain 4.9 dBi is observed at 6.1 GHz. The measurement result agrees well with the simulation result, where the gain is around 4 dBi within the operation band. The ripple in the measurement result is due to the measurement error, using a gain comparison method with a standard gain horn.

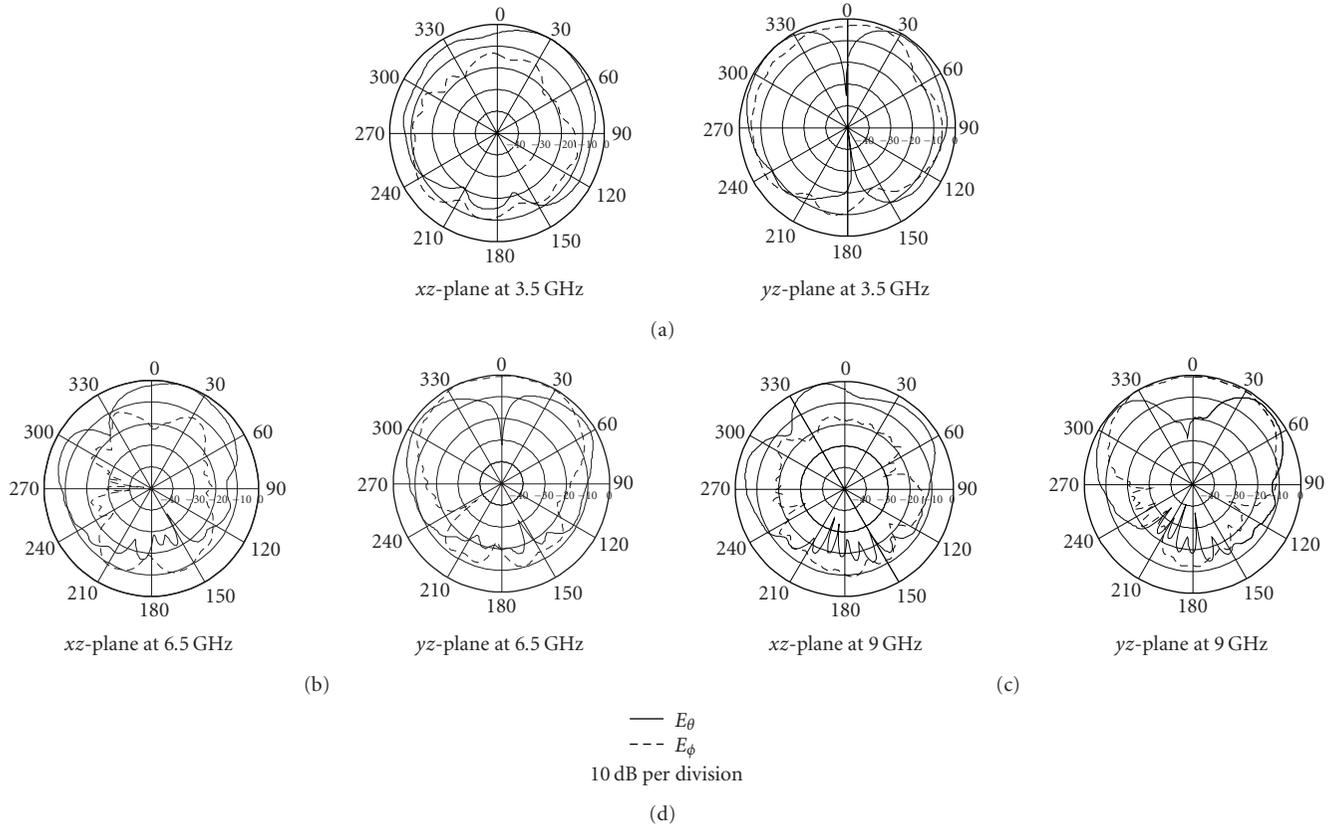


FIGURE 8: Measured radiation patterns for solution #1.

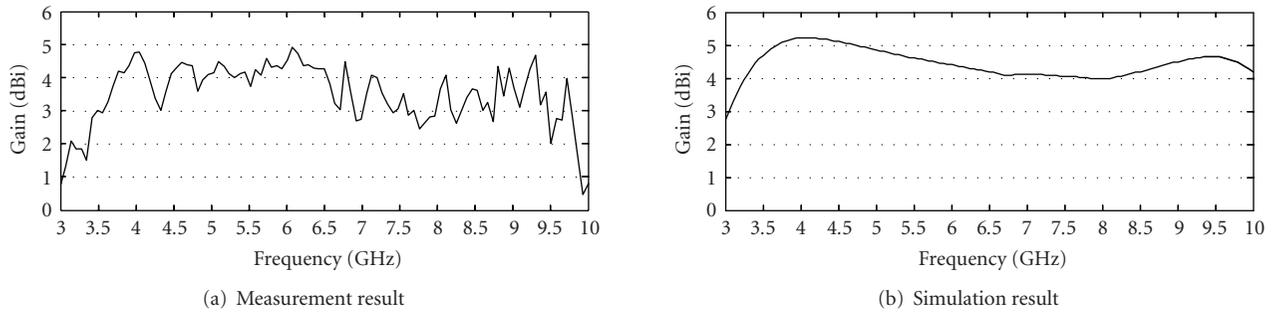


FIGURE 9: Measured and calculated antenna gain as a function of frequency for solution #1.

3.3. Stopping criteria

The other consideration of evolutionary computation scheme is the stopping criteria. The performance criteria can be an option for terminating the optimization process. But it has its shortcoming for obtaining suboptimal solutions due to premature termination or otherwise never stops if there no feasible solution is found.

In the case of using fixed number of generations, the obtained nondominated solutions based on 60 generations are shown in Figure 5. As for a direct comparison, the similar solutions being generated by performance criteria, that is, both F_1 and $F_2 < 2$, as the stopping criteria, are also superimposed in Figure 5. This clearly indicates that the performance cri-

teria for terminating the program do not always guarantee a better solution for design adoption due to premature termination.

To further reinforce the argument of using a fixed number of generations for termination, a simulation run was performed with a sufficiently high number of generations. The program is then designed to record the nondominated solutions at certain intervals of the simulation run. In this case, the intervals were designated at 20, 40, 60, 80, and 100 generations and their results are all shown in Figure 10. It is not difficult to conclude that the most computationally efficient termination criterion was around 60 generations. Although the higher number, say 80 to 100 generations, may be closer to the Pareto-optimal front, the extra time to proceed the

TABLE 2: Optimized parameters for the nondominated solutions #1, #2, and #3.

	Antenna parameters (mm)								Objective functions	
	l	w	h	w_e	l_e	l_f	h_f	p_o	F_1	F_2 (cm ³)
Solution #1	15.4	16.9	9.8	4.5	0.9	11.5	3.6	1.7	1.6037	2.6
Solution #2	13.6	15.1	8.2	5.1	0.8	10.1	3	1.1	1.9231	1.7
Solution #3	13	12.8	8.2	4.3	0.7	10.3	3	1.2	2.4481	1.4

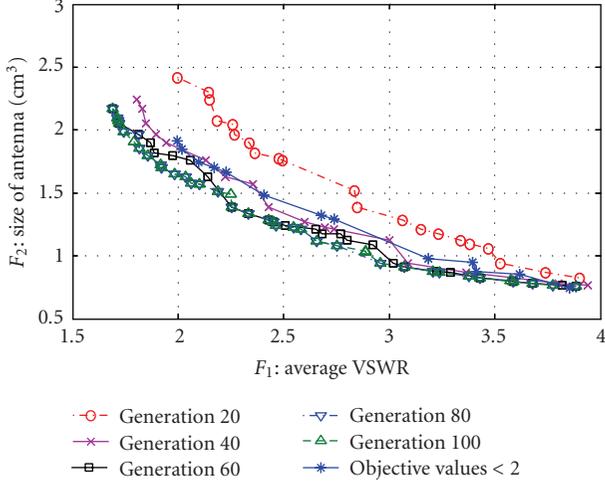


FIGURE 10: Evolution of the nondominated fronts.

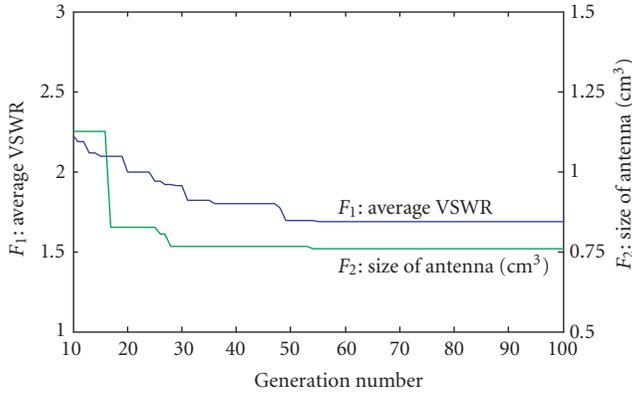


FIGURE 11: Best objective values against generation number.

computation is painfully long as one generation takes almost an hour to compute. Another 20–40 generations would then be not necessary.

Furthermore, the extra computational time plays little advantage for yielding a better VSWR and further size reduction of the antenna as indicated in Figure 11. This shows that the minimum objective values of F_2 for antenna size and F_1 for the performance of VSWR were both saturated after some 55 generations, and hence a number higher than 60 generations to terminate the program is therefore not necessary.

Although 60 generations of evolution was enough for the termination condition dealing with this E-shaped folded patch antenna configuration, it is not necessary true for any other antenna designs. In fact, the number of generations

used depends on the complexity of the antenna designs, for example, the number of the optimization variables, which is always case dependent. Hence the timing analysis such as in Figures 10 and 11 discussed in the previous paragraph should be performed to estimate the necessary number of generations for achieving the near optimal performance.

4. COMPARISON WITH PARTICLE SWARM OPTIMIZATION

Other than the MOEA that can be used for multiobjective optimization, there is also another optimization technique called particle swarm optimization (PSO) [24, 25]. This section will describe the program flow of PSO and compare its performance with JGEA.

PSO is a popular optimization technique applied in many optimization problems [26–33]. It is a population-based optimization technique which is inspired by studies of social behavior of insects and animals. The population is initialized by N random solutions called particles, where N is the population size. Then, in an iterative process, the N particles move towards the most promising area of the search space where the optimal solutions are found.

To guide the searching process, there are four parameters defined for each particle: position, velocity, personal best position, and global best position. Position $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})$ represent the solution, where D is the number of optimization variables. Velocity $V_i = (v_{i1}, v_{i2}, \dots, v_{iD})$ is the rate of change of the particle position. Personal best position $P_i = (p_{i1}, p_{i2}, \dots, p_{iD})$ is the best position this particle has visited so far, that results in the best objective values. Global best position $P_g = (p_{g1}, p_{g2}, \dots, p_{gD})$ is the position of the particle that have the best objective values in the population.

In each iterative step, each particle has its velocity and position changed according to two equations for each $d = 1, 2, \dots, D$ and $i = 1, 2, \dots, N$:

$$\begin{aligned} v_{id} &:= wv_{id} + c_1r_1(p_{id} - x_{id}) + c_2r_2(p_{gd} - x_{gd}), \\ x_{id} &:= x_{id} + \chi v_{id}, \end{aligned} \quad (3)$$

where c_1, c_2, w , and χ are constant for the adjustment of optimization performance. r_1 and r_2 are random numbers in the range of $[0, 1]$ to guide the search with a random process. In the first equation, each particle changes its velocity to a new value according to its previous velocity, position, personal best, global best, and two random numbers. In the second equation, each particle changes its position to a new value according to its previous position and the new velocity. By the iterative process of particles movement, the particles will

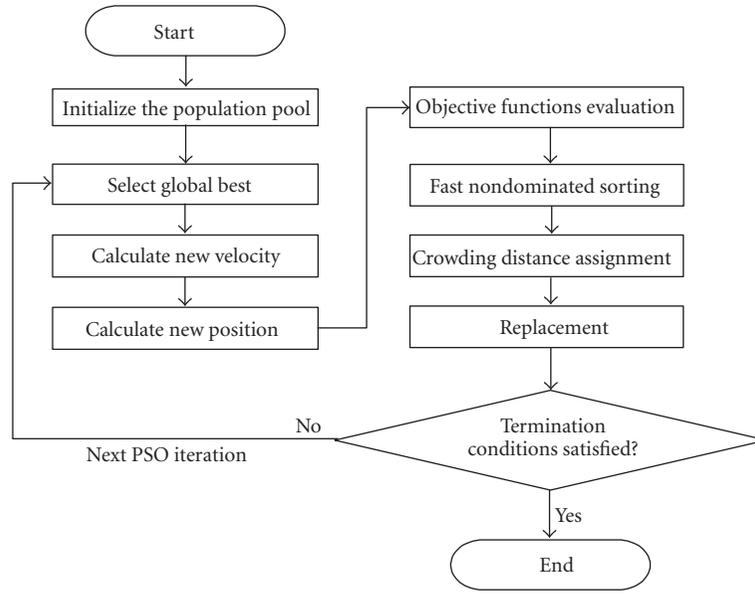


FIGURE 12: Flowchart of nondominated sorting particle swarm optimization.

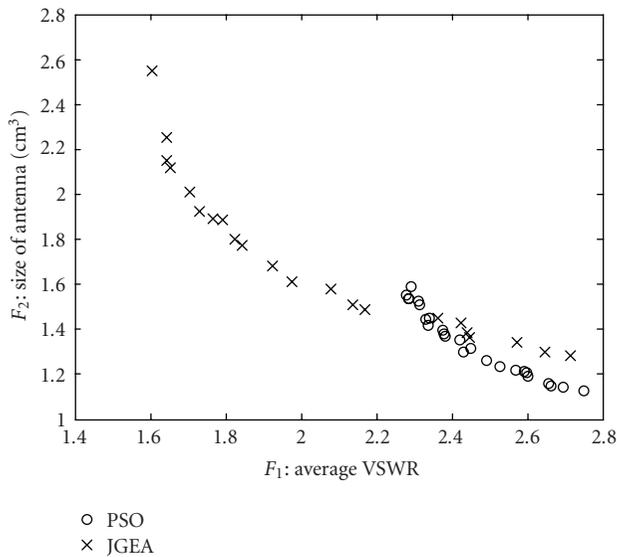


FIGURE 13: Comparing the solutions obtained by PSO and JGEA.

achieve the optimal positions in the search space. The termination condition of the iteration can be determined with a fixed number of iteration, which is also used by JGEA.

The original version of PSO can only be applied to single objective optimization tasks. However, with the adaptation of Pareto-optimal concepts and the nondominated sorting process, PSO can be used to find the nondominated solutions in multiobjective optimization effectively. This modified algorithm is called nondominated sorting (NS) PSO [25] proposed by X. Li. The flowchart of NSPSO is shown in Figure 12, for which it is similar to that of the JGEA in the ranking and replacement process, provided that they both have adapted the nondominated sorting to manage the mul-

tiobjective ranking of the solutions. With the Pareto-optimal sense, the global best is not a single individual, but instead it is the first nondominated solution front. For the implementation, the value of $P_g = (p_{g1}, p_{g2}, \dots, p_{gD})$ used for calculation of the new velocity would be randomly picked up in the nondominated solution front.

By applying the NSPSO for the same optimization objectives (2) and the same number of antenna evaluations ($3000 = \text{population size } 50 \times \text{number of iteration } 60$), the optimized solutions obtained are shown in Figure 13. The solutions obtained by JGEA are also included in the same graph for direct comparisons. It is clearly shown that the solutions of JGEA can obtain a better average VSWR, comparing with the solutions by NSPSO. An extreme solution by JGEA can achieve an average VSWR $F_1 = 1.6$. In the contrary, all solutions obtained by NSPSO have $F_1 > 2$.

5. CONCLUSIONS

In this paper, a new multiobjective optimization algorithm JGEA is applied for antenna design. To cope with the multiobjective functions, Pareto-front ranking has been applied for obtaining the nondominated solutions front. This new scheme not only provides the solution efficiently, but also reveals better diversity along the Pareto-optimal front. Hence more solution choices become available for designers. This is particularly useful when minmax optimization procedure is required and that the obtained solutions are not clustered together at a particular location along the Pareto-optimal front. Because of its speedy convergence capability, it has the advantage for shortening the computational time to gain the necessary results.

The design of an E-shaped folded patch antenna has been demonstrated by the use of this new method. The solution is optimized on the basis of VSWR and the antenna size.

A nondominated solutions set has been obtained. One particular solution from this set is chosen for hardware fabrication. A measured 90% impedance bandwidth was obtained. An additional 16% impedance bandwidth improvement was observed comparing to that of the original design.

An alternative optimization methodology nondominated sorting particle swarm optimization (NSPSO) is also applied for the same optimization problem. The optimized solutions are compared to JGEA, which shows that JGEA can obtain solutions with lower values of average VSWR, and hence better choices for the antenna solutions.

ACKNOWLEDGMENT

The work described in this paper was supported by CityU Strategic Research Grant (SRG) Project no. 7002091.

REFERENCES

- [1] K. C. Gupta and M. Abouzahra, *Analysis and Design of Planar Microwave Components*, IEEE Computer Society Press, New York, NY, USA, 1994.
- [2] T. Bäck, U. Hammel, and H.-P. Schwefel, "Evolutionary computation: comments on the history and current state," *IEEE Transactions on Evolutionary Computation*, vol. 1, no. 1, pp. 3–17, 1997.
- [3] K. F. Man, K.-S. Tang, and S. Kwong, *Genetic Algorithms: Concepts and Designs*, Springer, Berlin, Germany, 1999.
- [4] C. A. Coello Coello, D. A. van Veldhuizen, and G. B. Lamont, *Evolutionary Algorithms for Solving Multi-Objective Problems*, Kluwer Academic Publishers, Boston, Mass, USA, 2002.
- [5] K. Deb, A. Pratap, S. Agrawal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, 2002.
- [6] C. M. Fonseca and P. J. Fleming, "Multiobjective optimization and multiple constraint handling with evolutionary algorithms—I: a unified formulation," *IEEE Transactions on Systems, Man and Cybernetics, Part A*, vol. 28, no. 1, pp. 26–37, 1998.
- [7] M. Erickson, A. Mayer, and J. Horn, "The niched pareto genetic algorithm 2 applied to the design of groundwater remediation systems," in *Proceedings of the 1st International Conference on Evolutionary Multi-Criterion Optimization (EMO '01)*, vol. 1993, pp. 681–695, Springer, Zurich, Switzerland, March 2001.
- [8] C. Andrew, F. Peter, P. Hartmut, and F. Carlos, Genetic algorithm toolbox user's guide, version 1.2.
- [9] F. J. Villegas, T. Cwik, Y. Rahmay-Samii, and M. Manteghi, "A parallel electromagnetic genetic algorithm optimization (EGO) application for patch antenna design," *IEEE Transactions on Antennas and Propagation*, vol. 52, no. 9, pp. 2424–2435, 2004.
- [10] N. Fedoroff and D. Boststein, Eds., *The Dynamic Genome: Barbara McClintock's Ideas in the Century of Genetics*, Cold Spring Harbor Laboratory Press, New York, NY, USA, 1992.
- [11] A. B. Simoes and E. Costa, "Enhancing transposition performance," in *Proceedings of the Congress on Evolutionary Computation (CEC '99)*, vol. 2, pp. 1434–1441, Washington, DC, USA, July 1999.
- [12] A. V. Spirov and A. B. Kazansky, "Jumping genes-mutators can rise efficacy of evolutionary search," in *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO '02)*, pp. 561–568, New York, NY, USA, July 2002.
- [13] R. B. Kasat and S. K. Gupta, "Multi-objective optimization of an industrial fluidized-bed catalytic cracking unit (FCCU) using genetic algorithm with the jumping genes operator," *Computers & Chemical Engineering*, vol. 27, no. 12, pp. 1785–1800, 2003.
- [14] S. H. Sun, K. F. Man, B.-Z. Wang, and T. P. Wong, "An optimized wideband quarter-wave patch antenna design," *IEEE Antennas and Wireless Propagation Letters*, vol. 4, no. 1, pp. 486–488, 2005.
- [15] T. M. Chan, K. F. Man, K. S. Tang, and S. Kwong, "A jumping gene paradigm for evolutionary multiobjective optimization," to appear in *IEEE Transactions on Evolutionary Computation*.
- [16] T. M. Chan, K. F. Man, K. S. Tang, and S. Kwong, "A jumping gene algorithm for multiobjective resource management in wideband CDMA systems," *The Computer Journal*, vol. 48, no. 6, pp. 749–768, 2005.
- [17] T. M. Chan, K. F. Man, K. S. Tang, and S. Kwong, "Optimization of wireless local area network in IC factory using a jumping-gene paradigm," in *Proceedings of the 3rd International IEEE Conference on Industrial Informatics (INDIN '05)*, pp. 773–778, Perth, Western Australia, August 2005.
- [18] S. H. Yeung, W. T. Luk, H. K. Ng, K. F. Man, and C. H. Chan, "A jumping genes paradigm for the design of wide-band patch antenna with double shorting wall," *Microwave and Optical Technology Letters*, vol. 49, no. 3, pp. 706–709, 2007.
- [19] C. Y. Chiu and C. H. Chan, "A wideband antenna with a folded patch feed," in *Proceedings of the IEEE International Workshop on Antenna Technology: Small Antennas and Novel Metamaterials (IWAT '05)*, pp. 45–48, Singapore, March 2005.
- [20] L. H. Caporale, *Jumping Genes, in Darwin in the Genome: Molecular Strategies in Biological Evolution*, McGraw-Hill, New York, NY, USA, 2003.
- [21] F. Yang, X.-X. Zhang, X. Ye, and Y. Rahmat-Samii, "Wide-band E-shaped patch antennas for wireless communications," *IEEE Transactions on Antennas and Propagation*, vol. 49, no. 7, pp. 1094–1100, 2001.
- [22] B.-L. Ooi, S. Qin, and M.-S. Leong, "Novel design of broadband stacked patch antenna," *IEEE Transactions on Antennas and Propagation*, vol. 50, no. 10, pp. 1391–1395, 2002.
- [23] IE3D is a trademark of Zeland Software.
- [24] J. Kennedy and R. C. Eberhart, *Swarm Intelligence*, Morgan Kaufmann, San Francisco, Calif, USA, 2001.
- [25] X. Li, "A non-dominated sorting particle swarm optimizer for multiobjective optimization," in *Proceedings of the Genetic and Evolutionary Computation (GECCO '03)*, vol. 2723 of *Lecture Notes in Computer Science*, pp. 37–48, Chicago, Ill, USA, July 2003.
- [26] T. O. Ting, M. V. C. Rao, and C. K. Loo, "A novel approach for unit commitment problem via an effective hybrid particle swarm optimization," *IEEE Transactions on Power Systems*, vol. 21, no. 1, pp. 411–418, 2006.
- [27] S. Genovesi, R. Mittra, A. Monorchio, and G. Manara, "Particle swarm optimization for the design of frequency selective surfaces," *IEEE Antennas and Wireless Propagation Letters*, vol. 5, no. 1, pp. 277–279, 2006.
- [28] B. Zhao, C. X. Guo, and Y. J. Cao, "A multiagent-based particle swarm optimization approach for optimal reactive power dispatch," *IEEE Transactions on Power Systems*, vol. 20, no. 2, pp. 1070–1078, 2005.

- [29] N. Jin and Y. Rahmat-Samii, "Advances in particle swarm optimization for antenna designs: real-number, binary, single-objective and multiobjective implementations," *IEEE Transactions on Antennas and Propagation*, vol. 55, no. 3, pp. 556–567, 2007.
- [30] A. I. Selvakumar and K. Thanushkodi, "A new particle swarm optimization solution to nonconvex economic dispatch problems," *IEEE Transactions on Power Systems*, vol. 22, no. 1, pp. 42–51, 2007.
- [31] Z. Bayraktar, P. L. Werner, and D. H. Werner, "The design of miniature three-element stochastic Yagi-Uda arrays using particle swarm optimization," *IEEE Antennas and Wireless Propagation Letters*, vol. 5, no. 1, pp. 22–26, 2006.
- [32] Y. Ma, C. Jiang, Z. Hou, and C. Wang, "The formulation of the optimal strategies for the electricity producers based on the particle swarm optimization algorithm," *IEEE Transactions on Power Systems*, vol. 21, no. 4, pp. 1663–1671, 2006.
- [33] S. L. Ho, S. Yang, G. Ni, and H. C. Wong, "A particle swarm optimization method with enhanced global search ability for design optimizations of electromagnetic devices," *IEEE Transactions on Magnetics*, vol. 42, no. 4, pp. 1107–1110, 2006.

AUTHOR CONTACT INFORMATION

S. H. Yeung: Department of Electronic Engineering,
City University of Hong Kong, Kowloon, Hong Kong;
50402992@student.cityu.edu.hk

K. F. Man: Department of Electronic Engineering,
City University of Hong Kong, Kowloon, Hong Kong;
eekman@cityu.edu.hk



Hindawi

Submit your manuscripts at
<http://www.hindawi.com>

