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# Soft Computing Techniques for the Optimization of SAW Filters: A State-of-the-art Review

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## ABSTRACT
Surface Acoustic Wave (SAW) devices are an important class of piezoelectric devices, providing frequency control, frequency selection, and signal processing capabilities. The SAW devices, designed to handle complex signal processing functions, can offer considerable cost & size advantage over competing technology. The SAW devices, based on the transduction of acoustic waves, are used as filters, oscillators and transformers, devices. The SAW filters are electromechanical devices commonly used in radio frequency applications. The SAW filters are of 4 types; Linear Resonator and Resonator-Filter Devices, Linear Devices Using Unidirectional IDTs, Linear Devices Using Bidirectional IDTs and Nonlinear Devices. Most of work associated with SAW filters deals with the realization of FIR filters may be quite high, resulting in a large size filter. The realization of IIR filters on SAW devices lead to substantial reduction in filter size. But the introduction of reflective units (for realizing poles lead to complex optimizations issues. Soft Computing Techniques (SCT) are the optimization techniques inspired by the cognitive behavior of human mind. These are fusion of methodologies that were designed to model and enable solutions to real world problems, which are not modeled or too difficult to model, mathematically. SCTs are classified in to four important categories; Evolutionary Computation Techniques (ECT), Fuzzy Logic (FL), Neutral Network (NN) and Machine Learning (ML) [23]. The ECTs are probability-based approaches inspired by biological evolution and/or social evolution. The ECTs are based on mechanics of natural selection and natural genetics, of the likes Genetic algorithms (GAs) and local search have already been used in various forms for solving optimization issues related to SAW filter design. Newer ECTs like Memetic Algirithms (MAs), which blends GAs and local search to take care of both the exploration and exploitation of search space, have also been reported to be used for the optimization of some of the SAW filter design. The main goal of the report in this paper is to look in to the use of SCTs for tackling SAW filter design issues and in that context, probe the future scenario of these techniques for such design issues.

## Keywords
Soft Computing Techniques, SAW Filter

## 1. INTRODUCTION
SAW is Surface acoustic waves on a piezoelectric substrate. An acoustic wave traveling along the surface of a material exhibiting elasticity with amplitude that typically decays exponentially with depth into the substrate. The transduction from electric energy to mechanical energy (in the form of SAW) is accomplished by the use of piezoelectric materials. The SAW devices are an important class of piezoelectric devices, providing frequency control, frequency selection, and signal processing capabilities. The SAW filter is a small and thin filter using surface acoustic wave excited on piezoelectric substrate. SAW filters are currently available for mobile, wireless and personal communication systems such as cellular phones and personal data assistants (PDAs). SAW Filters are of 4 types Linear Resonator and Resonator – Filter devices. Linear Devices Using Unidirectional IDT’s Linear, Linear Devices Using Bidirectional IDTs and Nonlinear Devices.

The frequency response characteristics of SAW filters are governed primarily by their geometrical structures, namely, the configurations of inter-digital transducers (IDTs) and grating reflectors fabricated on piezoelectric substrates [17,18]. Therefore, in order to obtain desirable frequency response characteristics with SAW filters, we have to decide their suitable structures. SAW filters are not analytically solvable, computer-aided design approaches are often used to decide their optimal structures [19]. Most of the work associated with SAW filters deals with realization of FIR filters. For narrow band filters specification, order of the FIR filter may be quite high, resulting in a large size filter. The realization of IIR filter on SAW devices leads to substantial reduction in filter size. But the introduction of reflecting units (for realizing poles) shall lead to complex optimization issues.

Besides optimization methods based on iterative algorithms, computer-aided design techniques utilize the equivalent circuit model of IDT [4] for estimating the frequency response characteristics of SAW filters. The Global Optimization methods can be classified into two main categories: deterministic and probabilistic methods [22]. The deterministic methods since suffer from the curse of locality, they have to resort to the application of heuristics, such as modifying the trajectory (trajectory methods) or adding penalties (penalty-based methods), to escape from local minima. On the other hand, probabilistic methods rely on probabilistic judgments to determine whether or not search should depart from the neighborhood of a local minimum.

In contrast with different adaptive stochastic search algorithms, Soft Computing Techniques (SCTs) are inspired by the cognitive behavior of human mind. These are the fusion of methodologies that were designed to model and enable solutions to real word problems, which are not modeled or too difficult to model, mathematically. SCTs are classified into four important categories: Evolutionary Computation techniques (ECT), Fuzzy Logic (FL), Neutral space network (NN) and Machine Learning (ML). ECTs are probability based approaches inspired by biological evolution and /or social evolution. ECTs exploit a set of potential solutions, named population, and evolve the optimal problem

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solution through cooperation and competition among the individuals of the population. These techniques often find optima in complicated multi-modal optimization problems faster than traditional optimization methods [1]. One can hardly refute the fact that evolution has been an inescapable reality for man and other living species, but the more recent phenomenon is that even machines are beginning to face this reality. Greater and ever increasing functionality, greater speed, greater throughput, greater intelligence, etc. are expected from machines. It is, therefore, apt to say that just as non-adaptive species (like dinosaurs, etc.) have been shown the door of extinction; machines of tomorrow are doomed to failure if they do not adapt and evolve. Since nature marvels at the task of evolution, man can follow nature's model even for the adaptation and evolution of his machines [3].

The theory of survival of the fittest is the basis of biologically inspired ECTs. The GAs are the backbone of this kind of computational techniques. The GAs use a large number of candidate solutions (population) to converge over time to a global optimum [3]. The GAs start with a set of solutions, represented as chromosomes in a population. The chromosomes from one generation of population are taken and used to generate a new generation through operators which emulate biological reproduction and selection. In every generation, thus a new set of strings (of bits in case of binary coding; however other characters can be used in other coding schemes) is created using bits and pieces of the fittest among old creatures. New solutions (offspring) are selected from old population according to their fitness - the more suitable they are in terms of a user-defined fitness function, the more chances they have to be reproduced. This is repeated until some condition (such as a certain number of generations or some convergence criteria) is satisfied.

Newer optimization technique, Memetic Algorithm, based on the genetic evolution and social evolution of living species are promising to add another angle to GAs. It is recently emerging as future versions of ECTs and applicable to many complex problems like SAW filter design issue.

The paper mainly identifies and reviews the followings:

- SAW filters design and its design parameters.
- SCTs for optimization of parameters of SAW filters
- Future use of SCTs such as MAs for optimization issues in DSP design.
- This paper concludes by a comment on the future directions for the SAW filters design parameters.

The rest of the paper is organized as under:

Section 2 details about the SAW filter and various optimization issues related to SAW filter design. Section 3 details the Soft Computing Techniques. Section 4 describes the use of these techniques as optimization techniques for various optimization issues of SAW filter design. Section 5 details the comparison of these techniques with the tradition optimization techniques. Section 6 concludes the paper with a comment on the future directions.

## 2. SAW FILTER AND DESIGN ISSUES

SAW technology is one of the most modern technology that is used to perform signal processing. Their performance is based on piezoelectric characteristics of a substrate. The electrical signal is converted to the mechanical one and back again to the electrical domain at the output. After propagating through the piezoelectric element the output is recombined to produce a direct analogue implementation of finite impulse response filter. The SAW filters are electromechanical devices used in wide range of radio frequency applications providing frequency control, frequency selection and signal processing capabilities.

The basic structure of a SAW filter consists of one input and one output inter digital transducers (IDTs) deposited on a piezoelectric substrate. A basic IDT is a device consists of two interlocking comb shaped metallic coatings which are applied to piezoelectric substrate. The combination of two strips with opposite sign is called finger pairs. These inter digital transducers function as a transmitter and receiver for the surface acoustic waves. The inter-digital transducer can be designed to give the SAW device various characteristics and functions, the filtering function being among the most important. An inter-digital transducer includes electrode bus bars, and electrode fingers.

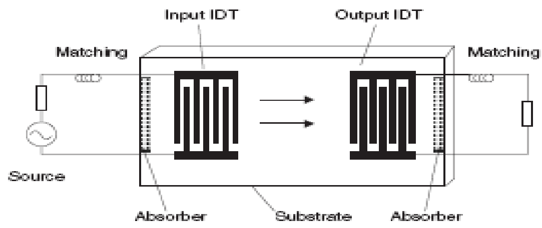


**Fig. 1: Structure of basic SAW filter [17, 18]**

The shape and spacing of the electrodes determine the center frequency & the band shape of the acoustic waves produced by the input transducer. In fact, the signal processing & frequency response characteristics of a SAW device are primarily governed by 3 interrelated factors; the geometry of two IDTs, the piezoelectric substrate and the wave propagation type. The IDT characteristics are also determined by 3 factors; the number of finger pairs, finger geometry in the period and the substrate material. Internal reflections do exist in SAW filters for structural reasons. The typical response of a SAW filter is given by:

$$H(f)=H_1(f).H_2^*(f)$$

Where $H_1(f)$ = frequency response of input IDT &

$H_2(f)$ = frequency response of output IDT.

### 2.1 Structure of 3-IDT type SAW Filter:

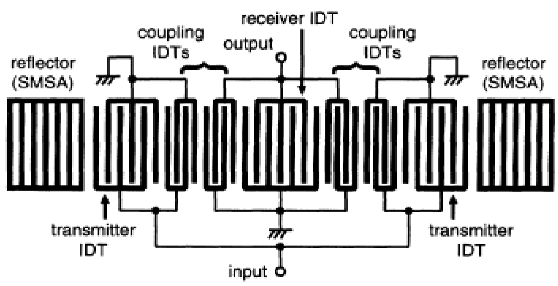


**Fig. 2: Structure of 3-IDT type SAW filter [17]**

An optimal configuration of a three-IDT type SAW filter is discussed in this section. It is used in a cellular phone as a band pass filter. The structural design of a three-IDT type SAW filter consists of three inter-digital transducers (IDT)

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and two reflectors. Three-IDT type SAW filter is shown in Fig. 1. The SAW filter consists of five components: one receiver IDT (IDT-I), two transmitter IDTs (IDT-2) and two reflectors realized by Shorted Metal Strip Arrays (SMSA). Each IDT comprises some pairs of electrodes which are sometimes called fingers, while SMSA has numerous metal strips connected electrically in parallel. These components of the SAW filter are arranged bilateral symmetry on a piezoelectric substrate. That is because the three-IDT type SAW filter is a kind of double mode resonator type SAW filter, where the first and third resonant modes are combined and the second mode is suppressed due to its symmetric structure.

## 2.2 Equivalent Circuit Model

Several equivalent circuit models are widely used in the [21]. design and analysis of SAW devices [17]. The acoustic-electric interaction caused by IDTs can be considered from the viewpoint of the electric circuit theory. By using the least equivalent circuit model of IDT, an entire equivalent circuit model of the three-IDT type SAW filter may be driven. The equivalent circuit model for N-pair of IDT, which corresponds to IDT-I and IDT-2 in Fig. I, can he described as shown in Fig.2. In the three-port equivalent circuit model in Fig.2, port-1 and port 2 are acoustic ports. Whereas port-3 is electric port[21]. The force factors $A_{10}$ and $A_{20}$ are the functions of the frequency and the number of finger-pairs of IDT. Admittance $Y_m$, and impedances $Z_1$ & $Z_2$, are given as follows:

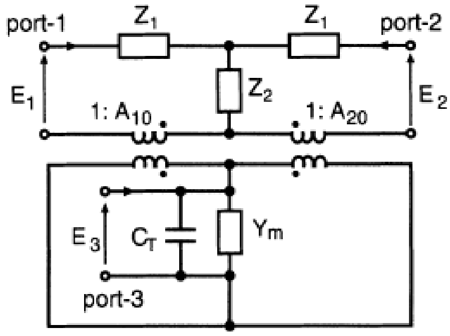



**Fig. 3: Equivalent model of 3-IDT type SAW filter [21]**

$$\left[\begin{array}{c} A_{10}=\tanh(\frac{\gamma_s}{2})\tanh(N\gamma_s) \\ A_{20}=\mp A_{10} \\ Z_1=\frac{R_0}{F_s}\tanh(N\gamma_s) \\ Z_2=\frac{R_0}{F_s}\operatorname{cosech}(2N\gamma_s) \\ Y_m=2G_0F_s\tanh(N\gamma_s).[2N-\tanh(\frac{\gamma_s}{2})\tanh(N\gamma_s)] \end{array}\right.$$

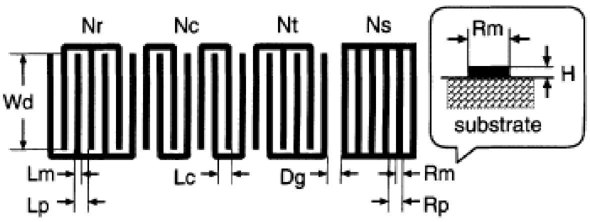
Where the dual sign ( $\mp$ ) means that the minus (-) is for $2N$ being an even number, while the plus (+) is for $2N$ being an odd number: $G_0$ is characteristic admittance, and $G_0 = 1/G_0$; $F_s$ and $\gamma_s$ denote image parameters.

As stated above, the frequency response characteristics of the SAW filter depend on the configurations of its components fabricated on a piezoelectric substrate. For deciding an optimal structure of SAW filter, we consider twelve significant design parameters listed in Fig.5. Since the resonator type SAW filter has a symmetrical configuration with respect to the receiver IDT, Fig 4. illustrates only its right half side. In Fig 4, the metallization ratio of IDT is defined by finger's width as $\lambda = L_m / L_p$. The metallization ratio of SMSA is also defined by strip's width as $\lambda_r = R_m / R_p$. On the other hand, the pitch ratio of coupling IDT is given by $\mu = L_c / Lp$. The pitch ratio of SMSA is also given by $\mu_r = R_p / L_p$. From now on, the twelve design parameters in Fig 4. are referred to as control factors [21] and represented by a vector of n = 12 elements: X = ($x_1$ , ... , $x_n$). By the way, some control factors, such as the number of fingers of IDT, take the values of positive integers. Besides, the lithographic resolution in SAW devices fabrication is also restricted to a finite value. So we introduce a minimum unit value $e_i$ ($i$ = 1 ~ $n$) into each of the Control factors $x_i \in$ X. Then we suppose that they take discrete values within the regions bounded by their parametric limitations are as follows:

$$\underline{x}_i \leq x_i \leq x_i\ ,\ i = 1 \sim n.$$

$$where\ (x_i - \underline{x}_i)\ mod\ e_i = 0,\ e_i > 0,\ i = 1 \sim n.$$

Transition-lines between components, such as IDTs and SMSA, also have their equivalent circuit models [17]. Since these components are connected acoustically in cascade on a piezoelectric substrate, the entire equivalent circuit model of the SAW filter is made up of their equivalent circuit models. Terminating acoustic ports with the characteristic impedance, we obtain a two-port equivalent circuit model, which is denoted by a transmission matrix for the three-IDT type SAW filter as shown in Fig.5.




| | | |
|---|---|---|
| $W_d$ | : | overlap between electrodes |
| $N_t$ | : | number of fingers of transmitter IDT |
| $N_r$ | : | ditto of receiver IDT |
| $N_c$ | : | ditto of coupling IDT |
| $N_s$ | : | number of strips of SMSA |
| $D_g$ | : | gap between transmitter and SMSA |
| $\lambda$ | : | metallization ratio of IDT |
| $\lambda_r$ | : | ditto of SMSA |
| $\mu$ | : | pitch ratio of coupling IDT |
| $\mu_r$ | : | ditto of SMSA |
| H | : | thickness of electrode |
| $L_p$ | : | pitch of fingers of IDT |

**Fig. 4: Design parameters of SAW filter [17].**

In order to evaluate the frequency response characteristics of the SAW filter, we adopt some performance criteria. Scattering coefficients which are used widely for analyzing the capability of SAW devices [18] can be derived from the transmission matrix in Fig 5 as follows:

$$\begin{cases} S_{21} = \dfrac{2\sqrt{Z_G.Z_L}}{A.Z_L + B + C.Z_G.Z_L + D.Z_G} \\ S_{11} = \dfrac{A.Z_L + B - C.Z_G.Z_L - D.Z_G}{A.Z_L + B + C.Z_G.Z_L + D.Z_G} \\ S_{22} = \dfrac{-A.Z_L + B - C.Z_G.Z_L + D.Z_G}{A.Z_L + B + C.Z_G.Z_L + D.Z_G} \end{cases}$$

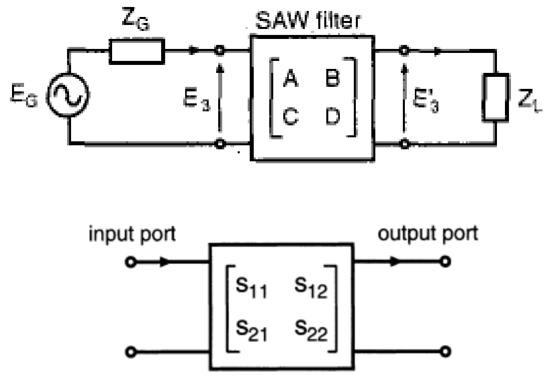



**Fig. 5: Two port network model of 3-IDT type SAW filter**

Where *A*, *B*, *C* and *D* are the transmission parameters. Among the scattering coefficients in *(3)*, $S_{11}$ and $S_{22}$ are often referred to as reflection coefficient. On the other hand, $S_{12}$ and $S_{21}$ are referred to as transmission coefficient where the relation $S_{12} = S_{21}$ holds for the SAW filter. From the reflection coefficient, standing wave ratios are defined for the input and output ports as follows:

$$\Gamma_1 = \frac{1 + |S_{11}|}{1 - |S_{11}|}$$

$$\Gamma_2 = \frac{1 + |S_{22}|}{1 - |S_{22}|}$$

Furthermore, from the transmission coefficient calculated by (3), the attenuation is defined as follows:

$$\Gamma_3 = -20\log_{10}(|S_{21}|)$$

A desirable feature of the SAW filter by the upper and lower hounds of the above three criteria $\Gamma_r$ ($r = 1 \sim 3$) is specified. Let $\Omega$ be a set of frequencies $\omega \in \Omega$ extracted from the remarkable frequency range including both of the passing and stop-hands of the SAW filter. Let $\Gamma_r(\omega.x)$ denote the value of the criterion $\Gamma_r$, measured at $\omega \in \Omega$ with a vector of design parameters x: let $U_r(\omega)$ and $L_r(\omega)$ represent the specified upper and lower bounds of criteria $\Gamma_r(\omega.x)$. Then, an objective function *f(x)* based on the penalty method [8] is defined as follows:

$$f(x) = \sum_{r=1}^{3} (a_r^u \delta U_r(x)^2 + a_r^l \delta L_r(x)^2)$$

where $a_r^u$ and $a_r^l$ ($r = 1 \sim 3$) are penalty parameters:

$$\begin{cases} \delta U_r(x) = \sum_{\omega\in\Omega} (\max\{|\Gamma_r(\omega.x)|.U_r(\omega)\} - U_r(\omega)) \\ \delta L_r(x) = \sum_{\omega\in\Omega} (L_r(\omega) - \min\{|\Gamma_r(\omega.x)|.L_r(\omega)\}) \end{cases}$$

## 2.3 Optimization Problem formulation

The structural design of a 3-IDT type SAW filter is formulated as a combinatorial optimization problem. Since some design parameters are positive integers and the objective function is discontinuous, it becomes a clear cut case of combinatorial optimization problem. Most design techniques are relied on optimization methods. For the optimum design of the three-IDT type SAW filter, problem can be mathematically defined as under:

Let *F* he the feasible region of solutions, namely a whole set of possible design parameters constrained by (2)**.** For minimizing the objective function *f*(x) may be defined by [10] the structural design of the SAW filter is expressed as an optimization problem as follows:

$$\begin{cases} \text{Minimize} \quad f(x) \\ \text{Subject to } x \in F \end{cases}$$

# 3. SOFT COMPUTING TECHNIQUES

SCTs are inspired by the cognitive behavior of human mind. These are the fusion of methodologies that work designed to model and enable solutions to real world problems, which are not modeled or too difficult to model, mathematically. SCTs are classified into four categories; Evolutionary Computation Techniques (ECT), Fuzzy Logic (FL), Neural Network (NN) and Machine Learning (ML). ECTs are probability based approaches inspired by biological evolution and/or social evolution. The existing, successful ECTs fall into three broad categories: local search-based, population-based search and hybrid of these two types.

In local search-based ECTs, a special ‘current’ solution is maintained, and its neighbors are explored to find better quality solutions [20]. Occasionally, one of these neighbors becomes the new current solution, and then its neighbors are explored, and so forth. The population-based techniques starts with a population of randomly selected solutions and then converges towards the global optimal through operators (crossover mutation, etc.). The hybrid one combines the population-base techniques with the local search-based techniques. These techniques judiciously use the various operators of earlier two techniques both for exploitation as well as exploration of search space. The various ECTs are detailed as under:

## 3.1. Local Search-based ECTs

Local search is a meta-heuristic for solving computationally hard optimization problems. Local search can be used on problems that can be formulated as finding a solution maximizing a criterion among a number of candidate solutions [10]. Local search algorithms move from solution to solution in the space of candidate solutions (the *search space*) until a solution deemed optimal is found or a time bound is elapsed. Most problems can be formulated in terms of search space and target in several different manners. For example, for the traveling salesman problem a solution can be a cycle and the criterion to maximize is a combination of the number of nodes and the length of the cycle. But a solution can also be a path, and being a cycle is part of the target. A local search algorithm starts from a candidate solution and then iteratively moves to a neighbor solution. This is only possible if a neighborhood relation is defined on the search space. Typically, every candidate solution has more than one neighbor solution; the choice of which one to move to is taken using only information about the solutions in the neighborhood of the current one, hence the name local search. When the choice of the neighbor solution is done by taking the one locally maximizing the criterion, the meta-heuristic takes the name hill climbing. Termination of local search can be based on a time bound. Another common choice is to terminate when the best solution found by the algorithm has not been improved in a given number of steps. Local search algorithms are typically incomplete algorithms, as the search may stop even if the best solution found by the algorithm is not optimal. This can happen even if termination is due to the impossibility of improving the solution, as the optimal solution can lie far from the neighborhood of the solutions crossed by the algorithms.

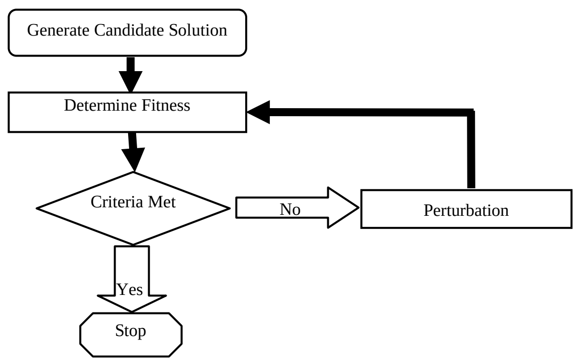



**Fig. 6: Basic steps in Local Search-based ECTs**.

Local search algorithms are widely applied to numerous hard computational problems, including mathematics, operations research, engineering, and bioinformatics. A pseudo-code for a local search procedure is given in Appendix B. It starts with an initial population of candidate solutions. Afterwards, a local search is performed on each population member to improve its experience and thus obtain a population of local optimum solutions unless some termination condition is met.

**Pseudo-code for local search-based ECTs**

```
procedure localSearch_Routine
        GenerateInitialSolution()
        EvaluateFitness()
        while (termination condition not met) do
            Pertubation()
            EvaluateFitness()
        end-while
end-procedure
```

The local search is an identified technique for shortest path algorithm and traveling salesman problem [17], routing problems in networks [ ] etc. It holds the potential to counter the delay related issues which arise due to longish data-paths in FPGA.

## 3.2 Population-based ECTs

The Population-based techniques are a subset ECTs that involve are inspired by biological evolution such as reproduction, mutation, recombination, natural selection and survival of the fittest. Candidate solutions to optimization problem play the role of individuals in a population, and the cost function determines the environment within which the solution is located. Evolution of the population then takes place after the repeated application of the above operators. In this process, there are two main forces that form the basis of evolutionary systems: Recombination and mutation create the necessary diversity and thereby facilitate novelty, while selection acts as a force increasing quality. Many aspects of such an evolutionary process are stochastic. Changed pieces of information due to recombination and mutation are randomly chosen. On the other hand, selection operators can be either deterministic, or stochastic. In the latter case, individuals with a higher fitness have a higher chance to be selected than individuals with a lower fitness, but typically even the weak individuals have a chance to become a parent or to survive.

The Genetic Algorithms (GAs), one typical population-based optimization technique, originated from the studies of cellular automata, conducted by John Holland, are the search techniques used in a host of fields to find approximate solutions to optimization and search problems. The GAs are a particular class of ECTs that use techniques inspired by evolutionary biology such as inheritance, mutation, natural selection, and recombination (or crossover). The canonical GA steps are as follows:

**Initialization:** Many individual solutions are randomly generated to form an initial population, covering the entire range of possible solutions (the search space). The population size depends on the nature of the problem, but typically contains several hundreds or thousands of possible solutions. Occasionally, the solutions may be "seeded" in areas (based upon a priori knowledge of problem domain) where optimal solutions are likely to be found.

**Selection:** During each successive generation, a proportion of the existing population is selected to breed a new generation. Individual solutions are selected through a fitness-based process. Popular and well-studied selection methods include roulette wheel selection and tournament selection [3].

**Crossover:** For each new solution to be produced, a pair of ‘parent’ solutions is selected to crossover. By producing a ‘child’ solution using crossover, a new solution is created which typically shares some of the characteristics of its ‘parents’, but more importantly the method offers possibility of creating even fitter solutions.

**Mutation:** This operator effects an incremental change to a member of the GA population. The probability of mutating each gene in a GA chromosome is chosen generally in the range of 0.01 to 0.03, symptomatic of very low copying errors from parents’ DNA pool to offspring in living species.

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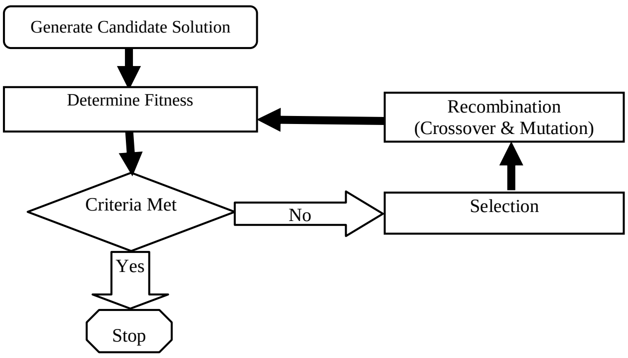


**Fig. 7: Canonical GA Steps [23]**

**Termination:** The generational process is repeated until a termination condition has been satisfied. The common terminating conditions are:

- A solution is found that satisfies the minimum criteria.
- Some fixed number of generation have been reached.

A pseudo-code for a GA procedure is given in Appendix B. An initial population is created at random. Afterwards, in each generation, parents are selected based on the fitness criteria. Then, crossover and mutation operators are applied unless some termination condition is met [23].

**Pseudo-code for GAs [23]**

***procedure*** *Genetic_Routine*
*GeneratePopulation()*
*EvaluateFitness()*
***while*** *(termination condition not met)* ***do***
*ParentSelection()*
*Recombination()*
*EvaluateFitness()*
***end-while***
***end-procedure***

The GAs have been applied in global optimization problems. The GAs have been applied for routing problem in VLSI. In [5], the GA has been used for optimization of frequency domain parameters of SAW filters. But a comprehensive GA processor is still awaited.

## 3.3 Hybrid ECTs

Unlike traditional ECTs, MAs are concerned with exploiting all available knowledge about the problem under study. This is not as an optional mechanism, but as a fundamental feature. From an optimization point of view, MAs are hybrid EAs that combine global and local search by using an EA to perform exploration while the local search method performs exploitation. Combining global and local search is a strategy used by many successful global optimization approaches, and MAs have in fact been recognized as a powerful algorithmic paradigm for evolutionary computing. In particular, the relative advantage of MAs over EAs is quite consistent on complex search spaces. MAs are also known as hybrid EAs, Baldwinian EAs, Lamarkian EAs, etc. [23].

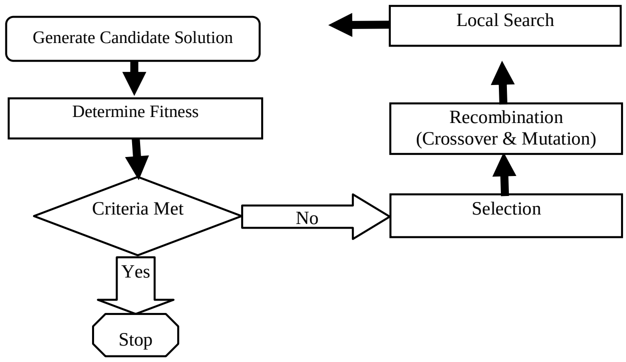


**Fig. 3: Canonical MA Steps [23]**

The MAs, inspired by Dawkins' notion of a meme (a unit of cultural evolution that can exhibit local refinement), are evolutionary algorithms (EAs) that apply a separate local search process to refine individuals (i.e. improve their fitness). These methods are inspired by models of adaptation in natural systems that combine evolutionary adaptation of populations of individuals with individual learning within a lifetime. The unique aspect of the MAs algorithm is that all chromosomes and offsprings are allowed to gain some experience, through a local search, before being involved in the evolutionary process [5]. As such, the term MAs is used to describe GAs that heavily use local search.

A pseudo-code for a MA procedure is given in Appendix B. As discussed, the parameters involved in MAs are the same four parameters used in GAs: population size, number of generations, crossover rate, and mutation rate in addition to a local-search mechanism. Similar to the GAs, an initial population is created at random. Afterwards, a local search is performed on each population member to improve its experience and thus obtain a population of local optimum solutions. Then, crossover and mutation operators are applied, similar to GAs, to produce offsprings. These offsprings are then subjected to the local search so that local optimality is always maintained [23].

**Pseudo-code for MAs [23]**

***procedure*** *Memetic_Routine*
*GenerateInitialPopulation()*
*EvaluateFitness()*
*LocalSearch()*
*EvaluateFitness()*
***while*** *(termination condition not met)* ***do***
*ParentSelection()*
*Recombination()*
*LocalSearch()*
*EvaluateFitness()*
***end-while***
***end-procedure***

MAs include a broad class of meta-heuristics. This method is based on a population of agents and proved to be of practical success in a variety of problem domains. MAs are one of the most successful approaches for combinatorial optimization in general, and for the approximate solution of NP Optimization problems in particular. MA is an identified technique for shortest path algorithm and traveling salesman problem [16], routing problems in networks [14] etc. It holds the potential to counter the delay related issues which arise due to longish data-paths in FPGA.

## 4. SCTs FOR OPTIMIZATION OF SAW FILTERS

As discussed earlier, that the GAs have been applied in global optimization problems [15]. In order to find desirable balanced SAW filters' structures, the design of them is formulated as an optimization problem. In [1] two types of Evolutionary Algorithms (EAs), namely Differential Evolution (DE) and Genetic Algorithm (GA) [6], are applied to the optimization problem. The performance of DE applied to the optimum design of balanced SAW filters was compared with GA. In order to evaluate the frequency response characteristics of balanced SAW filters based on the computer simulation, numerical models of them were derived. Then the structural design of balanced SAW filters was formulated as a function optimization problem. In order to apply the above EAs to the optimization problem, the distorted problem space was scaled and embedded in a regularized continuous search space. From the experimental results, it was shown that the basic DE had a greater probability of finding the better solution than a real-coded GA with the same computational cost.

In [9, 12, 13] an Imanishian GA based on an Anti-Darwinism, i.e., an alternative evolutionary theory advocated by a Japanese ecologist Kinji Imanishi [9] is discussed. The Imanishian GA to the optimum design of a resonator type SAW filter. Imanishi denied both of the essential principles of the Darwinism, namely, the natural selection and the random mutation. On the other hand, from the viewpoint of bionomics, he emphasized the coexistence of variant species instead of the struggle for existence. Furthermore, the Imanishism claims the adaptive change of respective species as well as the Lamarckism. Consequently, comparing with the Darwinism, it seems that the Imanishism is offering an inclusive analogy of evolution for designing a powerful optimization method. In the proposed Imanishian GA based on the Imanishism, an appropriate distance between solutions, or individuals, is used to recognize different species. Then generation model realizes a situation of the habitat segregation among various species in the population. Also, in order to find good solutions effectively, a local search is employed in a similar way with conventional hybrid GAs. As a result, the Imanishian GA can avoid the confusion of biological analogies and take a good balance between exploration and exploitation.

In [5], a robust optimization technique with the Taguchi method and a MA for the structural design of SAW filters based on the computer simulation in which designing imperfections are caused by the inevitable dispersion of parameters included in the equivalent circuit model of IDT, is described. They described the quality of SAW filters as the robustness of their frequency response characteristics against the variations of the above parameters. Besides the quality, they also we specified desirable functions of SAW filters with the upper and lower bounds for their frequency responses. Consequently, also formulated the robust optimum design of SAW filters as a constrained optimization problem in which the SNR of SAW filters is maximized under the constraints of their specified functions. This work provided the first application of the MA for the robust optimum design of SAW filters in connection with the Taguchi method.

## 5. SCTs VERSUS TRADITIONAL OPTIMIZATION TECHNIQUES

As SCTs give an alternative to designers to traditional optimization technique in a particular domain, so the comparison becomes imperative. The comparison can be made on following lines:

- In SCTs, the search is done from a population of points in parallel & not from a single point as in traditional techniques. The latter techniques often lead to the locations of false peaks in multi-modal search spaces.
- Search in SCTs is done using stochastic operators, not deterministic rules. Thus, if we run the same algorithm again, we are likely to obtain different result but quite close to the optimal one provided that the algorithms have been run with proper choice of parameters (such as population size, number of generations, step size, etc.). These techniques use random choice to guide a highly exploitative search.
- The SCTs work on encoding of the parameter set rather than the parameter set itself, so they do not require any other auxiliary knowledge.
- The SCTs can take the size of smaller members also into account while calculating the fitness function. It is not available in traditional techniques as these consider all the cells of same size.

All in all, these techniques appear to be promising alternatives over the traditional optimization techniques.

## 6. CONCLUSION AND FUTURE DIRECTIONS

The SCTs are quite effective techniques for optimization issues of SAW filters design. Genetic Algorithums have been an effective optimization technique based on the process of natural selection for optimization issues of SAW filter design. Also its variant Imanishian GA & DE have been successfully used to optimize the design related issues of SAW filters. The MAs outperformed the traditional optimization techniques by a judicious mix of both exploring and exploiting the search space. But still the newer Evolutionary computational techniques of the likes of Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Shuffled Frog Leaping Algorithms (SFLA), which have already emerged as state of the art techniques for most combinatorial optimization problems by incorporating the features (intelligence, knowledge, experience) of animals, are not experimented for SAW filter design issues. All in all, we can say that optimization based on the SCTs for SAW filter design is still in the nascent stage & the future of these techniques seems to be a brighter one. Also, synergetic approaches are likely to emerge, drawing upon the most effective elements from the seemingly disparate approaches.

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