3G TRI BAND PROBE FED PRINTED ECCENTRIC SPIRAL ANTENNA FOR NOMADIC WIRELESS DEVICES USING OPTIMAL CONVERGENCE FOR PARETO RANKED GENETIC ALGORITHM.

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ABSTRACT
In this paper the design of a printed eccentric spiral Antenna optimised for 3G nomadic devices such as personal data assistants is discussed. An optimum chromosome selection method for chromosomes that constitute points on a Pareto surface of 3 dimensions is used in a Genetic Algorithm (GA). The GA is used with a Method of Moments (MoM) technique [1] and small populations of less than 25 and seeks to synthesize a single arm spiral antenna suitable for use at UMTS, GSM1800 and GSM900 frequencies. Two Pareto ranking algorithms are explored and their resulting Pareto optimal chromosome sets compared using a novel False Pareto Vector Magnitude metric. A suggested strategy for optimisation of tri band antennas using a GA is presented.

INTRODUCTION
Spiral antennas generally offer advantages of circular polarisation, wide bandwidth and high efficiency, and as the authors have shown [2] may be configured to provide squinted beams through variation of the spiral parameters. UMTS in particular requires relatively larger bandwidths than current popular antenna solutions whilst seamless roaming requires multiple frequency bands. These factors will generate increasing demand for conformal antennas on handheld nomadic wireless devices such as personal data assistants. Such devices will support streaming video. For the first time limited comparisons will be able to be made in performance between products. For example two products side by side with users watching the same televised event. The need for performance enhancement via highly specified multi-band antennas is therefore to become more important with poor antenna performance being identified more easily by a layman.

ANTENNA SYNTHESIS USING GENETIC ALGORITHMS
GAs have now seen much application to wire antennas where MoM models are used to assess fitness. Haupt [3] used a GA to optimise radar cross-section scattering on thinned grids of strips and resistively loaded strips. Boag [4] applied a GA to both ultra wide-band antennas and their matching networks. More recently, Altshuler [5] simulated a circularly polarised GPS/IRIDIUM vehicle antenna and used a GA to drive the Numerical Electromagnetics Code (NEC) for his simulation and Coaosi [6] applied a GA to a scattering problem involving dielectric cylinders. The electromagnetic community is now showing increased interest in GAs that can be used to efficiently assist with the design of electromagnetic structures. However, application of the GA to electromagnetic problems is a comparatively recent event and very few implementations currently exist, and those that do generally have dependence on cost functions. To elaborate, GAs have been likened to natural selection and simplistically the concept is that nature first creates an entity out of the available genetic material and then tests it for viability against its environment. Here, environment is taken to include all other entities. If this creature survives then it becomes part of the available genetic material from which future generations are made. The process then, sometimes called ***natural selection***, can be considered as a filter. A genetic algorithm is a search technique, which mimics the natural selection process and uses for example a set of antenna parameters grouped together to form a chromosome.

The environment to which the antennas are subjected comes in two parts. Firstly, antenna specifications are generated from parameters such as material characteristics, element lengths and geometries of elements. Each antenna set forms a ***chromosome*** and is evaluated for one or several properties using an electromagnetic software model. Secondly the chromosomes are sorted (***ranked***) according to how well or poorly they satisfied the desired criteria. For example, if the criterion looked for by the model is radiation efficiency then chromosomes with the best radiation efficiency will have the highest rank. The desired criterion, in this case efficiency, is described in GA terms of ***fitness*** or ***cost***. A cost function may be single objective or multi-objective. The authors have previously discussed in [7,11] that the search space for the GA may be adversely limited due to poor choice of weighting and ranges of the fitness parameters used to create the cost function which, is the key function of procreation for a typical GA. In essence, the choice of likely ranges made by an engineer will have a significant influence on possible outcomes and since the choice is intuitive then valuable and interesting genetic material may be excluded. Most GAs with antennas use a weighted function of antenna goals, for example gain and radiation efficiency, to rank designs. The weighting functions are subjective and to achieve best results from a simulation are, in practise often modified during the design process. This would seem reasonable since for example it is difficult to correctly assign a weight to a goal of gain since it is not generally known what range

of gains are possible for a new antenna. Also certain properties may be more important than others.
For example Gain may be considered twice as important as input impedance and therefore have a weighting of two.

Pareto Ranking

Pareto ranking [7, 8] as used by the authors ameliorates this cost function handicap by mapping goals onto free running axes, one axis per goal, and allowing goal ranges to run to and from infinity thus allowing the creation of a closed Pareto surface upon which all chromosomes are considered equal in each generation. The novel Pareto ranking as adopted by the authors is based on the fact that there exists no simple solution as to which range of parameters will specify the ideal antenna. This implies that parameters resulting from the model should not limit the range of the search and that the search should therefore be constrained only by the specification of the antenna. In this way all possible permutations as a function of specification can exist. Clearly, the Pareto set from which antennas are bred cannot be infinite and therefore a method for reducing the size of the Pareto surface to dimensions containing a manageable number of chromosomes has to be used.

CHOICE OF PARETO RANKING ALGORITHM

The choice of which chromosomes are used to yield genetic material for forthcoming generations is critical [8]. In Figure 1 a pseudo code Pareto ranking algorithm is shown. One objective or optimisation criteria would be ranked by this algorithm; for example a good circularly polarised main lobe. A tri-band version of the same antenna would involve three objectives and therefore three separate axes in the Pareto space.

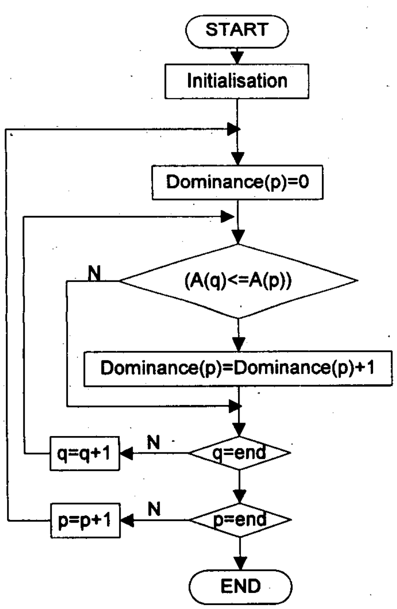

Figure 1. Pseudo code Pareto ranking algorithm. (most dominating)

The algorithm can be used to define a **Pareto set**. In this way better genetic material is sought for successive generations of the GA. A ***Pareto optimal chromosome*** is said to be Pareto optimal if no gene can be altered without producing a worse antenna in some important respect. A ***Pareto optimal set*** is formed by a group of Pareto optimal chromosomes. Chromosomes plotted on a multi-dimensional surface with an axis for each sought after antenna property are consider equal and form a ***Pareto surface*** in that they are all actually better than other chromosomes but are not better than each other. The overall goal of the GA is that by selective breeding through successive generations an optimum antenna can be found that is bred from antennas on the Pareto surface (plus an amount of mutated gene diversity). Clearly, in the limit all antennas on the surface would be Pareto optimal and form a ***Pareto optimal set.***

Chromosomes ranked by an algorithm are generally used in two ways. Both [1,8] suggest for choice of dominance that best least dominated is better since it may avoid premature convergence where one chromosome is so dominating that no other chromosome can surpass it. This would be equivalent to getting stuck in a local minimum. However, both best least dominated and best most dominating have been used by the authors with success. The difference may be due to the fact that [8] did not use small populations and in addition used a vector function to prevent niching.

IMPLEMENTATION ON A PRINTED SPIRAL

A typical implementation is now described with reference to a printed spiral antenna. The antenna can be fully described for manufacture using six specifications (note that this is not a constraint). For a microstrip eccentric spiral antenna these might be those shown in the Table 1.

Table 1. Specifications of a Printed Spiral Antenna mapped to six genes of a chromosome.

No	Spiral Specification mapped onto Gene
1	The winding angle
2	The radius of the conductor
3	Rate of growth of the spiral
4	Substrate ε_r. ($\mu_r = 1$))
5	The length of the linear feed
6	The eccentricity constant

To allow meaningful comparison to be made between ranking algorithms and dominance regimes the antenna sought in this research was deliberately chosen to be one that was thought to be very difficult to locate within the constricted search space available. Physically the antenna was required to sit on a space similar to that of existing PDAs being 100mm x 70mm x 3mm. The material for the substrate was chosen to be a typical plastic with relative permittivity of 1.5 to 3.(Assumed loss less)

The type of spiral antenna investigated here is a variation on the Curl antenna, Nakano et al [9, 10]. A single spiral arm is fed by a probe running through the dielectric, this feed arrangement obviating the need for a balun.

Eccentric spirals can be described in parametric form as

$$\underline{\rho} = (\rho_o + a\phi)(\cos\phi + K)\hat{x} + \sin\phi\ \hat{y}) \qquad \text{Equn. 1.}$$

with ρ_0, a and K as constants.

Table 2 shows the ranges of the specifications used for each of the six genes used to form each chromosome. For this work the thickness of the substrate was set to 2mm which is reasonable for a PDA cover or lid.

Table 2. Genes ranges.

Gene	Value
Winding Angle ϕ	½ to 20 (π)
Wire radius	0.1 to 1.5 (mm)
Spiral Constant (a)	(8 to 16) × ((wire rad)/2π) mm/rad
Perm. of substrate	1.5 to 3.0
Length of Feed	5 to 20 (mm)
Eccentricity Constant	0.1 to 0.8

Arbitrarily, the objective used for this research was good axial ratio on main beam at three frequencies. Thus a three dimensional search space was created. Consequently, 24 chromosomes each one containing an antenna specification is put to the electromagnetic engine, which produces a set of characteristics for each antenna. This process is repeated three times, once for each of the three chosen frequencies. Clearly a perfect antenna would have unity axial ratio at each frequency.

Table 3 shows the initial results for the three goals prior to any sort of ranking. Values of 1000.0 for axial ratio show that a non-convergent integral was encountered in the model and that these antennas are to be discarded by low ranking. Even with such a small population it can be quite difficult to easily pick out an antenna from Table 3 that has merit over all others. For example, antenna number 18 has good axial ratio at UMTS2015. but poor axial ratio at GSM900. Nevertheless, these 24 chromosomes form the initial genetic pool and a decision must therefore be made as to which of these chromosomes be allowed to pass on its genetic material and also which of these antennas has such merit when compared to others that it should be kept un-bred as well and therefore copied back in after the breeding process.

The previously mentioned electromagnetic analysis code is therefore run 72 times for the first set of chromosomes, and the four chromosomes having the highest dominance are copied. The four worst chromosomes are discarded. The 20 remaining chromosomes including the duplicates of the four best are now randomly paired for cross breeding, with an additional mutation probability of 0.2 applied to each chromosome. Mutation requires that one gene of that chromosome is randomly recreated. Twenty new chromosomes and the four previously saved best examples now form the new population.

Table 3. Initial Population Characteristics for Axial Ratio (dB) at GSM900, DCS1800 & UMTS2015

No	GSM 900	DCS1800	UMTS2015
1	65.76	5.17	6.94
2	20.07	55.07	45.73
3	46.24	29.78	61.76
4	24.57	30.87	70.21
5	40.98	1000.00	6.87
6	31.75	2.13	15.69
7	9.16	10.86	9.27
8	38.92	41.45	8.92
9	55.16	18.44	12.47
10	24.16	44.61	1000.00
11	99.05	17.66	1000.00
12	44.40	9.23	2.27
13	3.08	10.10	28.26
14	44.55	37.21	37.38
15	50.32	72.54	30.05
16	33.16	47.12	39.41
17	38.67	5.05	42.75
18	19.11	17.31	1.49
19	72.81	22.77	39.54
20	49.41	10.90	14.52
21	72.27	4.80	39.18
22	27.94	37.33	25.96
23	39.00	31.47	26.64
24	82.77	40.65	4.19

For clarity let the goals have the designations shown in Table 4.

Table 4. Goal Designations.

GSM900	A
DCS 1800	B
UMTS2.05	C

Thus, the two Pareto ranking algorithms to be considered are in pseudo code shown in Table 5. Each sub-term forms the kernel of Figure 1 and three such sub-terms form a complete ranking algorithm.

Table 5. Pareto Ranking algorithms.

1	(A(q) ≤A(p)) AND (B(q) ≤ B(p)) AND (C(q) ≤C(p))	ANDed Most dominating
2	(A(q) ≥A(p)) AND (B(q) ≥ B(p)) AND (C(q) ≥C(p))	ANDed Least dominated

Table 6 tabulates the top 6 chromosomes from Table 3 as ranked by each of the algorithms of Table 5. The right hand column shows either how many chromosomes are dominated by that chromosome or how many chromosomes dominate the chromosome depending on whether algorithm one or two is used. Additional mini-terms can be added if required for example a mini-term seeking low axial ratio and high gain at one frequency would be written as

$$((A(q) \leq A(p)) \text{ AND } (D(q) \leq D(p)))$$
$$\text{AND}$$
$$\ldots\ldots$$

Table 6. Axial ratios (dB) of 1st six ranked chromosomes from each of the Pareto ranking algorithms after 1 generation.

Case 1, ANDed and most dominating				
Rank	GSM 900	DCS1800	UMTS2015	Dom
1	19.11	17.31	1.49	16
2	9.16	10.86	9.27	14
3	31.75	2.13	15.69	10
4	3.08	10.10	28.26	10
5	44.40	9.23	2.27	9
6	49.41	10.90	14.52	4
Case 2, ANDed and least dominated				
1	65.76	5.17	6.94	1
2	31.75	2.13	15.69	1
3	9.16	10.86	9.27	1
4	44.40	9.23	2.27	1
5	3.08	10.10	28.26	1
6	19.11	17.31	1.49	1

In case 1 each goal is ANDed with every other as per ranking algorithm number 1. From Table 6 we see that there is one chromosome that dominates sixteen others for all three antennas. (Note that by default with the algorithm a chromosome always dominates itself). The algorithm of Case 2 is that most commonly used for Pareto ranking and shows six chromosomes that are dominated only by themselves. More importantly it should be noted that in Case 2 the ranking is quite harmonious with many chromosomes of equal merit and may not be well suited to the choosing of good chromosomes from small populations.

The simulation is run for 10 generations for both cases of algorithm. This involved 720 runs of the EM model or 1440 in total. The final populations are then compared for merit using the following method.

Table 7. Axial Ratios (dB) after 10 Generations.

Case 1, ANDed and most dominating			
Rank	GSM 900	DCS1800	UMTS2015
1	9.16	10.86	9.27
2	31.75	2.13	15.69
3	28.12	5.82	10.63
4	19.11	17.31	1.49
Combined FPVM = 108.98			
Case 2, ANDed least dominated			
1	65.76	5.17	6.94
2	31.75	2.13	15.69
3	9.16	10.86	9.27
4	44.40	9.23	2.27
Combined FPVM = 164.18			

FALSE PARETO VECTOR MAGNITUDE

As previously defined all members of a Pareto set are equal. Consequently the algorithms are used only to decide which chromosomes have enough merit to exist on the newly defined Pareto surface (24 points in this implementation). However, a way must be devised to determine a figure of merit for a part or whole population. We therefore introduce the **False Pareto Vector Magnitude (FPVM)** metric by treating each chromosome as a 3 component vector. Components are axial ratio at each frequency. The magnitude of the vector is then taken and the all of the magnitudes for the top four chromosomes then added. (Note that where only a single objective exists per axis normalisation is not necessary). Since the axial ratio is better as it gets lower, the lower the FPVM the higher the merit.

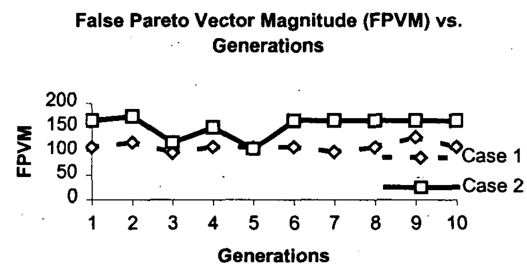

Figure 2. Relative merits for top four chromosomes after 10 generations.

DISCUSSION OF RESULTS

The chart in Figure 2 shows that the best chromosomes in 90% of the generations are found by ranking algorithm 1 (the dotted line) and that these are significantly fitter than those chosen by the normal ranking algorithm 2 that uses least dominating. However, even the best of those chromosomes found by the algorithm is not particularly good which may be caused by the constricted physical space upon which the antennas were sought. Results for these are not presented here since better solutions are likely to exist.

CONCLUSIONS

A new ranking algorithm has been shown that can be used with a Genetic Algorithm with small populations of less than thirty. Results presented here have shown that a least dominating regime may lead to blandness amongst a significant number of chromosomes and therefore prevent satisfactory copy out when elitism is used. Thus a most dominating algorithm can be applied which gives rise to a more diverse ranking and allows chromosomes to be ranked more accurately. A general strategy for tri-band antenna assessment using a GA with Pareto ranking has been illustrated. The presentation will show the results of further analysis, with antenna performances which are better than that could be achieved via intuitive runs of the electromagnetic engine alone, in terms of good axial ratios with viable gain and efficiency values.

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