Wire-Antenna Geometry Design with Multiobjective Genetic Algorithms

David J. Caswell and Gary B. Lamont
Department of Electrical and Computer Engineering
Graduate School of Engineering,Air Force Institute of Technology
Wright-Patterson AFB, OH 45433-7765
{dcaswell, lamont}@afit.af.mil

Abstract - Two different multiobjective genetic algorithms, built using the GENOCOP III system are employed, for the design of wire antenna geometries. Designs are examined using *a priori* and *a posteriori* decision criteria. The relative advantages of each of these criteria and their applicability to the problem domain are examined.

I. Introduction

Wireless communication has become a vital aspect to modern society. Communication via wireless methods are seen in all aspects of life; cellular telephones, wireless hubs, radio communication, and television broadcasting are all examples of the progression of technology towards this medium. A common trait of all these wireless items is their need for an antenna to broadcast and/or receive. In this respect improving antenna design becomes a vital role in the future of communication. The shape of the wire antenna decides its electromagnetic attributes. Thus, when designing these antennae it is vital to create shapes that maximize their effectiveness based on the specific needs of their intended function.

Because of the large amount of variables and the complex equations involved in determining the electromagnetic properties, standard deterministic methods for designing effective antenna are inadequate for the task. Current development practices design simple wire structures using inductive processes followed by mathematical calculations for determining current distribution across the wires. Only then can the electromagnetic properties be calculated. Thus the process is very time consuming and quite complex especially for testing multiple different antenna shapes [1]. Computers have made the process easier, programs like the Numerical Electromagnetic Code (NEC), has dramatically increased the ability of designers to quickly test different proposals of wire-antenna designs to determine their effectiveness [2]. Unfortunately the engineer must have a wire design *a priori* in order to use this software. Their are uncountably infinite possibilities for wire designs based solely on altering the length and relative angles of the wires for even simple antennae.

Since the problem search space for antenna design is very complex, analytical approaches are incapable of finding optimal solutions. Classical antenna design approaches need starting positions that are close to the global optimum otherwise they tend to get stuck in local peaks or troughs [1]. This opens the door for evolutionary algorithms in all their various forms. Evolutionary Algorithms allow for testing of solutions outside the current optima, thus they have no need of initial starting points near optimal solutions [3]. While various forms of EA's have been made for dealing with antenna optimizations, the most common implementation technique is with the use of genetic algorithms [1], [4].

Since there exists such a large variety of antenna applications in the world today, each antenna must be examined in regards to the tradeoffs necessary based on the requirements of that antenna's intended function. This translates to multiple objectives that must be fulfilled and examined in order to create the best antenna possible for each situation. This paper makes an examination of two different multiobjective genetic algorithm approaches and the benefits and disadvantages they each present to the problem domain. To understand this process, an example antenna system is visited in Section II. Section III describes the basic principles of multi-objective problems, followed by Section IV which compares an *a priori* to an *a posteriori* version of a multiobjective Genetic Algorithms. Conclusions and proposals for further research are discussed in Section VI.

II. Applications of Antenna Design

Each application of antenna design is different based on the constraints of the problem. Just like there is no

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free lunch for genetic algorithms [5] their is no perfect antenna for all users. Antennae have a vast number of applications requiring a large variety of spatial dimensions. Large scale broadcasting and receiving use large satellite dishes and antenna arrays with very focused beams and minimal sidelobes [6], [3]. Other antennae, like cell phones, prefer smaller sizes with a wide range of receivable angles. Because of these wide varieties of preferences for different antenna each case should be analyzed with regards to the needs of the user(s) of the antenna.

A. Remote Intrusion Monitoring System

A practical military example of where antenna design is critical to mission success is in the Remote Intrusion Monitoring System(RIMS) [4]. The RIMS system is based on the concept of a remote sensor being dropped into a location that requires monitoring. A distant receiving system would watch all the sensors to detect if changes around that sensor occur.

In order for RIMS to work the remote antennas must be robust enough to be able to work without user interaction. Because of the nature of these systems it is imperative that they be as inconspicuous as possible. Yet if they do not have the electromagnetic performance that is needed to transmit to the repeaters then they are ineffective. Another tradeoff that must be considered for the successful outcome of the project is the size vs. frequency choice. This tradeoff comes from the antenna being concealed under foliage or in camouflage. One has to weigh the decision of how high a frequency is needed so that it is powerful enough to penetrate its cover, yet not so physically large as to be able to be seen. Other criterion that must be weighed for the RIMS problem include omnidirectional azimuth for widespread transmission, robust components for zero maintenance, and low level voltage source [4]. Each of these tradeoffs represent a different objective that can be examined by the researcher individually, or in a multiobjective formulation.

III. Multiobjective Evolutionary Algorithms

In general a multi-objective problem(MOP) is where multiple objective functions influence the overall success of any given possible solution. This creates a potential solution search space whereby there could exist a possibly uncountable amount of solutions, each solution representing some tradeoff between the different objectives [7]. The total set of all possible vector solutions is termed the *objective space*; the search of this space for a global optimum may be an NP-Complete problem in itself [8]. As opposed to single objective problems some multiobjective approaches can result in a very large number of possible solutions, each being in themselves an optimal tradeoff of objective fitnesses.

A. Multi-Objective Approaches

MOPs can be decomposed into three distinct groups based upon the decision as to solution selection [7]. These types are:

- *A Priori* Preference Articulation (*Decide* $\longrightarrow$ *Search*) The decision maker (DM) creates a scalar cost function, turning the MOP into a single objective problem (aggregation).
- *Progressive* Preference Articulation (*Search* $\longleftrightarrow$ *Decide*) Optimization occurs on a partially articulated preference set. A final decision is made by the DM off of this set once optimized.
- *A Posteriori* Preference Articulation (*Search* $\longrightarrow$ *Decide*) A Pareto optimized set is generated and the DM chooses from this set.

A recent study shows evidence that the popularity of multiobjective evolutionary algorithm(MOEA) applications has substantially increased during the last seven years [9]. During this time the popularity of the *A Posteriori* approach has been by far the prominent choice of MOEA developers. A great deal of those researchers use Pareto-based selection approaches. A more detailed examination of the most common implementations of *a priori* and *a posteriori* algorithms helps to clarify the distinctions.

A.1 Weighted-Sum Selection MOEA

A standard implementation of *a priori* multiobjective optimization techniques is the use of a weighted-sum objective value, otherwise known as an aggregate function [10]. This approach combines all of the objective functions ($f_i(x)$) into a single function of the form

$$min \sum_{i=1}^{k} w_i f_i(x) \tag{1}$$

where $w_i \geq 0$ are the weights that are applied to each objective by the decision maker prior to the program being run. This approach works when the decision maker has enough knowledge of the system to be able to specify the exact weights for each objective in order to direct the search towards the requirements desired. Aggregate functions have the advantage of being comparatively easy to implement in that it does not change any of the standard GA routines. The disadvantages lie in the fact that having the appropriate system knowledge for what to make the weights prior to running may be difficult or even impossible and might require multiple weighting schemes to find appropriate results. Another, perhaps more devastating, disadvantage is the fact that regardless of what the weights may be, when the Pareto Front is concave the aggregate function is unable to determine all viable members of the Pareto optimal set, even when the surface is known [11].

A.2 Pareto-based Selection MOEA

A Pareto based MOEA searches the problem space using all objectives defined by the problem in an attempt to seek out a list of non-dominated vector solutions. Using the terminology defined by Van Veldhuizen [7] the list of non-dominated solution vectors comprises the Pareto optimal set ($\mathcal{P}$) and the evaluated objective vectors of P form the Pareto Front ($\mathcal{PF}$). Each objective fitness value is calculated independent of the other objective fitness values. These values are each included in the chromosomes solution vector. It is this solution vector that defines whether the chromosome is non-dominated and thus would be included in the current Pareto Optimal set. The collection of all non-dominated vectors up to generation t of the EA is stored and is known as $PF_{known}(t)$, the actual chromosome is stored and known as $P_{known}(t)$. Thus the EA searches to find P_{known} such that $P_{known} = P_{true}$.

There exists multiple implementations for storing the secondary population of $P_{known}(t)$. One common approach is to simply add the current population at each step (ie- $P_{known}(t) := P_{current}(t) \bigcup P_{known}(t-1)$ and periodically removing any dominated chromosomes from the population. This removal process is done through the use of what is termed Pareto Ranking. In order to attempt a uniform distribution of solutions across the Pareto Front an operator to ensure Fitness Sharing can be used. Many varieties of the Ranking and Fitness Sharing operators exist, an examination of these algorithms is beyond the scope of this paper but the reader is refered to [7].

Once the Pareto Front has been found, the job of the DM is to select which point would be best for the needs of the specific project. Thus making Pareto Optimization an *a posteriori* technique. With proper operators this formulation can find fully enumerated optimal surfaces for which dynamic selection at run time is available, depending on the problem, of equally non-dominated solutions.

IV. Antenna Design MOEA Approaches

A priori and *a posteriori* approaches for designing antenna each have their own advantages and disadvantages. Understanding what each of these offer to the engineer allows for more effective movement towards project requirements. Examining these two different MOEA approaches using a similar GA software foundation, that of GENOCOP III, provides insight into what model to employ.

A. Aggregate Approach

In terms of wire-antenna design problems a weighted sum implementation of a multi-objective genetic algorithm was used to solve for a geometry [4]. This design was for the Remote Intrusion Monitoring System (RIMS), where objectives were chosen based on the constraints of this problem. GENOCOP III was used for the implementation where the chromosome was composed of the coordinates of each wire segments endpoint [12]. GENOCOP III is a real valued generic Genetic Algorithm that allows the user to choose the different parameters and operators for the user's objective function.

Four objective functions needed to be optimized based on the requirements of the antenna problem. These are power gain, azimuthal symmetry, input resistance, and input reactance. Each of these are calculated with the use of the Numerical Electromagnetic Code (NEC) version 4.1 [2]. They were selected based on the specific requirements of the RIMS project. Power gain needs to be maximized in order for the field strength of the signal to be strong enough that it can reach the distant reciever units. Due to the time restrictions on the antenna placement in a RIMS system antenna orientation is not always optimal. Optimizing the symmetry of the azimuthal radiated power gain provides leeway for the placement of the unit so that it can transmit over a wide azimuthal area. This calculation is done by finding the average gain at 32 field locations based off of a combination of four zenith (θ) of

$$\theta = 89.80,\ 89.85,\ 89.90,\ 89.95 \tag{2}$$

and eight azimuthal (ϕ) angles of

$$\phi = 0, 45, 90, 135, 180, 225, 270, 315 \tag{3}$$

As for the resistance and reactance, these are optimized in order to counteract the possibility of the high gain reflecting most of the power from the source, which can occur with impedance mismatch [13].

Once calculated these functions are mapped to the interval [0,1] so that they represent the corresponding percentage necessary for the weighted sum. The mapping functions are

$$f_1(t_1) = 1 - exp(-K_1 t_1) \tag{4}$$

for the power gain objective(t_1), and

$$f_{i=2,3,4}1(t_i) = 1 - exp(-|(t_i - S_i)|/K_i) \tag{5}$$

for symmetry(t_2), resistance (t_3), and reactance (t_4) where $K_1 = 10000, K_2 = 10000, K_3 = 50, and\, K_4 = 5$ and $S_{2,4} = 0\, and\, S_3 = 50$ are chosen *a priori* based on knowledge of the range of possible values for the functions. Once done the functions are then summed for the optimization of the aggregated model:

$$max \sum_{i=1}^{4} w_i f_i(t_i) \tag{6}$$

where the weights(w_i) are 60, 20, 10 and 10 respectively[4].

B. Pareto Approach

We modified Michaelewicz's GENOCOP III code to incorporate a Pareto ranking scheme. Due to the ease of implementation with GENOCOP III we chose to use Fonseca and Flemings Ranking function of,

$$rank(\vec{x}, t) = r_u^{(t)} \tag{7}$$

where $r_u^{(t)}$ is the amount of the population at generation t that dominates x_u. In this manner the fitness value of each chromosome are measured according to its Pareto rank as opposed to the weighted sum of the aggregate approach.

The original GENOCOP III chromosome consisted of a vector $\vec{x}$ where $\vec{x}(0) = f(\vec{x})$. Because Pareto fitness is based off of not one but multiple objective values this is modified such that

$$\vec{x}(0), t = rank(\vec{x}, t) \tag{8}$$

where the ranking is based on the fitness values returned by each of the objectives. Once again the values are mapped to the interval $[0, 1]$ using equations 4 and 5.

The code of GENOCOP III is modified only slightly with functionality for the ranking of the entire population added as well as a member comparison function. This function takes two members of the population and ranks them against the whole population comparing their resulting rank and returning which rank is greater. The populations are expanded to store the objectives, thus all routines that copy the population members are modified as well to incorporate the objective values.

One constraint of using the GENOCOP III for the antenna design problem is that all of the objective values must be in the same direction for optimization(ie. all max or all min). Using this mapping, all of the objectives for this problem are formed as a maximization. These values once calculated are stored at the end of the vector so that recalculation is not necessary every time the population needs to be reranked. Since the Pareto functionality was built on pre-existing validated work, ensuring its operability was relatively easy. Benchmarks were run and validated for the pareto operability using standard metrics such as spacing and generational distance [7]. Extending the research of the forerunner of this model [4] we ran experiments on a four wire antenna model as well as testing a more complex 13-wire model. The 13-wire antenna is composed of a main trunk of four wire segments with three branches of three wires segments each at the intersections of the trunk wire segments.

V. Computational MOEA Results and Analysis

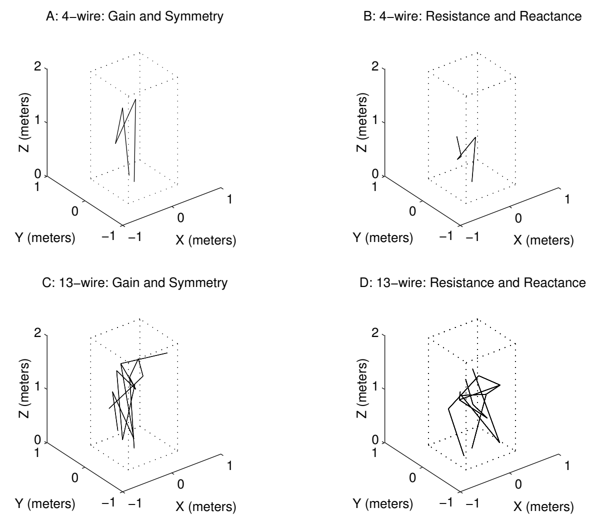

Fig. 1. Generated P_{known} 13/4-Wire Antennae

Direct comparison of *a priori* aggregate and *a posteriori* Pareto implementations are difficult due to the fact that one produces a single answer while the other a vector of solutions. If the entire Pareto Front is enumerated, on it the aggregate result would be found. However, this actually happening is improbable due to the complex search space of the problem and the large Pareto Front that would exist due to the four objectives in the antenna design problem .

To compare the results for the 4-Wire experiments, runs are made using the intialization as stated by the 4-wire column of Table I. The results were found as shown in Table II when a weighted sum was applied. Visually some examples of the phenotypic structure of the 4-wire antenna are displayed in Figures 1A and 1B. In comparison with the historical results of the aggregate GENOCOP III implementation the MAX weighted sum results occasionally provided better results.

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Parameter	4-Wire	13-Wire
Number of Variables	39	12
Num of Domain Constraints	39	12
Ref Population Size	25	25
Search Population Size	30	50
Number of Operators	8	8
Total Num of Evaluations	1500	3020
Ref. Pop Evolution Period	100	50
Num of Offspring for Ref. Pop.	20	10
Search Point Replacement Ratio	0.6	0.6
Ref. Point Init. Method	0	0
Search Point Init. Method	1	1
Objective Function Type	0	0
Precision Factor	0.0001	0.0001

TABLE I
GENOCOP III 13/4-Wire Initialization

	Best Fitness				
Run #	**Agg**	**Pareto**			
		MIN	MAX	MEAN	Std Dev
1	75.5	49.76	70.00	63.33	3.75
2	73.0	49.79	73.93	65.49	4.49
3	69.8	22.70	71.33	59.39	11.84
4	78.8	23.91	69.51	61.82	6.31
5	70.2	48.49	69.80	62.80	4.45
6	73.2	46.50	71.88	63.46	4.67
7	75.5	60.88	72.39	66.01	2.77
8	74.2	47.55	71.68	64.19	4.42
9	78.7	45.78	71.19	66.29	5.09
10	70.4	42.02	71.02	62.53	5.46
Mean(μ)	73.91	43.74	71.28	63.54	5.33
Var(σ^2)	9.71	139.35	1.76	4.41	6.14

TABLE II
Comparison of Aggregate and Pareto GENOCOP III Results

Statistical analysis on comparing the MAX results of the Pareto GENOCOP III to the Aggregate GENOCOP III show that the variances of the two groups are not equal, this is based on a test statistic of 30.44 and a student F test with an alpha of 0.1 and a result of 2.44. Thus using a hypothesis test on the equivalence of the means, with a student T test equaling 1.289 (alpha=0.1) and a Test Statistic of 0.84278 we determine that the mean weighted sum is statistically equal.

It is interesting to note the geometries in Figures 1A and 1B. Figure 1A is a wire that is optimized primarily for Power Gain with a secondary optimization of symmetry. This wire is a strong shape for broadcasting with the tall wires that are near perpendicular to the X-Y axis. On the other hand Figure 1B is optimized for Resistance and Reactance. The small wire with short segments is intuitively good at this with the short wire lengths producing minimal resistance and reactance, yet still producing a signal.

To compare the results of the aggregate versus the Pareto versions of the 13-wire experiments, computations are done using parameter initialization as stated by Table I under the 13-wire column. The 39 variables and domain constraints are used such that the first four tuples of numbers are the endpoints of the main antenna structure and each successive trio of tuples defines a branch off of this main antenna.

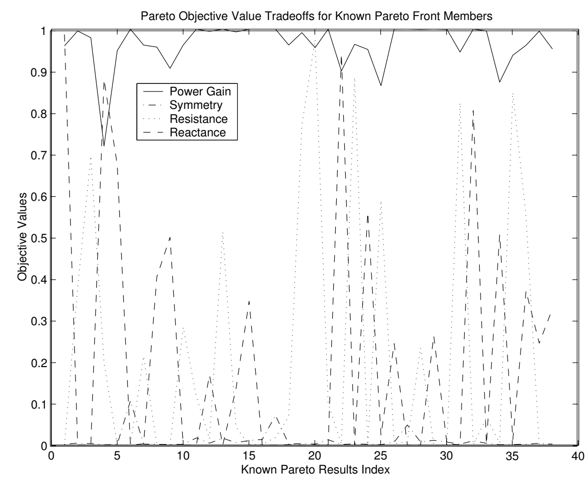

Fig. 2. Objective Tradeoffs on the 13-Wire Pareto Front

Applying the weights used in the aggregate implementation, the results of the 13-Wire Pareto search returned minimum and maximum values in a 95% confidence interval of 48.17 ± 7.93 and 70.28 ± 2.34 as opposed to runs of the aggregate GENOCOP III with results of 71.84 ± 2.66. The large range of pareto results produced a variety of geometries as seen in Figures 1C and 1D. These differences can be explained by the area of search that each implementation uses. The Pareto implementation examines across a large percentage of the search area, attempting to find a broad range of non-dominated values.

Figure 2 displays the varied levels of each of the objectives across the pareto front. The aggregate implementation instead focuses on a certain area of the solution space to find a specific answer. Initial runs of the aggregate implementation with 3000 evaluations produced results as high as 79.7 for the weighted fitness, increasing the number of evaluations for the Pareto implentation should provide improved results as well. Niching may also help to spread the data more evenly across the surface and thus to the extremes, such as that found by the aggregate approach.

When examining the Pareto GENOCOP III MOEA against the more well known multiobjective implementations like the MOGA[14], NSGA[15], and NPGA[16] the GENOCOP III most closely imitates the MOGA. However it does not incorporate any fitness sharing as of yet. The Pareto GENOCOP III version has some advantages to these other MOEAs because of the way that the initial GENOCOP III was designed. GENOCOP III works on real valued loci, increasing the possible search space which for some algorithms may be beneficial. GENOCOP III also incorporates many different potential operators to evolve the chromosome. These operators are applied using probability distributions generated based on the size of the populations, and help evaluate the Pareto Front of the problem.

VI. Conclusions

Implementation of Pareto Operators on top of existing real-valued GA systems such as GENOCOP III is an effective and efficient way of doing multiobjective optimizations. This is not only much easier and faster to implement than creating a wholly new MOEA, it also has the benefits of using prevalidated code. With the Pareto modifications we give the decision maker the ability of choosing from a vector of equally non-dominated solutions for the antenna's desired attributes. This vector may or may not include the most optimal solution that the DMs desire due to searching over the entire landscape. If the DMs do know exactly how they want the objectives to compare in terms of overall quality they can specify that using the *a priori* techniques. This motivates the genetic algorithm to search specifically in that area of the problem landscape.

We have shown that the Pareto GENOCOP III finds solutions across the Pareto Front, allowing the DM to choose what tradeoff of objective values would be best for the system. Also, we have shown that it can match the results of an aggregate approach as well for simpler problems. When dealing with very complex problems (like the 13 wire implementation) a directed search such as an aggregate approach is beneficial when the weights are known to help reduce the time needed for computation. When dealing with simpler problems the Pareto approach allows the DM to decide after the front is found, helping expand the possibilities of available geometries to pick from.

Further research into this area will include the use of niching functions, further examination on the number of evaluations necessary for a Pareto algorithm to approach different values of an aggregate function. Work has also been suggested to use a genetic algorithm to test different configurations of wire branch structures for their applicability to the RIMS problem as well as others.

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