Finding Improved Wire-Antenna Geometries with Genetic Algorithms

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Abstract— **A remote monitoring system's performance is measured largely by its associated antennas' efficacy. Improving antenna performance is not a straightforward process, as many (sometimes conflicting) design trade-offs must be considered. An alternative approach specifies desired antenna properties and then searches for antenna geometries producing those properties. We implement this approach of designing a wire antenna having optimal performance under user-defined adverse conditions by using a genetic algorithm, where fitness of promising designs is analyzed using the Numerical Electromagnetics Code (NEC) Version 4.1. Two versions of an** *integrated* **GA-NEC code are implemented; both produce geometries showing improvement over current designs. Results for both versions are presented, compared, and discussed.**

I. Introduction

Today's world offers a proliferation of "wireless" systems: cellular phones, packet and broadcast radio, television and satellites, radars, and pagers, to name but a few. These systems are used for communication, security, sensing, and a myriad of other tasks. However, these systems have at least one component in common - their associated *antenna*. For some of these devices antennas are quite easy to design and build; others, such as radar or radio transmitter/receivers, involve a time-consuming process which is *not* guaranteed to produce optimal results.

Many common antennas, such as the rhombic, Yagi, or log periodic, have been and continue to be designed using an inductive process. Integral equations for current distribution on each wire are formulated, then the electromagnetic antenna properties are calculated. This design process is generally limited to producing relatively simple wire structures [1]. The constant demand for better antenna performance motivates a better design technique, as the existing one is time-consuming and requires much designer creativity. And, since improved antenna designs often include several conflicting trade-offs and are known to involve many parameters, one wishes to find a technique able to deal with these constraints. Genetic Algorithms (GAs) are a proven tool in engineering search and optimization applications like that of antenna design [2].

An alternative design approach allows up-front specification of desired antenna electromagnetic properties, then the use of a GA to search for an antenna configuration producing those desired properties. These specified properties are evaluated via the GA's fitness function; each individual antenna geometry is evaluated for performance based on that function. In this case the *fitness* of a particular design *is* a combination of its associated electromagnetic properties.

An appropriate evaluation function must then be encoded for the GA's use. Fortunately, many existing codes are already capable of computing these antenna properties. It is more appealing to reuse implemented algorithms describing these properties than to recode them from scratch. Thus, we propose integrating a GA with an existing electromagnetic evaluation code to complete our design approach.

The "No Free Lunch" Theorem [3] implies an algorithm is most effective when it has incorporated problem domain knowledge. A GA capably *searching* for promising antenna designs interfacing with code directly *evaluating* design properties thus seems to be both an effective and efficient approach. However, our proposed implementation must prove its utility. To perform this task we identify a suitable wire antenna geometry design problem, integrate an appropriate electromagnetic evaluation code, and search for better antenna geometries using two existing GA techniques. We evaluate the improved geometries for their benefit over existing ones and also critique our GA approach.

II. System Description and Restrictions

Military and civilian applications of remote security, sensing, and communication systems continue to expand. A typical military implementation is the Remote Intrusion Monitoring System (RIMS), which alerts some central station when an intruder is detected. A typical RIMS implementation is shown in Figure 1 and contains the following components:

Unattended Sensors. Physically located in the region of interest. Sensors are frequently buried leaving only the antenna(s) above ground or camoflauged in some like manner. They can be customized to provide magnetic, seismic, passive infrared, or acoustic data.

Optical Sensor. An unattended sensor providing visual information, thus requiring an attached camera unit.

Field Processor. Receives sensor information, formatting that data for input to analysis software located in Field and Central Analysis Units.

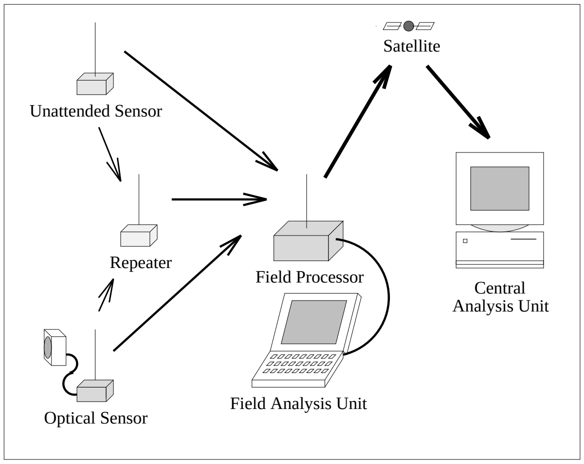

Fig. 1. **Typical Components of a Remote Intrusion Monitoring System (RIMS)**

Field Analysis Unit. Normally a laptop computer connected directly to the Field Processor.
Central Analysis Unit. Normally a personal computer receiving remote data via satellite.
Repeater. Receives and retransmits sensor signals, allowing for greater distance between unattended sensors and the field processor.

RIMS must meet stringent user requirements. The sensors and field processor are generally located in non-supportive environments, i.e., users *cannot* access them. For example, system components might be air-dropped or covertly emplaced to monitor strategic locations. The system's antennas are the primary determinant of overall system utility. Thus, the greatest possible antenna performance is desired while keeping the antenna's physical structure as inconspicuous as possible. Numerous antenna variables must be considered when engineering a proposed design. Some of the possible antenna trade-offs follow.

- System antennas should not be large or bulky. Current RIMS implementations meet this requirement by using a thin, wire monopole antenna.
- Sensors and the field unit are often located in foliage or other cover. An electromagnetic wave's ability to penetrate foliage increases when its frequency decreases, leading to an important antenna size vs. frequency decision [4]. Larger antennas are required for successful communications at lower frequencies. For these reasons the Very High Frequency (VHF) band is commonly used as a good compromise.
- The amount of power used by the sensors when transmitting a message to the field analysis unit must be sufficient for VHF line-of-sight communications, but the power supply's size cannot force sensor physical dimensions to unreasonable levels.
- The voltage source driving the antenna should be located very close to or on the ground. A bulky transmission line feeding the antenna at some point above the ground *cannot* be used.
- The antenna should be omni-directional in azimuth. Because of the non-supporting environment antenna orientation cannot be guaranteed.
- Little or no opportunity for maintenance exists. The system's remote components are often considered expendable. Therefore, the design should incorporate dependability and a zero-maintenance requirement, as well as reasonable cost.

We choose to focus effort on obtaining an effective and efficient wire antenna design ensuring maximum RIMS performance by meeting the above requirements as robustly as possible. This implies finding antenna designs which perform well in the following areas: radiated power gain, azimuthal symmetry of radiated power, input resistance, and input reactance. In other words, we attempt to optimize antenna performance for these attributes.

Qualitatively speaking, radiated power gain is a ratio of the power observed at a point away from the antenna to the power accepted by the antenna's excitation source [5]. Simply put, this measure quantifies the antenna's ability to transmit source energy. Regarding symmetry, it is important that the radiated power is equally distributed in the azimuthal plane. As previously mentioned, component placement may not be optimal. Optimizing the input resistance and reactance is important for maximum power transfer from the antenna. Basic circuit design teaches the greatest amount of power is delivered to the load when the load and source impedance are matched. In this case, the antenna is the load and the signal generator circuitry connected to the antenna is the source.

III. Methodology

Several problem and algorithm domain issues still require resolution before implementing the GA. We must impose certain requirements ensuring reasonable computation time and enforcing the previously described design constraints. Although an appropriately implemented GA should find optimal antenna designs, the evaluation of the antenna's performance is better performed by appropriate electromagnetic codes. Thus, we create *integrated* GAs whose fitness function is computed by the specialized electromagnetic code in Section III-B.

A. GA Design

In a manner similar to that used by a like effort [1] the proposed antenna's wires are confined to a bounded space. For this problem, we assume electromagnetic parameters appropriate to an operational environment [6]. The space requirements in which any proposed antenna must fit is a rectangular box above the x-y plane, bounded by

$$a \leq x, y \leq b \text{ (meters)} \quad (1)$$

$$c < z \leq d \text{ (meters)} \quad (2)$$

It has been noted that many non-intuitive antenna configurations may perform as well as or better than intuitive ones [1]. However, a complicated geometry may unacceptably hamper performance analysis. A series-connected wire antenna is relatively easy to both physically construct and analyze. Our research antenna is thus composed of a series of straight wires; the first wire is connected to a voltage source at the origin and successive wires are connected in series. Because continuous space is searched for optimal antenna designs we chose real-valued alleles.

Each gene represents the endpoint of the associated wire in Cartesian coordinates for our series-connected antenna, e.g.,

$$g_m = (x_m, y_m, z_m) \tag{3}$$

describes the coordinates of the m^{th} wire's endpoints. The wires are connected in series with the first wire beginning at the origin, (0,0,0), and ending at (x_1, y_1, z_1). The m^{th} wire begins at $(x_{m-1}, y_{m-1}, z_{m-1})$ and ends at (x_m, y_m, z_m). Each chromosome then has M genes where M is the number of antenna wires. For example, a four-wire antenna ($M = 4$) defined by the following coordinates

Wire #1: $(0.000, 0.000, 0.000)$ to $(0.000, 0.140, 1.618)$
Wire #2: $(0.000, 0.140, 1.618)$ to $(0.214, 0.484, 1.025)$
Wire #3: $(0.214, 0.484, 1.025)$ to $(0.046, 0.327, 0.430)$
Wire #4: $(0.046, 0.327, 0.430)$ to $(0.390, 0.171, 1.805)$

is thus represented as

$$\begin{aligned} c_i = \quad & (0.000, 0.140, 1.618, 0.214, 0.484, 1.025, \\ & 0.046, 0.327, 0.430, 0.390, 0.171, 1.805). \end{aligned}$$

B. GA Integration

The fitness evaluation uses a weighted-sum approach to combine the multiple objectives of power gain, symmetry, resistance, and reactance into a single scalar fitness value. The objectives themselves are computed using the Numerical Electromagnetics Code (NEC) Version 4.1 [7], then appropriately combined via a user-specified GA-NEC interface and returned as the fitness value. Because the GA itself makes no distinction between feasible and infeasible designs prior to requesting a fitness evaluation, the interface is capable of detecting instances when NEC determines the geometry is infeasible.

Because NEC expects feasible antenna designs as input and unmodified GAs offer no solution feasibility assurances, the feasibility function returns a 'zero' fitness cost for any *infeasible* antenna design (as determined by NEC). This improves GA convergence to designs computable by NEC. No attempt was made to modify problematic designs; minimizing computation was deemed more important. Additionally, infinite iterations may result when attempting to 'fix' infeasible designs. In either of our GA instantiations, the algorithm makes a function call passing the appropriate endpoint parameters and is returned the NEC-based computed fitness value for that particular configuration.

We must also consider the general *fitness landscape* we search. An optimal antenna fitness value doesn't necessarily mean the associated geometry is *desirable*. We wish the geometry's fitness to be located within a *fitness plateau* and not to be sensitive to small genotype (wire endpoint) perturbations. Additionally, we must analyze any optimal geometry as to its physical implications, ensuring its feasibility in the "real-world."

IV. Experiment

We chose to implement and analyze two integrated GA-NEC versions based on the preceding information. The following sections present specific GA parameters, discussing and explaining their choice.

A. GA-NEC Design

The bounded search space for the proposed antenna is defined by the following range constraints:

$$-0.5 \le x, y \le 0.5 \text{ (meters)} \tag{4}$$

$$0.001 < z \le 2.0 \text{ (meters)} \tag{5}$$

For our initial work we chose a four-wire antenna configuration ($M = 4$). This was an arbitrary choice, but appeared to be a good compromise between existing monopole antennas and a "jumbled mess." Thus, each individual is represented by a chromosome

$$c_i = (x_1, y_1, z_1, x_2, y_2, z_2, x_3, y_3, z_3, x_4, y_4, z_4)$$

whose coordinates are as defined in Section III-A. Finally, we mathematically represent our problem as maximizing a weighted sum of the antenna's four objective functions,

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

where k_i is a weight coefficient and $f_i(\cdot)$ is a function mapping the raw objective value, t_i, to the interval $[0, 1]$. For the power gain objective, t_1, the mapping function is defined as

$$f_1(t_1) = 1 - exp(-K_1 t_1) \quad . \tag{7}$$

For the objectives of symmetry (t_2), resistance (t_3), and reactance(t_4), the functional form of $f_i(\cdot)$ is

$$f_{i=2,3,4}(t_i) = exp(-|(t_i - S_i)|/K_i) \quad . \tag{8}$$

Figure 2 shows each $f_i(t_i)$ and their associated values of S_i and K_i.

Each mapping function performs the necessary transformation from the raw value returned by NEC to a corresponding percentage which is multiplied by the associated weight coefficient. Thus, we chose the functions such that $0 \le f_i(t_i) \le 1$ for all possible raw values. We chose the K_i terms *a priori* using knowledge of the raw values obtained during preliminary research phases. Conversely, each S_i represents a raw value that is a desirable characteristic of the antenna design. For example, we set $S_3 = 50.0\ \Omega$ to obtain higher fitness for designs with an input resistance of 50.0 Ω. Likewise, we establish $S_4 = 0.0\ \Omega$ because an input reactance of 0.0 Ω is desirable. It is common knowledge that many electromagnetic sources have a resistance equal to 50.0 Ohms (Ω) and a reactance of 0.0 Ω. The raw azimuthal symmetry value is really a measure of asymmetry, so larger values correspond to designs that radiate less symmetrically. Therefore, $S_2 = 0.0$ enforces the azimuthal symmetry objective. The function shapes in Figure 2 show

how this mapping scheme works. More desirable raw values return larger *mapped* values. Consequently, the larger *mapped* values translate into larger portions of the corresponding weights in the fitness sum of Equation 6.

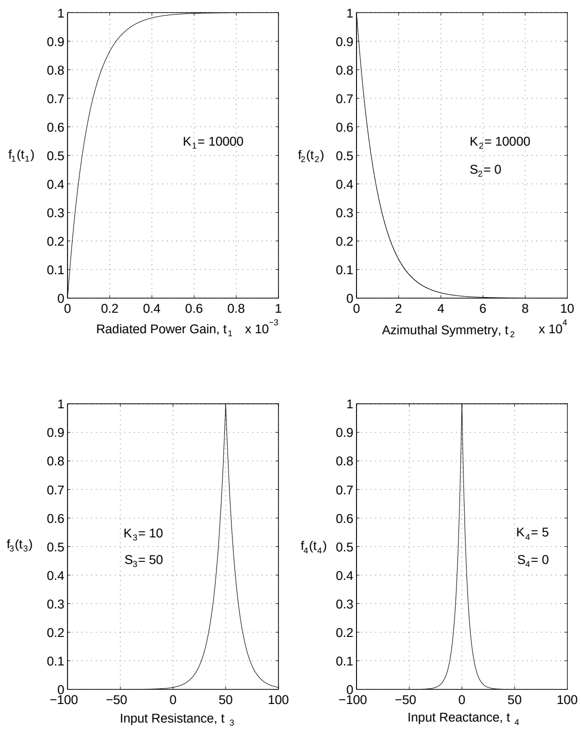

Fig. 2. **Objective Function Mappings**

The weight coefficients were defined as $k_1 = 60$, $k_2 = 20$, $k_3 = 10$, and $k_4 = 10$. These values were chosen based on problem domain knowledge. They reflect that the power gain of the antenna is the most important objective of the design followed by the symmetry of radiated power. Least important for our purposes is the consideration of input resistance and reactance. Our choice of mapping functions and weights ensures all fitness values lie in the interval $[0, 100]$.

Both GAs were executed for 100 generations (about 3020 function evaluations). Preliminary research indicated the simple GA nearly always converged by that generation; it was kept constant for the sake of comparison with the GA introduced in Section IV-C. Both GAs used a population of 50 individuals as suggested by Bäck [8] and others. Finally, ten runs of each algorithm were performed for statistical comparison purposes.

B. Simple GA-NEC

This GA was written in Fortran 77 and intended as a *proof- of-concept* for our approach. Implemented similarly to previous research [1], it is a *steady state* GA, retaining 40% of the population between generations. An eight-member tournament selection strategy is the basis for selection of chromosome pairs for crossover. That is, eight members of the entire population are chosen at random, selecting the two chromosomes with highest fitness for crossover. We implemented the crossover process successfully used in a related research effort [9]. Crossover is a simple linear averaging scheme producing three individuals, where if C_p and C_q represent the two non-identical chromosomes selected for crossover, the resulting chromosomes, C_a, C_b, C_c are found by

$$C_a = \frac{C_p + C_q}{2} \quad , \tag{9}$$

$$C_b = \frac{3C_p + C_q}{4} \quad , \tag{10}$$

and

$$C_c = \frac{C_p + 3C_q}{4} \quad . \tag{11}$$

To implement mutation the GA-NEC incorporates a uniform random number generator which sequentially selects a wire endpoint, and then a coordinate within that endpoint for mutation. The mutated value of the selected allele is uniformly distributed along its appropriate constraints as defined in Equations 1 and 2. With $M = 4$ this corresponds to a fixed mutation rate of 8.3%. A higher mutation rate of 25.0% was investigated in early phases of this research, but algorithms using this higher rate consistently achieved lower fitness levels. The GA-NEC implements mutation only in the offspring chromosomes. By so doing the integrity of the gene-pool's steady-state portion is preserved.

C. GENOCOP III-NEC

In order to gauge relative effectiveness of the simple GA-NEC approach, we compared its results against those produced by the GENOCOP III system [10]. GENOCOP III was chosen because it brings unique capabilities to bear on our problem. For example, GENOCOP III has a wide variety of reproductive operators available for use; one is randomly chosen to perform reproduction each generation. For added flexibility, the user can specify the relative frequency with which these operators are invoked during the search. The use of such a diverse set of reproductive operators results in a much more balanced search of the fitness landscape than that which might occur using only a single operator.

In addition, GENOCOP III is designed to ensure *all* chromosomes evaluated by the system meet a set of predefined constraints falling into three categories: domain, linear and non-linear. The fittest chromosomes meeting every constraint are kept in a reference population (P_r). A separate search population (P_s) is used as a pool of potential solutions. Chromosomes from P_s meeting all constraints are evaluated for inclusion into P_r. Those chromosomes that violate constraints are repaired by generating a feasible solution along the boundary formed with the closest point in P_r. We utilize this feature of GENOCOP III to enforce the domain constraints specified in Equations 4 and 5.

Relevant search parameters used by the GENOCOP III runs are shown in Figure 3. They were tailored to match those of the simple GA-NEC algorithm as closely as possible to ensure we compared "apples to apples." However, the number of fitness evaluations performed by each algorithm may still be different, as individuals in GENOCOP

	Best Fitness	
Run #	**GA-NEC**	**GENOCOP-NEC**
1	70.0	75.5
2	73.9	73.0
3	69.9	69.8
4	70.2	78.8
5	70.1	70.2
6	70.0	73.2
7	69.9	75.5
8	70.1	74.2
9	70.1	78.7
10	70.2	70.4
Mean(μ)	70.44	73.91
Variance(σ^2)	1.34	9.71

TABLE I

Comparison of GA-NEC and GENOCOP-NEC Results

III's reference population may be evaluated several additional times [10].

Number of variables	12
Number of domain constraints	12
Reference population size	25
Search population size	50
Number of operators	8
Total no. of evaluations	3020
Reference population evolution period	50
Number of offspring for ref. population	10
Search point replacement ratio	0.6
Reference point initialization method	0
Search point initialization method	1
Objective function type	0
Precision factor	0.0001

Fig. 3. GENOCOP III Search Parameters

V. Results, Analysis, and Conclusions

The experiment results are shown in Table I. As the table indicates GENOCOP III-NEC achieved the best overall solution and had the higher mean. In fact, GENOCOP III-NEC decisively outperformed the GA-NEC algorithm. A Student T test performed on the results yielded a T value of 3.14 at 18 degrees of freedom. This is sufficient to label the GENOCOP III-NEC algorithm superior with 99.5% confidence.

The difference in performance between the two algorithms most likely has two contributing factors. First, GENOCOP III generates an initial set of possible solutions from both the entire feasible region *and* points on the boundary [11]. GENOCOP III also employs a greater range of genetic operators. These combined factors may have enabled GENOCOP III to explore the landscape in a more comprehensive manner than GA-NEC.

We must also analyze the resulting geometries in terms of their geometrical and electromagnetic properties. The best resultant four-wire antenna geometry designed via the GA-NEC has an associated fitness value of 73.9; the geometry designed via GENOCOP III-NEC has an associated fitness value of 78.8. The physical representation of these designs is shown in Figures 4 and 5. It is evident from the peculiar geometries the designs are somewhat non-intuitive. It is also interesting to note the designs' physical similarity. We also observe both designs offer improvement over current RIMS' antennas, and that neither design poses difficulty for real-world implementation.

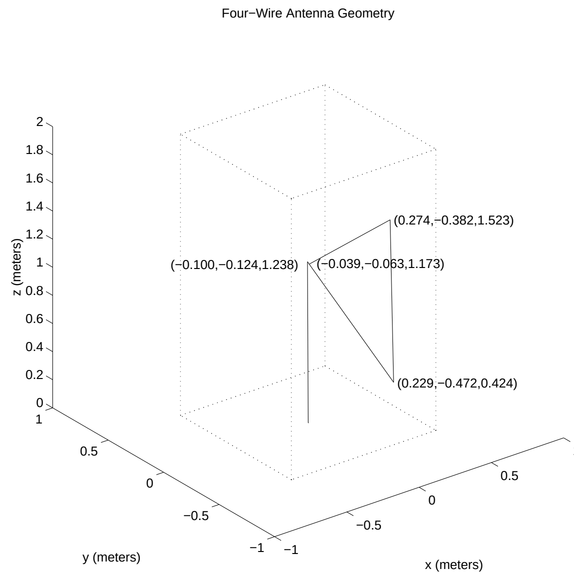

Fig. 4. **Best Performing Design via GA-NEC**

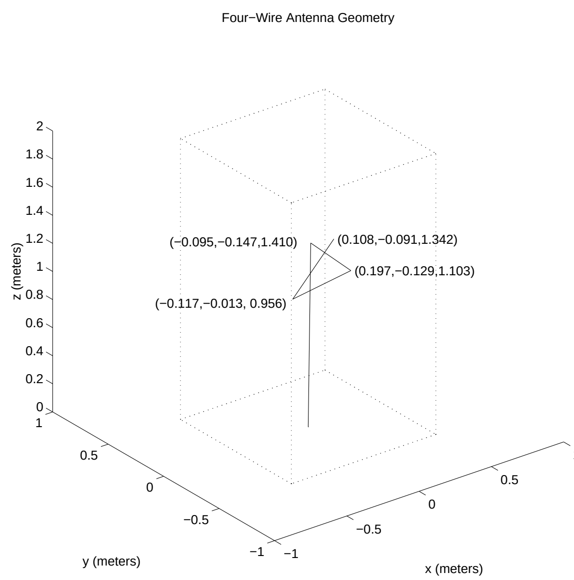

Fig. 5. **Best Performing Design via GENOCOP III-NEC**

A typical RIMS uses a quarter-wavelength wire monopole antenna. The power gain of each GA-designed antenna is shown in Figures 6 and 7, and is directly compared with a typical RIMS monopole. Power gain values for the four basic azimuth planes are all higher than that of the monopole. Of particular interest is the improvement at high zenith angles (80-90°). For instance, at a zenith angle of 86° the monopole provides -10 dB of total power. For the same zenith angle and an azimuth of 0° the GENOCOP III-NEC design provides approximately -7 dB of total power. This improvement of 3 dB is significant and an important result because it translates into larger distances between RIMS components.

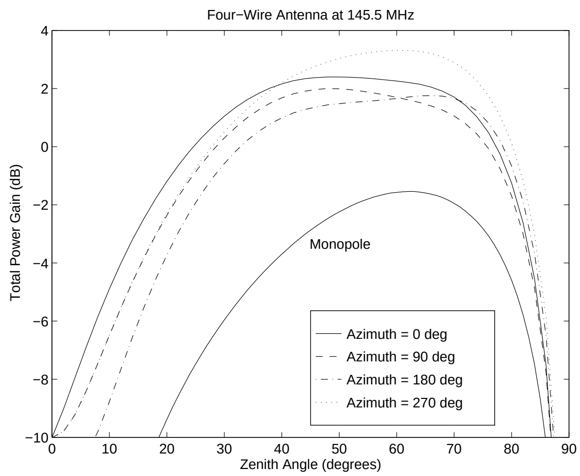

Fig. 6. **GA-NEC Design Analysis of Total Radiated Power**

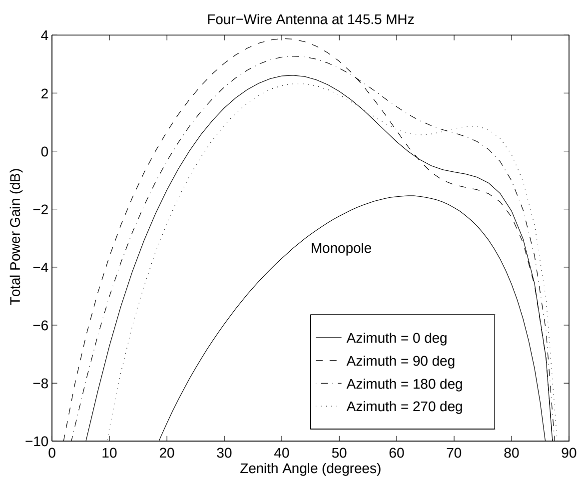

Fig. 7. **GENOCOP III-NEC Design Analysis of Total Radiated Power**

Symmetry of radiated power was another optimization objective. Both GA's enforcement of this condition is relatively good for most azimuth angles. We considered the input resistance and reactance as the least important of our objectives. We found input resistance/reactance for the GA-NEC design to be 54.54 Ω/0.12 Ω, and 49.77 Ω/0.01 Ω for the GENOCOP III-NEC design, which is clearly closer to our desired values of 50 Ω/0 Ω.

VI. Summary and Future Work

A new approach for designing wire antennas has been presented. A mapping scheme was developed to consider multiple objectives in optimizing wire antennas, operating in an interface used by two versions of an integrated GA-electromagnetic code. After implementation an experiment was performed to test code performance. Experiment results clearly indicate the integrated GA has utility. Detailed discussion and analysis of our antenna design process is found in Sandlin's recent thesis [12].

The GENOCOP III-NEC approach resulted in an improved antenna geometry physically suitable for use in RIMS components. We are interested in investigating more complex geometries (such as a variable number of wires), and believe GENOCOP III's ability to deal with both linear and non-linear constraints will serve us better than pursuing the simple GA. We also intend to investigate other multi-objective optimization approaches and explore any further antenna geometry improvements.

VII. Acknowledgments

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