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An Investigation of the Performance Limits of Small, Planar Antennas Using Optimisation

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Abstract

This paper presents a generalised parametrisation as well as an approach to computational optimisation for small, planar antennas. A history of previous, more limited antenna optimisation techniques is discussed and a new parametrisation introduced in this context. Validation of this new approach against previously developed structures is provided and preliminary results of the optimisation are demonstrated and discussed. For the optimisation, a binary Multi-Objective Particle Swarm Optimisation (MOPSO) is used and several methods for generating a viable initial population are introduced and discussed in the context of practical limitations computational simulations.

Keywords: Small Planar Antennas, Performance Limits, Optimisation, Binary MOPSO

1 Introduction

The design of antennas has for several decades used methods based on numerical simulation, since the physics governing their operation and performance is well-understood and finds mathematical expression in Maxwell's equations. However, optimisation of their performance is more difficult as there is no analytical formulation of the impact of structural changes on performance except for simple types of antennas. Over the past decade, radio frequency (RF) designers have increasingly turned to the use of computational optimisation approaches to solve this problem. Initially a matter of "cut-and-try" computation of the results for a handful of competing design changes, the development of sophisticated metaheuristic optimisation algorithms, especially those readily adaptable to parallel computation, and the rapidly increasing access to powerful computing resources have enabled more systematic approaches to comprehensive design optimisation.

This paper will describe how studies using optimisation algorithms in the design of a particular class of small, planar antennas has evolved into an approach to attempt to discover the performance limits of small, planar antennas in general. In Section 2 the prior work undertaken over a number of years is described to show the foundations for the current studies, Section 3 shows how the precursor work and methods used were adapted to the general small, planar

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antenna design problem, Section 4 describes computational experiments undertaken and the preliminary results obtained, and Section 5 discusses the results and outlines directions for future work.

2 Background and prior work

In 2006, the authors chose to use Ant Colony Optimisation (ACO) [4, 5] to optimise the efficiency of meander line Radio Frequency IDentification (RFID) antennas [16]. RFID tags are used in a wide range of applications, and practical considerations have driven a need for smaller tags with longer reading range. The read range can be explained as the maximum distance at which RFID reader can detect the returned signal from the tag [17]. This vital factor can be increased by designing antennas with higher gain, or efficiency, and lower resonant frequency.

Meander line antennas [21] are a subset of particular interest for RFID as, by their nature, they are compact and tags may be readily manufactured. These antennas normally have a planar structure and consist of printed conductive tracks on thin plastic substrates [6]. The approach used for design of the meander line was to progressively link nodes on a Cartesian grid. This is a combinatorial optimisation problem, for which ACO has been a favoured solution strategy. The ants are agents that iteratively construct solutions, ideally suited to path planning problems. Thus ACO provided not only an algorithm for performance optimisation of the meander line antennas but also, by virtue of its fundamental mechanics, a method for automated construction of trial solutions.

Following the promising results from the use of ACO on the single objective of improving antenna efficiency, the method was refined to use local search techniques to further improve efficiency [22], and then extended to a multi-objective formulation of the problem, simultaneously optimising efficiency and resonant frequency [13, 12]. As previously noted, one of the crucial performance criteria for RFID tags is their read range, which is directly proportional to the wavelength used. Lower frequencies, or longer wavelengths, tend to increase the read range but also generally require larger antennas. The antenna design problem therefore became one of maximising the antenna efficiency, η, and minimising the resonant frequency, f_0. The multi-objective optimisation approach used determined relative attractiveness of solutions using Pareto dominance relations.

More recently, the authors and colleagues have explored the use of a number of different metaheuristics for design of RFID antennas. Differential Evolution (DE) was used on the meander line antenna design problem [15]. Taking inspiration from the production of self avoiding walks [1], relative rather than absolute directions were use to define links between nodes in the grid, allowing the adaptation of the antenna construction method to a probabilistically-weighted random walk. Subsequently, Extremal Optimisation (EO) was applied to a modified meander line in which the restriction of generating a single continuous line was relaxed [7]. This allowed the design of antennas with loops, mesh segments and parasitic elements. Instead of linking numbered *nodes*, the structure of the antenna was defined by a collection of numbered *links*.

A comparison of Pareto-fronts achieved using ACO and DE is shown in Figure 2 and the aggregated fronts for ACO, DE and EO are shown in Figure 3.

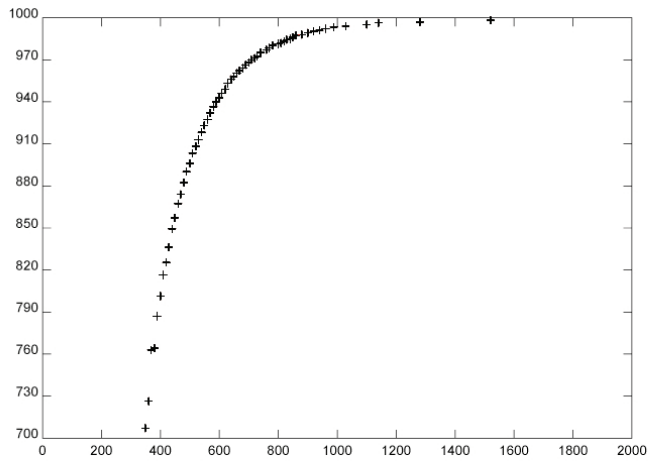

Figure 1: ηf_0 attainment surface for the 25×56 mm^2 antenna.

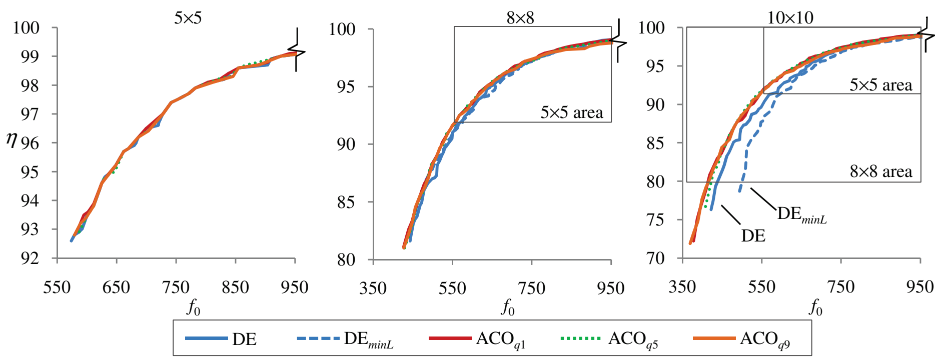

Figure 2: Lower frequency portions of fronts produced by DE and ACO for 5×5, 8×8 and 10×10 grids

3 Generalisation to small, planar antenna design

From the precursor work described in the previous section there arose a more general question of what the performance limits of electrically-small, planar antennas might be. The successful approach of using computational optimisation algorithms to *discover* the performance capabilities of small, planar (RFID) antennas suggested a similar approach might be used to explore the practical performance limits.

As the parametrisation used in the previous studies was limited to continuous meander line antennas, a new parametrisation was developed. At present this comprises a fixed feed point and a grid of $n \times n$ potential patches, which are mirrored on both sides of the feed point. The corners of patches are chamfered to avoid infinitely small contact points which would lead to incorrect simulation outcomes. As this necessitates finer meshing for the simulation, the

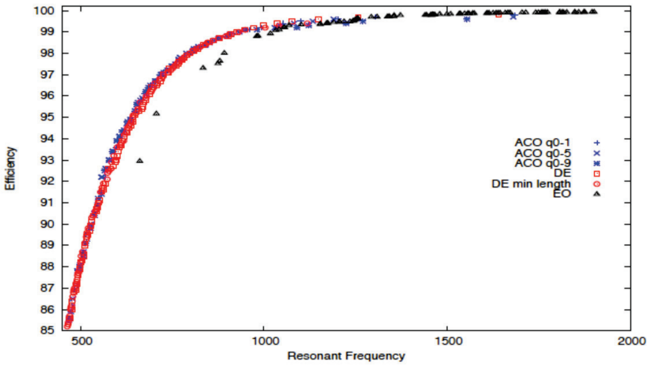

Figure 3: Pareto-fronts for the 7×7 bi-objective RFID antenna design problems

authors investigated a more adaptive approach in a separate study [20]. For the purposes of optimising structures based on this parametrisation, each antenna can be represented as a binary string of length n^2, allowing standard binary optimisation techniques to be applied. In future, further relaxations to the parametrisation are planned, allowing arbitrary feed points and non-symmetric antennas.

In follow-up work, structural changes are planned to extend the search space to a generalised circular plane in order to explore practical performance limits and their relation to the theoretical limits as theorised by Gustafson [8, 9]. An investigation of these limits for the special case of meander line antennas was conducted by Shahpari *et al* [18].

The following section will provide a brief comparison of a representative set of antennas for validation, and the limits thereof for results from the different parametrisations.

3.1 Validation of OpenEMS results

The precursor studies to this work modelled antennas as wires of 1mm thickness using NEC [2]. With the changes to the parametrisation described in the previous section, the area of the antenna now comprises $n \times n$ thin tiles which can either be conductive or empty. In this study, $n = 10$ was chosen as a means of limiting compute time. Due to these differences, an exact replication of previously investigated antennas is not possible. To overcome limitations of the previously used NEC software, openEMS [14] was chosen for these simulations.

As a means of establishing a relationship for a broad range of antennas, the antennas investigated in Shahpari *et al.* [18] were taken where possible (Figure 1 in [18], antennas a-f, h and i. Antennas g, j and k were excluded due to a feed point that is currently not possible in the new parametrisation). These antennas represent a variety of structures with minimum resonance frequencies ranging from 576 to 1757MHz.

A notable aspect of this comparison is that the efficiency will inevitably differ between the NEC and openEMS based simulations. Apart from the inevitable structural differences from the different parametrisations, this is largely caused by different material properties used for the simulations. In the NEC simulations copper wires were modelled. On the other hand, in Shahpari's openEMS investigation the material was set to be a perfect electric conductor to simplify the simulation. As a remedy, the material independent Q factor was used as an alternative secondary objective for this comparison.

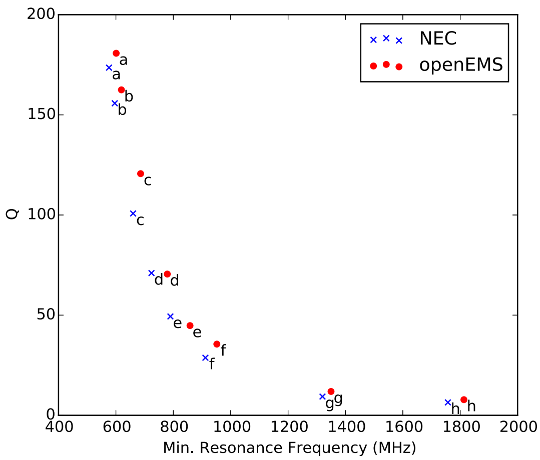

Figure 4: Comparison of a representative range of antennas in the NEC-based vs. openEMS-based parametrisation and simulation.

The results of this comparison are presented in Figure 4. There is generally good correspondence between results obtained using NEC and those from openEMS. Antenna C shows a higher value of Q for the result obtained with openEMS but, given the structural differences of the antenna models, the differences in results can be considered to be relatively minor.

3.2 Construction of antennas

Metaheuristic optimisation methods require some mechanism of generating an initial population prior to starting the optimisation. In the absence of *a priori* knowledge of relevant minima, this population is usually chosen uniformly randomly across the feasible space. The intention is to avoid prematurely biasing the search towards areas, potentially limiting the algorithm in its ability to discover arbitrary promising areas.

Using the described openEMS-based approach, calculating large frequency ranges is costly from a computational point of view. For practical purposes, this necessitated setting an upper limit for the frequency range. Antennas that resonate outside the simulated range will appear as infeasible to the algorithm despite not being infeasible in reality. Consequently, a number of points in the initial population could be ignored, resulting in a loss of diversity.

For the purpose of increasing the number of feasible initial points, the simplifying assumption can be made that the minimum resonance frequency is inversely proportional to the maximum length of continuously connected patches on the grid. Several construction methods for an initial population guided by this assumption were created and tested.

Uniform Random This method represents the baseline for the experiments. Every grid point is assigned a patch with a probability of 0.5. For practical purposes, the grid point next to the feed point was always assigned a patch as the antenna would otherwise comprise only the feed point. An illustration of a small population generated this way is shown in Figure 5.

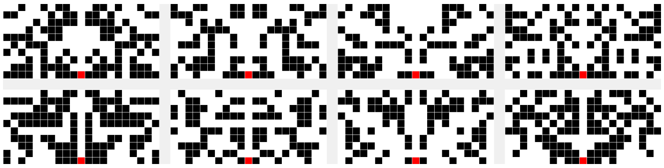

Figure 5: Sample popular with uniform random antennas. While the structural bias is minimal, many of the structures will likely be infeasible given the constraints of the simulation.

Random with variable patch probability This method represents a variation of the uniform random antennas where the probably for a patch is varied on a per antenna basis. To give a bias to denser antennas, the interval for this was chosen to range from 0.4 to 0.8. This allows biasing towards denser structures while still limiting structural biases in the population, as illustrated in Figure 6.

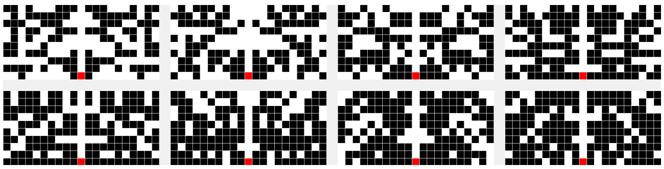

Figure 6: Sample population with variable random patch probability. With this approach larger continuous structures are generated but a strong bias is given towards adding patches.

Gaussian distribution based population This method attempts to more strongly bias towards feasible antennas by basing the patch generation on the Gaussian distribution with the mean at the feed point. Contrary to the previous methods, a set number of patches is given for each antenna. The number of patches is varied withinin a given interval. For a $10x10$ grid, coordinates were generated by randomly generating x and y values using the normal distribution with $\sigma = 0.0$ and $\mu = 0.5$ and applying $floor$. The algorithm iteratively adds patches until the given number of patches is achieved. The number of patches was varied between 30 and 60. A small sample population from this approach is shown in Figure 7.

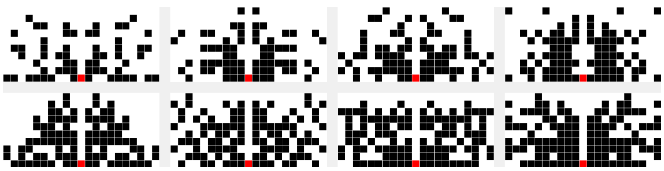

Figure 7: Sample population using a Gaussian distribution around the feed point. The approach produces some continuous structures around the feed point with many disconnected elements around them. A possible downside will be the lack of patches in the corners far from the feed point, leading to a potential bias in the search.

Random Walker Lastly, a random walker / jumper was developed that produces antennas with more ordered structures. The walker always starts at the feed point with a one or two patch structure. Each step has a length of two patches. The walker determines its next step using the following algorithm:

- Find legal moves. A legal move is any move that does not lead outside the grid and does not end on a grid point that is already marked as containing a patch.
- Select next move. A score is calculated as $s = \frac{1000}{1+(9-n)+p}$ with n representing the number of adjacent grid points and p representing the number of adjacent patches. If the move requires no directional change, the score is increased by a factor of 20 to give preferences to straight structures. Roulette wheel selection is applied to choose a move.
- If no legal move can be found, a random legal point (based on the same criteria) is chosen and a jump to this point is performed (i.e. no connection is made to the previous point).

As Figure 8 illustrates, the resulting structures closely resemble conventional meander line antenna structures. The interval $[15, 25]$ was chosen for the number of patches.

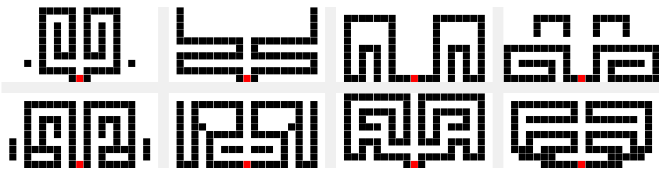

Figure 8: A sample population generated using the random walker method. With a relatively small number of patches the walker can generate antennas with relatively long continuous structures. However, it also represents the most strongly structurally biased population.

4 Computational experiments

As described in Section 3, the parametrisation presents itself to the optimiser as a binary string of length n^2. For this study, a binary MOPSO algorithm was used to perform the optimisation. MOPSO is the multi-objective adaptation of PSO, first proposed by Kennedy and Eberhart [10], and Shi and Eberhart [19]. The precise variation used in this study is the MOPSO algorithm developed by Coello Coello and Lechuga [3] modified to optimise binary problems based on the single-objective binary PSO by Kennedy and Eberhart [11].

MOPSO iteratively improves a population of particles using a velocity vector. This velocity comprises a momentum, a global guide and a personal guide as well as static and random weights. The global guide is chosen from an archive of globally non-dominated points while the personal guide comes from an archive of non-dominated points for each particle. The size of the personal archive is frequently chosen to be one. Guides are chosen based on a hypercube score and roulette wheel selection, prefering areas with fewer known non-dominated points. The archive size is limited and particles are removed based on crowding distance when its size is exceeded.

In this binary variation, the algorithm still uses a continuous velocity equation. However, the resulting velocity is transformed into a probability for a bit flip using the sigmoid function as

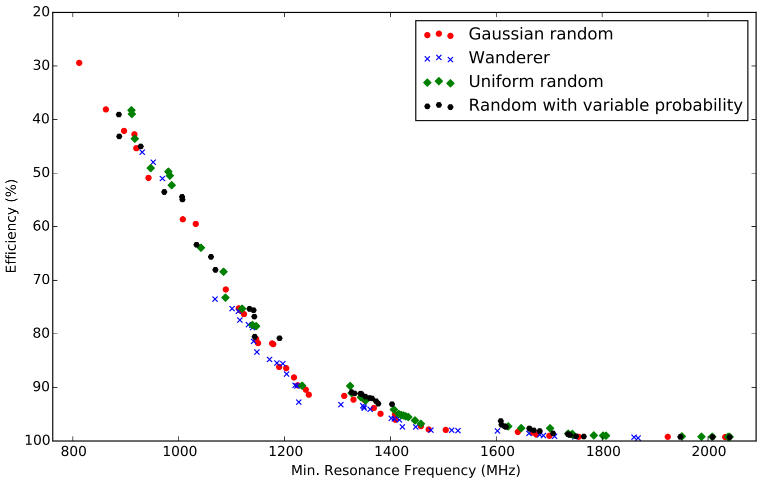

Figure 9: Comparison of MOPSO runs with different initialiser functions after 325 iterations.

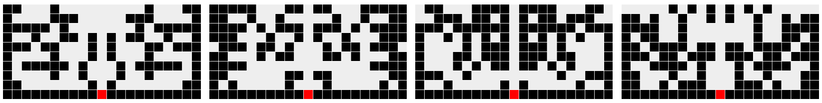

Figure 10: Illustration of four randomly chosen antennas from the results of a MOPSO with Gaussian distribution-based initialisation.

suggested in [11]. The initialisation of particles was performed using the four methods described in Section 3.2. Each algorithm was given a population of 20 particles.

As arbitrarily large intervals can lead to numerical inaccuracies in the simulation, an earlier version of the openEMS based compute kernel was limited to a maximum resonance frequenct of 1200MHz. However, the results were generally poor with only the Gaussian-distribution based approach producing some results. In response to this, the interval was extended to 2400MHz, making it feasible for all four methods to produce viable populations.

A representative set of the preliminary results is shown in Figure 9. While these results should be considered preliminary, the data suggests that the Gaussian distribution-based initialisation proved most successful across the entire front. The walker-based MOPSO appears to be more limited in terms of the structures it explores and consequently is most successful on a only a subsection of the approximated Pareto-front. The other two methods still perform reasonably well but appear to be more slightly less successful in terms of coverage of the front and convergence. Further analysis of the Gaussian distribution based structures shows that no obvious bias towards points close to the feed point has persisted in the population. A set of four randomly selected antennas from a current run can be found in Figure 10.

With the current 10×10 grid approximately 150-200 iterations can be achieved per week on modern hardware with short scheduling delays. In our case, several dedicated machines are shared between multiple runs. At present the authors have 75 cores across 15 machines available which process 5 concurrent runs of the optimiser. This represents a compromise between minimising idle times and limiting queue delays to a minimum. In this setup, each

MOPSO instance can progress up to 150 iterations per week. As an increase in grid size to 20×20 results in processing times in excess of one hour per simulation, additional resources will have to be acquired to further reduce delays. In addition, a global caching strategy will be added.

5 Conclusion

A new parametrisation for optimising small planar antennas was introduced and demonstrated using the free, open-source software openEMS. The validity and comparability of the results was established based on a range of previously published antennas. Preliminary results of an optimisation study using binary MOPSO were presented and the combination with several novel methods for generating an initial population were investigated.

The preliminary results highlight the viability of the approach and suggest the extension to finer grid resolutions, potentially using the Gaussian distribution-based initialisation. In addition, other metaheuristics will be investigated on this problem with respect to their applicability. Due to the computing time required for the simulations, only a few runs were possible to generate the results reported. Future work will extend this, in particular by restructuring the simulations to utilise parallel computing resources and reduce run times.

Given the viability of the approach presented, the work will be further extended as the basis for investigating the practical limitations of small planar antennas with regards to the established theoretical limits. To this end, the extension of the model to a circular plane base structure will be developed.

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