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Review

Application of Genetic Algorithm for Binary Optimization of Microstrip Antennas: A Review

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Abstract: Researchers have proposed applying optimization techniques to improve performance of microstrip antennas (MSAs) in terms of bandwidth, radiation characteristics, polarization, directivity and size. The drawbacks of the conventional MSAs can be overcome by optimizing the antenna parameters while keeping a compact configuration. Applying a global optimizer is a better technique than using a local optimizer or a trial and error method for performance enhancement. This paper discusses genetic algorithm (GA) optimization of microstrip antennas presented by the antenna research community. The GA optimization procedure, antenna parameters optimized by using GA and the optimization objectives are presented by reviewing the literature. Further, evolution of GA in the field of MSAs and its significance are explored. Application of GA optimization to design broadband, multiband, high-directivity and miniature antennas is demonstrated with the support of several case studies giving an insight for further developments in the field.

Keywords: cost function; design optimization; genetic algorithms; microstrip antennas

1. Introduction

1.1. Background

Microstrip antennas (MSAs) are compact in size, light in weight and inexpensive. More importantly, they can be easily integrated with the circuit inside the electronic devices. However, the conventional MSAs have inherent drawbacks of narrow bandwidth and low gain. Numerous performance improvement techniques such as modifying the patch geometry, shorting the patch and the ground, incorporating parasitic patches, stacking multiple substrates and keeping an air gap between the patch and the ground have been suggested by researchers in order to obtain broadband, multiband, miniature, high-directivity and polarization properties. Such modifications are applied after performing several trials for tuning antenna parameters. It is a primary technique, which does not facilitate designing of multiple parameters in parallel. That limitation reduces the possibility of obtaining the global optimum. The solution space is also lessened and ultimately a local optimum is produced. Even though the local optima have better performance than classical MSAs, they do not perform outstandingly as the global optimum. Therefore, antenna researchers have incorporated optimization techniques [1–3] such as genetic algorithms (GAs) [4–6], particle swarm optimization (PSO) [7], invasive weed optimization (IWO) [8] and differential evolution (DE) [9] for performance improvement in the field of electromagnetics. Among the aforementioned techniques, GA optimization has been widely used for MSA design. It is classified as a global optimizer, having many advantages over the local optimizers [4]. GA has demonstrated its suitability to solve complex electromagnetic problems in the last two decades.

1.2. GA antenna design procedure

Applying GAs on MSA optimization starts with a randomly generated group of antenna topologies, which is called the initial population (Figure 1: step 1). Even though the common practice is to keep the population size constant throughout the optimization process, some researchers have reported use of a large population at the initial population with the objective of creating a pool of designs with better performance from the very beginning [10]. A smaller population size was kept in the subsequent generations for minimizing the time taken for simulations. GA implementations with different population sizes such as 20, 32, 40 and 200 [11–14] are reported in the literature. However, it is recommended to keep a population size of 30-100 as it needs to be large enough to perform GA operations effectively and small enough to avoid running antenna simulations over several days [4]. Larger populations facilitate the achievement of optimization objectives within a lower number of generations due to the higher diversity of the designs. On the other hand, smaller populations consume less simulation time per generation.

Pairs of chromosomes are selected randomly and the GA operators (crossover and mutation) are applied on each pair creating a new pair (Figure 1: step 2 and step 3). After applying GA operators, an expanded population comprising parent designs and children designs is formed (Figure 1: step 4). Usually, the size of the expanded population is twice the regular population size. Selection of the best designs for the next generation from the expanded population is done by evaluating the fitness of each design. A cost function needs to be derived to select the best performing antenna designs. When the cost function is applied in the optimization process, the average fitness of the population improves gradually over the iterations. Cost functions are problem-specific and objective-focused. When the cost functions are defined well based on the antenna performance expected, they facilitate designing the globally optimized antenna instead of a local optimum.

Once the performance of the antenna designs is evaluated in terms of the fitness, the least fit designs are removed and the generation is replaced by the individuals with the best fitness (Figure 1: step 5). Likewise, the GA process is repeated until the termination criterion is met. The termination may simply be specified in terms of the simulation time or the number of iterations [16]. Convergence of the fitness over iterations or reaching a pre-defined fitness value can also be considered for termination.

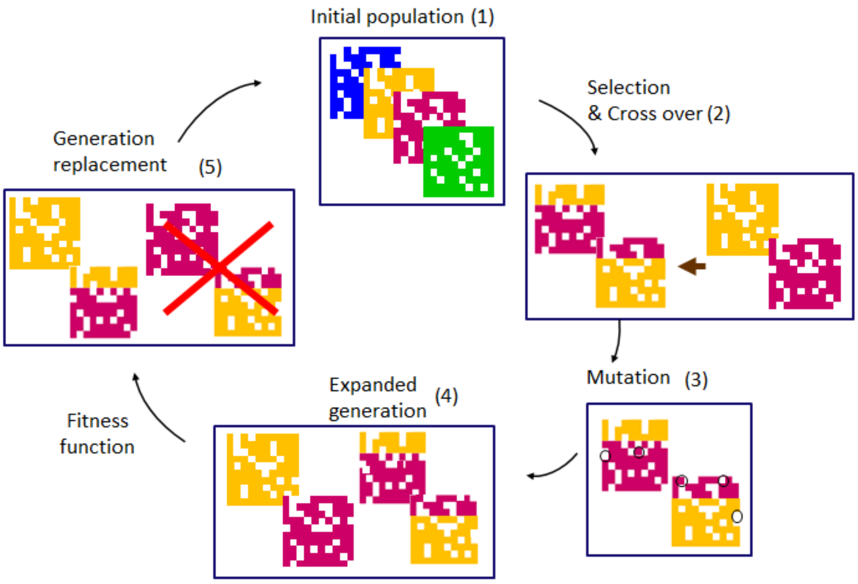


Figure 1. GA antenna design procedure.

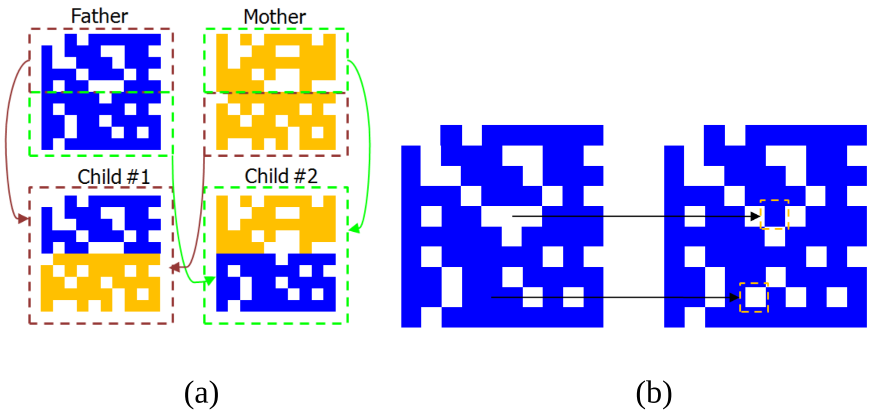


Figure 2. GA operations (a) Crossover (a pair of parent chromosomes produce children); (b) Mutation (only a few genes are changed).

1.3. GA operators

In order to apply GA, antenna parameters are encoded creating a string of bits called a chromosome. It is a data structure that holds genes, which are usually "1"s and "0"s. During the crossover operation, genes of a pair of candidate designs (parent chromosomes) are exchanged in order to form two new designs (children chromosomes) for the next generation. For example, Figure 2a illustrates the crossover operation performed on a pair of MSAs in which the coloured region represents the conducting patch and corresponds to “1”s in the chromosome. Similarly, the white colour spaces corresponding to “0”s in the chromosomes represent non-conducting areas of the antenna. The crossover probability is normally higher than 60% giving a considerable portion of the population the opportunity to produce better chromosomes [4]. The probability may be 100% assuring all parent chromosomes involve in generating children chromosomes [15]. In mutation, a gene "0" is changed to a "1" and vice-versa. Correspondingly, the conducting region turns into a non-conducting space and vice-versa (Figure 2b). Mutation ensures that no potential solutions are lost and prevents repeated mating. Keeping the mutation probability low is recommended in order to confirm reaching towards the optimum solution without deviating from the gradual improvement [4].

This paper reviews applications of GA for performance enhancement of MSAs. In Section 2, the antenna parameters fine-tuned in the GA optimization applications are explored and their impact is analyzed. Section 3 presents the optimization objectives the antenna researchers tried to achieve by applying GA on MSAs. The impact of the different fitness functions is also analyzed. In Section 4, GA is compared with some other high performance optimization techniques applied in the field of MSAs. Moreover, the future directions are envisaged.

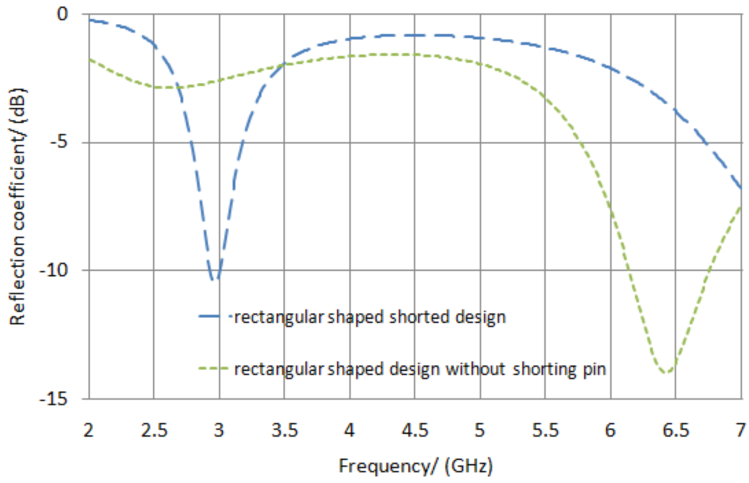
2. Optimization of antenna parameters

2.1. Outline

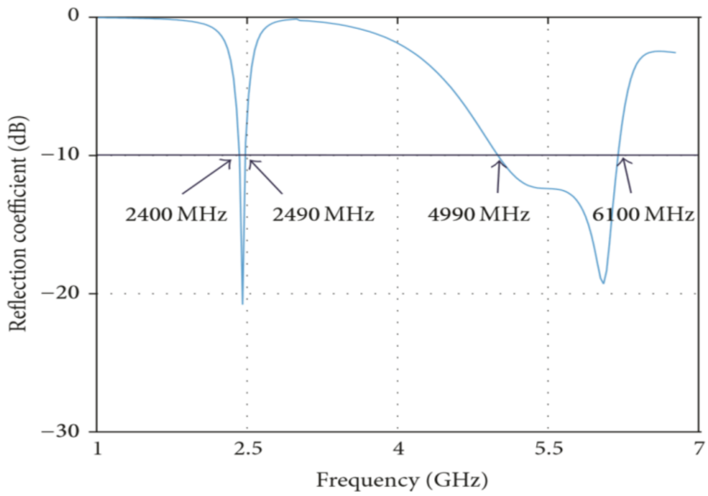
GA optimization is used in the field of MSAs mainly to design the characteristics of the patch, substrate and the feed with the objective of performance enhancement. Further, conventional performance improvement techniques such as modification of the patch shape, use of shorting pins or strips and use of an air gap were integrated with GA. In the field of antenna optimization, fine-tuning a single parameter as well as multiple parameters was proposed. Out of the two approaches, parallel optimization of multiple antenna parameters is more effective due to the higher degree of freedom, which enables exploring the entire search space.

2.2. Optimization of the geometry

As per the literature related to GA-based MSA optimization, the mostly reported MSA parameter optimized by using GA is the patch geometry. This paper reviews only binary optimization problems where the patch is divided into smaller elements and the final shape is obtained by turning some of these elements off. Though there are continuous problems as well, where one or more physical dimensions of the antenna are tuned over a continuous range using GA to optimize the antenna, no continuous problem is addressed in this paper. In the related research studies conducted about last two decades ago, only the patch geometry was optimized, while the substrate parameters and the feed position were kept fixed [4]. Nevertheless, optimization of both the patch shape and feed position is more effective as it expands the solution space while giving freedom to match the impedance of the modified shape [16]. When a shorting mechanism such as a pin, strip or a wall is used for antenna miniaturization, parallel optimization of the patch shape and the positions of feeding and shorting is the most effective method [11]. For example, the resonant behavior of a rectangular patch antenna with and without a shorting pin is compared in Figure 3a. The antenna with a rectangular-shaped patch resonates around 6.4 GHz at the fundamental mode of operation. The shorted patch exhibits miniature performance resonating around 3 GHz as the shorting pin alters the classical current pattern. With GA optimization, the resonant frequency of the miniaturized MSA could be reduced further to 2.45 GHz as a result of proper positioning of the shoring and feeding pins on the radiating patch with a modified shape (Figure 3b). Such a behavior proves that the modified patch geometries are helpful to create elongated current paths resulting longer electrical lengths. More importantly, the bandwidth could be improved due to parallel optimization of three parameters.



(a)



(b)

Figure 3. Parallel optimization of the patch shape, feed position and shorting position (a) Resonant behavior of rectangular antennas (b) Resonant behavior of the optimized antenna.

In the antenna designs with an air gap between the patch and the ground plane, its thickness and the feed position were optimized with the patch geometry simultaneously [17]. Parallel GA optimization of more than three antenna parameters such as the patch geometry, feed position, substrate thickness and relative permittivity was also proposed. However, use of GA to optimize substrate thickness and dielectric constant is not much effective due to the small solution space of each parameter. Hence, keeping such parameters fixed at suitable values derived based on related theory or determined by performing a simple set of simulations can be recommended.

2.3. Different patch topologies

In case of optimizing the patch geometry, researchers proposed dividing the patch area into a grid of small rectangular [18] or square [12] cells. Each cell is assigned either conducting or non-conducting property based on the value of the corresponding gene of the chromosome. A gene with value "1" may represent a conducting region while that with value "0" may represent a non-conducting region. As the dielectric substrates are usually Copper plated, a printed circuit board (PCB) prototyping machine or a chemical process is used to remove Copper in the area corresponding to the non-conducting genes. When diagonally connected cells remain on the patch, a proper electrical connection cannot be guaranteed between them. Due to such disconnections, the expected current path is disconnected making the performance of the antenna highly deviated from the simulated performance. Therefore, techniques such as overlapping cells with a constant [19] or a variable overlap [20], array of overlapping sub-patches [13], 2D median filter [21] and amorphous shapes using ellipses [22] have been proposed to ensure connectivity at the corners of the cells. In case of using overlapping conducting regions, constant overlaps [13] as well as non-uniform overlaps [20] were proposed. A patch geometry divided into an array with the size of 4 x 5 and assigned conducting properties to eleven of them is shown in Figure 4a. The connection between diagonally connected conducting regions is infinitesimal. In contrast, the adjacent regions connect well diagonally when constant overlaps are introduced (Figure 4b). Figure 4c illustrates the patch with non-uniform overlaps, which facilitates a wide range of sizes for the conducting regions.

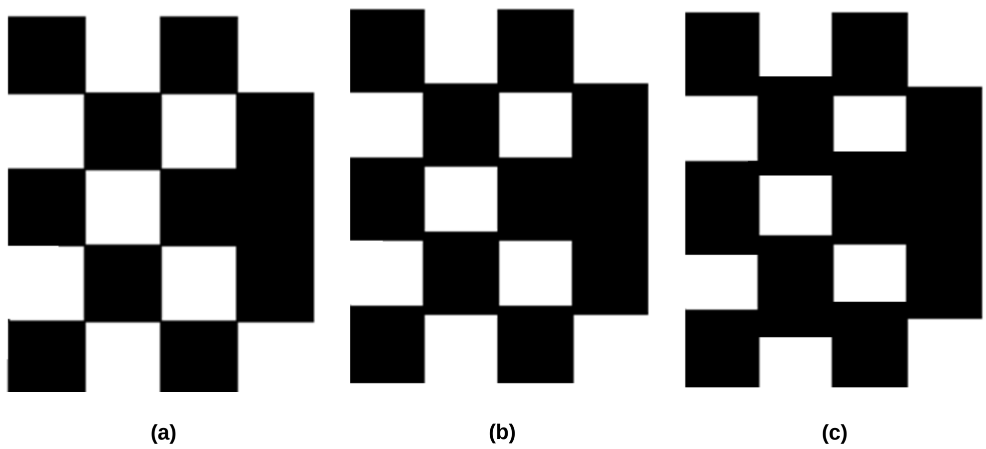


Figure 4. Different patch topologies a) A traditional grid with infinitesimal connections. b) Scheme with constant overlaps. c) Scheme with non-uniform overlaps.

Use of fixed overlap sizes as well as non-uniform overlaps on the radiating patch is demonstrated in [20]. Four MSAs with fixed overlap sizes of 0 mm, 0.5 mm, 1 mm and 2 mm and one MSA combining all the options were optimized using GA. Both the patch geometry and the feed position of each antenna were tuned and the variation of the best fitness over the iterations was recorded. The MSA with non-uniform overlapping cells converged resulting in a penta-band design, while the other MSAs produced multiband designs with less number of resonances and narrowband performance. Analysis of the results indicate that the non-uniform overlapping method has resulted better antenna performance than use of any constant overlap, due to the higher degree of freedom.

Usually, a significant portion of the chromosome is dedicated to define the patch geometry. GAs with larger chromosome sizes consume more time for simulation of the corresponding designs. Some researchers have proposed modeling only a half of the patch structure in order to reduce the size of the chromosome [10]. Antennas with symmetrical geometries exhibit symmetrical radiation patterns, which is beneficial in mobile communication applications. However, this approach limits the solution space and the solution may be optimized towards a local optimum. Another method to reduce the chromosome size is GA optimization of sub-domains on a patch creating meander edge notches instead of optimizing the whole patch area [23]. Moreover, design of a switch array on the aperture facilitating reconfiguration is proposed [24]. Another simplified method for optimizing the shape is etching a small slot on the patch by using GA to design only the size and location of the slot [25]. When the slots are placed at the opposite corners of a square-shaped patch, the MSA demonstrates circularly polarized characteristics [26].

Expanding research beyond the shape optimization of a MSA having a patch foot print of a conventional shape such as rectangular or square, complex shapes such as bow-tie have also been considered in GA optimization [27]. Moreover, Fractal antennas with the shape of Sierpinski carpet [27], Sierpinski Bow-Tie [29], Koch [30], Fudgeflake [31] and Gosper island [31], which have non-conventional complex shapes, have been genetically optimized with the objective of starting the optimization process with an already modified geometry instead of a conventional shape. However, only a limited number of research studies were done on GA optimization of non-conventional patch shapes, which may produce outstanding performance. For example, local optimizers applied on a Sierpinski carpet fractal antenna of the fourth iteration improved the resonant behavior (Figure 5). Its performance may be further enhanced by applying a global optimizer. In this sense, research avenues exist in the field to expand the research.

Another GA optimization approach is the design of antenna parameters on a predetermined patch shape. One such example is optimizing the locations and widths of the shorting strips between the rectangular patch and the ground [32]. Optimization can be further simplified by applying GA only to find the most suitable shorting position on a patch, which has a pre-specified shape [33]. Another approach is to optimize the properties of the dielectric substrate such as the length, width, thickness and the dielectric constant [36]. When the design objective is too simple, optimization parameters and their range can also be simplified. Optimization of the feed position and patch dimensions of a classical rectangular [34] or circular [35] patch is reported, when the objective is simple as impedance matching.

Moreover, optimization of the feed network of MSAs has been proposed. In such approaches, the major objectives were obtaining circular polarization [37] and bandwidth enhancement [38]. In case of an aperture-coupled rectangular MSA, optimizing the feed parameters such as the aperture dimensions and stub length is proposed [39].

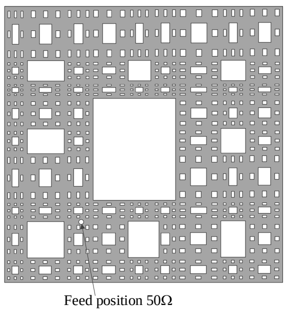


Figure 5. Optimization of a Sierpinski carpet fractal.

In this sense, antenna parameters to be optimized highly depend on the structure of the MSA and the expected antenna performance. Optimization of multiple antenna parameters and consideration of a wider range of values demand a chromosome with a higher number of genes.

Modeling and solving an MSA, which is represented by a larger chromosome, consume more computation time. As the antenna designs are simulated over iterations until the pre-defined termination criterion is met, a high performance computer or a cluster of CPUs is required for GA optimization of MSAs.

2.4. Cost of computation

An MSA optimization problem solved in 2004 reported that the simulation time of an individual chromosome consisting of 48 binary elements was 13 minutes on a Pentium III-450 MHz CPU with 512 MB RAM and an 8 GB hard drive [10]. As the estimated simulation time for the completion of the GA process was longer than a month, a cluster of 26 CPUs was used. As a result of using multiple nodes, the GA optimization process could be completed within two days. Thanks to the continuous advancements in the performance of computers taken place during the last decade or so, optimization of complex design problems could be done on a single computer within a reasonable time. For example, optimization of an MSA represented by a chromosome with a size of 35 bits reported completion of the simulation process within a day on an Intel Core i7 processor with 2 GHz speed and a RAM of 6 GB a few years ago [20]. With the availability of high performance computers, optimization of multiple parameters has also become convenient. Simulation of an MPA on a 5th generation Core i7 processor consumes only a few seconds nowadays. However, even with high computational facilities, complex GA optimization problems run over multiple days continuously. Use of commercially available software such as Ansys HFSS, CST and IE3D for MSA simulations has been reported by the antenna research community.

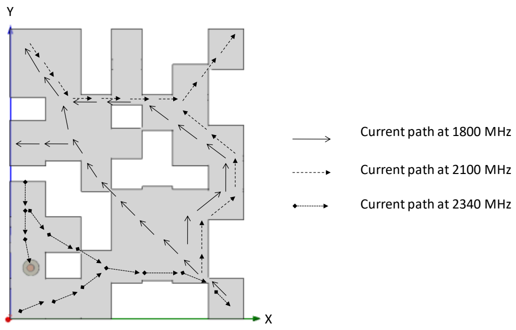
3. Optimization objectives

3.1. Introduction

The classical MSAs are etched on a thin dielectric substrate with Copper layers on both sides resulting in a planar configuration. Even though such an antenna topology is suitable to be integrated with the circuit in small handheld devices, the MSAs with classical shapes have low performance and are not suitable for wireless communication applications. Therefore, the application of GA on MSAs has been proposed with the objective of enhancing the performance by means of the resonant behaviour, radiation, efficiency and polarization. The antenna size also needs to be optimized as the half-wavelength or quarter-wavelength of MSAs is not compact enough for some applications, particularly at low frequency operation. In this context, the design objectives highly depend on the applications for which an MSA is designed. Different types of GA optimization projects developed to design broadband, multiband, directive and compact MSAs are found in the literature.

3.2. Improve the resonant behaviour

As the conventional MSAs exhibit narrowband properties and do not show multiband resonance at a multiple number of frequency bands closer to each other, GA optimization has been applied to improve the resonant behavior [97]. When the patch shape is conventional, the current flows along a direct line, resulting in narrowband performance at the fundamental mode as well as at the higher order modes. Genetically optimized patch shapes alter the direct current flow and allow multiple current paths on the patch resulting multiband operation (Figure 6a). Design of multiband MSAs using GA is reported in the literature [61–72]. When the patch shape facilitates the current paths in order to make the MSA resonate at multiple frequencies closer to each other, broadband performance can be obtained. For example, an MSA resonating at multiple frequencies of 1800 MHz, 2100 MHz, and 2340 MHz operates over a wide band ranging from 1710 MHz to 2500 MHz (Figure 6b). The bandwidth enhancement of a single patch element resulting genetically optimized UWB [40–43] and broadband [43–61] antennas were reported since late 1990s. Some MSAs optimized by using GA to obtain UWB performance are summarized in Table 01.



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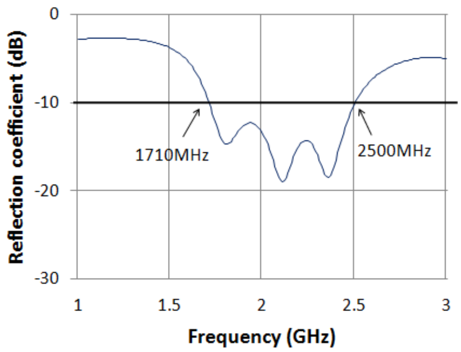


(b)

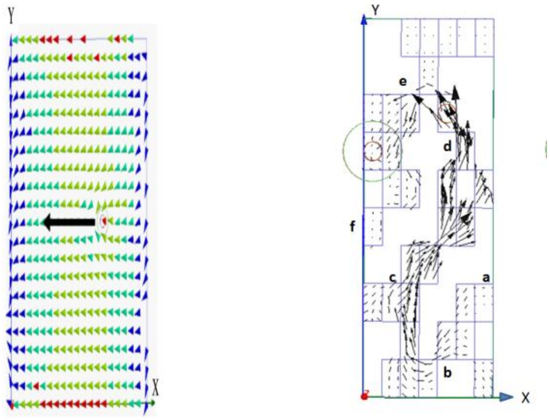
Figure 6. A GA optimized broadband antenna (a) Multiple current paths (b) Multi-frequency broadband behaviour.

Table 1. GA optimized UWB MSAs.

Reference	Antenna dimensions (mm^3)	S_{11}<-10dB Bandwidth (GHz)
[40]	21.2 x 34.45 x 0.795	3.1–12
[41]	33 x 28 x 1.57	3.1–10.6
[42]	45 x 55x 0.762	3.3–10.55
[43]	25 x 25 x 1	2.5–11
[98]	20 × 15 × 0.508	3.18–3.75 and 4.785–14.25

3.3. Miniaturization

Another objective of GA optimization is miniaturization of MSAs to make them suitable for applications such as biotelemetry and handheld wireless devices, which demand very small antennas [74–76]. Genetically optimized patch geometries create elongated current paths resulting the MSA resonating at a lower frequency than at the fundamental mode, which ultimately produces a miniature antenna [11]. For example, a rectangular-shaped patch (Figure 7a) was divided into a 7 × 10 grid and optimized by applying GAs. At the fundamental mode of operation the length of the current path is equal to the patch length and that of the optimized design is longer along the path a-b-c-d-e (Figure 7b). As a result, the resonance frequency could be reduced by 62%.



(a) (b)

Figure 7. Genetically elongated current paths (a) current pattern on a rectangular antenna (b) current pattern on the optimized antenna.

3.4. Improve radiation

Moreover, GA optimization was applied to improve the radiation characteristics as required for specific applications (Table 02). For example, making the radiation pattern along the broadside direction and improving the directivity or gain while maintaining the necessary bandwidth requirements are reported in the literature [77–80]. Moreover, GA has been used to design the MSAs with a low radar cross section [81]. In-phase current on the genetically optimized patch (Figure 8a) has made the antenna highly directive along one direction. As a result, a genetically designed single patch element which occupies the same area of a 1 × 4 array could replace the array by means of the bandwidth and the directivity. A measured directivity of 12 dB was obtained with antenna efficiency of 81% (Figure 8b). Further, the GA optimized MSA has demonstrated better results than fractal antennas with the same foot print in terms of the directivity [15].

Moreover, GAs were used to optimize the polarization characteristics as required for the antenna application of interest [82–86]. Synthesizing MSAs to achieve circular polarization with a single feed [82] and dual polarization with dual frequency operation [83,84] are among them.

Table 2. GA optimized high-directivity MSAs.

Reference	Antenna dimensions (mm^3)	S_{11}<-10dB Bandwidth (MHz)	Gain (dB)
[15]	140 × 60 x1.52	160	12.1
[78]	590 x170 x 98	100	13.8
[78]	80x80x1.52	70	10.5
[15]	120 × 120 x1.52	40	13.2

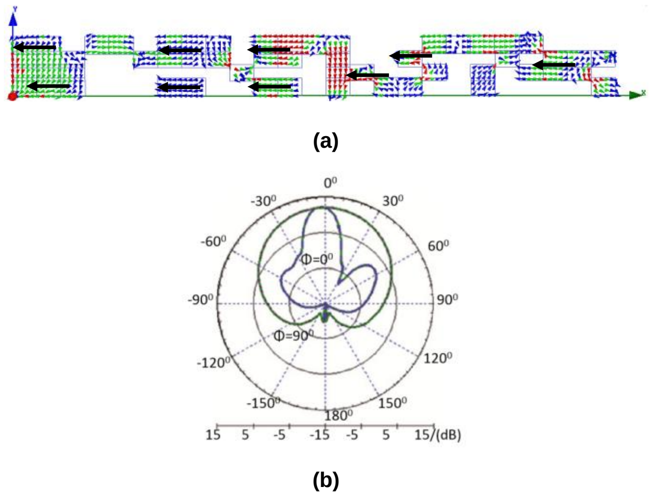


Figure 8. GA optimized high-directivity MPAs (a) Current pattern (b) Radiation cuts.

3.5. Multi-Objective optimization

As briefed above, the optimization of antenna performance by means of bandwidth, resonant frequency, directivity/ gain, radiation pattern and polarization has shown an explosive growth in the field of MSAs. Design exercises related to single-objective optimization as well as multi-objective optimization are among them. Optimization efforts put only on bandwidth enhancement may generate MSAs with distorted radiation patterns or low gain. Similarly, optimization with the objective of directivity improvement may result in narrowband MSAs. For example, when the broadband performance was the only objective in GA optimization, a fractional bandwidth of 75% could be achieved with a broadside gain limited to 5.8 dB [58]. When multi-objective optimization was applied to the same problem, the optimized MSA demonstrates fractional bandwidth of 60% and a broadside gain increased up to 7 dB.

In this sense, solving the design problems with conflicting objectives is a challenge. It can be addressed by designing a fitness function, which represents all the objectives with necessary weight on each of them. Performance of MSAs optimized by using five different sets of weighting coefficients in the fitness function are compared by means of bandwidth, gain and linear polarization factor in Figure 9. It indicates that the performance in terms of each criterion varies significantly though the overall fitness is very high and closer to each other. In this sense, weighting coefficients of the partial fitness functions need to be set depending on the importance of each objective. Even if the optimization problem is single-objective, the globally optimized design can't be obtained unless the most suitable cost function is used. Use of numerous cost functions to design broadband MSAs is evident in the field [85]. Analysis of several cost functions shows that the optimum design and the bandwidth performance highly depend on the cost function used in the optimization process (Table 3).

As per the comparison presented in Table 3, the fitness functions which force to have a reflection coefficient less than -10 dB give a better bandwidth than those consider the reflection coefficient at the expected resonant frequency or over a frequency band. When multiple objectives in addition to the broadband performance are considered, the cost function needs to be modified by considering all the objectives (Table 4). Circular-polarization, high gain and multiband performance are some of the objectives considered in the fitness function. This paper reviews only the problems where the objective function is calculated using high fidelity full-wave solvers though approaches where low-fidelity surrogate models used for optimizing antennas are also available [95,96]. Moreover, surrogate models significantly reduce the computation cost.

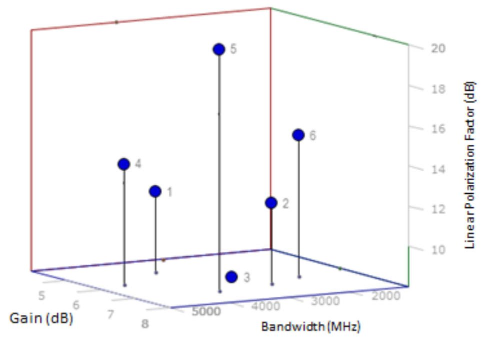


Figure 9. Performance of GA optimized antennas for different weighting coefficients

Table 3. Comparison of cost functions used to design broadband MSAs.

Cost function	S_{11}<-10 dB impedance bandwidth (%)
$F=-\rho(f_i)$ $\rho(f_i)$ is the reflection coefficient at frequency	10
$F=-\sum_{f_i=f_1}^{f_2}\rho(f_i)$	16
$F=-\sum_{f_i=f_1}^{f_2}L(f_i),\quad L(f_i)=\begin{cases}\rho(f_i)_{dB} & \rho(f_i)_{dB}\geq -10dB\\ -10dB & \rho(f_i)_{dB}<-10dB\end{cases}$	28
$F=\sum_{f_i=f_1}^{f_2}\rho(f_i)\sin\frac{\pi(f-3.4)}{1.2}$	21
$F=-\sum_{f_i=f_1}^{f_2}L(f_i)\quad L(f_i)=\begin{cases}\rho(f_i) & \rho(f_i)\geq -10dB\\ -15dB & -15dB\leq\rho(f_i)<-10dB\\ -30dB-\rho(f_i) & -30dB\leq\rho(f_i)<-15dB\\ 0 & \rho(f_i)<-30dB\end{cases}$	33

4. Discussion and conclustions

4.1. Discussion

In case of optimizing the geometry, if a patch area is divided into a grid of 100 small cells, it has a large solution space of 2100 (1.26 × 1030) candidates. Even if the simulation time taken per design is 1sec, solving the whole solution space takes 4 × 1022 years. Solving such complex design problems within a few days by using GA optimization is reported.

High performance optimization techniques such as PSO, ant colony optimization (ACO), Bacterial Foraging Optimization (BFO) and DE have also been applied for performance enhancement of MSAs. Use of PSO, GA based PSO and ACO to optimize the feed position of a rectangular patch antenna is presented in [91]. The best feed position could be found within the least number of iterations when GA based PSO is used, but it consumes more time. In contrast, PSO is faster, though it ran over a higher number of iterations. Performance of DE, PSO and BFO in optimizing the patch length, patch width and the inset feed is presented in [92]. DE is the fastest and BFO is faster than PSO as per the research findings.

Modification of the GA optimization process and creating hybrid versions of GA incorporating advanced features of other optimization techniques may be the future direction in the field of MSA optimization. As per the studies, hybridization of the GA optimization process with particle swarm optimization, space-mapping and mixed potential based method of moments have been proposed [89–92]. The modified GA optimization techniques have resulted in a better design with accelerated convergence than the classical GA [90]. Moreover, local constrained optimization of GA optimized MSAs without increasing their footprint has considerably improved antenna performance due to the utilization of all available degrees of freedom.

4.2. Conclusions

This paper investigates single-objective or multi-objective GA optimization of MSAs. GA optimization was successfully used to design broadband, multiband, high-gain, directive, miniature or circularly polarized MSAs. As per the findings, antenna parameters such as the patch geometry, properties of the substrate and position of feeding or shorting probe have been optimized in order to achieve the objectives. GA parameters, particularly the cost function, need to be defined carefully, in order to facilitate global optimization (Table 04). As the wireless communication industry demands multifunctional devices, multi-objective GA optimization will play a vital role in the field.

Table 4. Cost functions used in multiobjective GA optimization.

Ref.	Cost function	objectives
87	$F = W_1 \times (\frac{1}{VSWR}) + \sum_{i=2}^{n} W_i \times AR_i$ W_1 and W_i are weight coefficients, AR_i is the ith axial value at the elevation angle Θ_i, n is the number of elevation angles required.	Circularly-polarization Conical-beam
56	$F = \sum_f k(\frac{S_{11}(f)}{-100} + \frac{1}{AR(f) \times 10} + k)$ $f \in \{2.05, 2.25, 2.35, 2.4, 2.45, 2.55, 2.75 \text{ GHz}\}$ $k = \{1$ when $S_{11}(f) \le -10dB$ and $AR(f) \le 3\text{dB}$; 0 when $S_{11}(f) > -10dB$ and $AR(f) > 3\text{dB}\}$ $AR(f)$ is the axial ratio at the sampling freq. f.	Broad/dual-band characteris-tics Circular polarizati-on
88	$F = \sum_{i=1}^{N_{freq}} A_i + \begin{cases} 0, & if \lvert\Gamma_i\rvert < \Gamma_{max} \\ 2\lvert\Gamma_i\rvert, & if \lvert\Gamma_i\rvert \ge \Gamma_{max} \end{cases}$ A_i is the axial ratio and Γ is the reflection coefficient	Broadband Circularly polarizati-on
58	$F = k_1 F_1 + k_2 F_2 + K_3 F_3$, $F_1 = G(\theta = 0^0)$, $F_2 = -\sum_{f_i = f_1}^{f_2} L(f_i)$, $F_3 = \sum_{f_i = f_1}^{f_2} (E_c - E_x)$ $L(f_i) = \begin{cases} \rho(f_i) & \rho(f_i) \ge -10dB \\ -15dB & -15dB \le \rho(f_i) < -10dB \\ -30dB - \rho(f_i) & -30dB \le \rho(f_i) < -15dB \\ 0 & \rho(f_i) < -30dB \end{cases}$ G is the gain, $\rho(f_i)$ is the reflection coefficient, E_c and E_x are copolarization and cross polarization, k_1, k_2 and k_3 are weighting coefficients	Broadband High gain Linear polarizati-on

Conflict of interest

The author declares that there is no conflict of interest.

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