A GENETIC ALGORITHM FOR THE OPTIMIZATION OF THE ANALOG CHANNEL FILTER

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Abstract: This paper presents a method for optimizing the transfer function of the channel filter within the Zero-Intermediate Frequency radio receivers of Orthogonal Frequency-Division Multiplexing (OFDM) broadcasts. The method is based on a genetic algorithm (GA) and has several distinctive features: the type and order of the transfer function can be changed during the optimization process; the optimal solution is calculated based on three objective functions that allow an independent control of the pass band and stop band; a real test signal including wanted and adjacent channels is applied at the filter's input, which allows the estimation of the nonlinearity effects of the filter. Another important feature is that for a given set of conditions, the GA is run multiple times, taking full advantage of the random permutations employed by the algorithm: the multiple results are not only used to select the very best but they are also analyzed statistically in order to estimate the convergence of the algorithm.

Keywords: *circuit optimization, genetic algorithm, analog channel filter, OFDM radio receiver*

I. INTRODUCTION

A constant trend in the development of integrated radio receivers over the last two decades has been the expansion of the digital signal processing at the expense of analog. Recently, this trend has been accelerated due to the fact that some of the shortcomings of analog signal processing became more significant when integrating blocks in modern nano-metric CMOS technologies: analog circuits are, in general, not scalable—their area is dominated by capacitances and so it does not decreases proportionally when integrated in a finer technology; also, analog designs are not very portable: porting a block from on technology to another usually involves a major redesign effort.

Therefore there is real pressure to reduce the number and scope of analog blocks within a receiver signal path. This is very much the case for analog filters, as they require significant area. In principle, the channel filter within a radio receiver can be removed from the signal chain if an Analog-to-Digital Convertor (ADC) with high-enough resolution and suitable dynamic range was available. Despite major improvements in ADC performances, especially the oversampling sigma-delta ADCs, such an approach is not possible today and it is unlikely to be a viable option in the near future [1]. Instead, more research has been focused on optimizing the analog filters.

Numerous CAD tools for filter design are available [2] but most of them are based on the classical transfer functions, such as Butterworth, Cauer, Chebyshev, etc. which meet only requirements related to the magnitude or phase responses, such as the cutoff frequency, the pass band ripple and the stop band ripple [3]. However, many applications have additional requirements and for these cases using the classical approximations result in sub-optimal solutions.

The particular application envisaged in this paper is the channel filters for OFDM integrated radio receivers with Zero-IF architectures. OFDM is used in most of the modern broadcastings, from Wi-Fi to digital TV. For the channel filters within these receivers it is important to control in the same time the maximum attenuation in the pass band, the minimum attenuation in the stop band and the width of the transition band. In reference [4] the authors have proposed *a genetic algorithm* (GA), tailored for the optimization of the transfer functions of such filters. The aim of the present contribution is to improve on and expand significantly the method presented in [4], from the definition of the optimization criteria to the actual Matlab implementation, and the addition of new features such as the possibility of changing the filter's order during the optimization process.

When dealing with design optimization in electrical engineering, GA is a better alternative for classical algorithms. GA is based on the theory of evolution [5], [6] and the research in this subject has been expanded a lot. Most of the existent literature on evolutionary techniques concentrates on optimization of *digital* structures. However, several approaches for design and optimization of the *analog* filters were proposed. For example, the GA applied in [7] uses as the optimization function the difference between the transfer functions of the ideal and the filter given by the GA, where the ideal filter is the asymptotic Bode plot. It is not clear however the composition of a chromosome; also, other parameters (i.e. the quality factor) are not controlled. In [8], the fitness function measures the deviations of the numerator and denominator coefficients of the transfer function. It is indeed a simpler and faster way, but an accurate control would be done by considering the

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poles and zeros deviations. In [9] the fitness function is calculated as a weighted difference between the magnitude responses of the filter resulted from the algorithm and an approximation filter model. A common disadvantage of the above methods is that the algorithm cannot control independently the pass band and the stop band. Numerous papers – and even commercial products – have appeared recently, that use the GA in analog IC synthesis for a given topology of the circuit [10] or in calculating/selecting the component values and the circuit topology [11], but they basically consider the transfer function of the optimized circuit as a given, set outside the optimization process.

The approach used in this paper has several distinctive features: the type and order of the transfer function can be changed during the optimization process; the method implies multiple-runs for each set of conditions, so that one can take full advantage of the random permutations the GA is based on; the optimal solution is calculated based on three objective functions that allow an independent control of the pass band and stop band.

Section II of this paper presents a brief analysis of the filter optimization problem and a general mathematical description of the optimization criteria that are taken into account for the application mentioned above. Section III focuses on the proposed optimization method based on a tailored genetic algorithm. The method is validated through an example for the application, presented in Section IV: optimization of the channel filter for a DVB-H receiver.

II. THE FILTER OPTIMIZATION PROBLEM

A filter is generally designed to satisfy a frequency response specification. Analog filter design normally focuses on satisfying a magnitude response specification. If the phase response is essential, it is usually satisfied by a phase compensation filter.

The main criterion of the channel filter optimization is usually to minimize the linear distortions of the wanted signal, which are caused by the deviations of the magnitude response from the ideal one – which lead to a non-flat gain in the pass band – and the perturbations caused by the unwanted signals from the adjacent channels.

In the context of the channel filter for the Zero-IF OFDM radio receivers considered here, we focus on a real-life case: the 8 MHz version of the DVB-H broadcast standard [12], [13]. First, we developed in Matlab an OFDM signal generator, able to provide test signals with two components: *the wanted channel* (0–3.325 MHz) and *the adjacent channel* (4.675 MHz–11.325 MHz), with a very narrow guard band of 1.35 MHz between them [4]. The spectrum of this OFDM signal is represented in *Figure 1*. The power levels of the two components can be set independently.

In this paper we exploit two advantages of using a real test signal. First, the possibility of estimating *the nonlinearity* effects of the filter, which lead to adjacent channel interference by intermodulation, as it will be seen in the results Section. Second, the possibility of calculating *the ratio of the powers* of the output signal in the adjacent and wanted channels. The minimum attenuation in the adjacent channel is less significant than the average attenuation. On the other hand, the ripple in the pass band leads is equivalent to an average attenuation in the pass band. For this reason, we believe that a more accurate evaluation of the filter's efficiency can be defined by the ratio of the powers in the adjacent and wanted channels, in the presence of a test signal having uniform power in the two channels. This power-ratio was thus included as one of the objective functions in the implementation of the GA presented here.

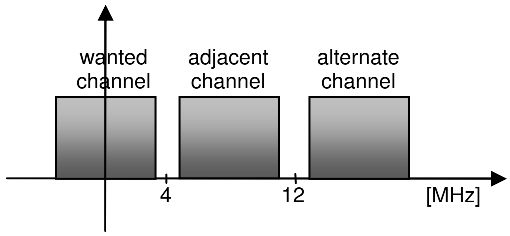

Figure 1. The spectrum of the generated OFDM signal

System-level analysis of the receiver yields the following requirements: the ripple in the pass band of 0.5 dB, the -3 dB cutoff frequency (F_{c0}) of 3.325 MHz and the minimum attenuation in the stop band of 20 dB.

The GA searches among a set of different possible solutions, starting from a *specimen* – which is a filter that meets the requirements but is not optimal. The quality of each solution is given by a mark, called *fitness*, which is a weighted sum of several *objective functions* which express, in one way or another, deviations of the solution from the ideal. The fitness function used in this application for the optimization of the transfer function depends on three objective functions:

1. *the ripple in the pass band*:

$$R = \left|\max\left\{A(f)\right\} - \min\left\{A(f)\right\}\right|,\ f < F_c \qquad (1)$$

where $A(f)$ is the magnitude of the filter and F_c is the -3dB cutoff frequency;

2. *the relative error of the cutoff frequency*:

$$\Delta F = \frac{F_c - F_{c0}}{F_{c0}} \qquad (2)$$

3. *the power-ratio* as explain above, that is:

$$PR = \frac{P_a}{P_w} \qquad (3)$$

where P_a is the average power in the adjacent channel, P_w is the average power in the wanted channel, both calculated with a similar expression:

$$P = \frac{1}{N}\sum_{k \in B}\left|Y(k)\right|^2 \qquad (4)$$

where N is the number of samples of the Fourier transform of the filter's output (Y) in the frequency bandwidth B of the wanted / adjacent channel.

The fitness function is therefore given by:

$$F_f = R \cdot w_R + \Delta F \cdot w_{\Delta F} + PR \cdot w_{PR} \qquad (5)$$

where w_R, $w_{\Delta F}$, w_{PR} are the corresponding weights, set by the user so that $w_R + w_{\Delta F} + w_{PR} = 1$. Finding the appropriate weights is a real challenge, and therefore they have to be adjusted adaptively during several runs of the GA. For a given set of weights, the smaller the fitness, the closer to the optimal the solution is, because the optimization criteria consist in minimization of all three objective functions.

III. MATLAB IMPLEMENTATION OF THE GA

The GA generates useful solutions to optimization problems using techniques inspired by the process of natural evolution. The members of the population (the individuals) are represented by *chromosomes*, which in our case encodes *filters*. A chromosome contains several *genes* which are represented in binary, as array of bits. In this paper, the genes are assigned to the singularities (poles and zeros) of the filters. Each chromosome is organized as follows:

$$[\ \underbrace{0...1}_{p_0}\ \ \underbrace{0...1}_{\mathrm{Re}\{p_1\}}\ \ \underbrace{0...1}_{\mathrm{Im}\{p_1\}}\ \cdots\ \underbrace{0...1}_{\mathrm{Re}\{p_N\}}\ \ \underbrace{0...1}_{\mathrm{Im}\{p_N\}}\ \ \underbrace{0...1}_{\mathrm{Im}\{z_1\}}\ \cdots\ \underbrace{0...1}_{\mathrm{Im}\{z_M\}}\ ] \qquad (6)$$

where: p_0 is the real pole; $\mathrm{Re}\{p_n\}$ and $\mathrm{Im}\{p_n\}$, $n = \overline{1,N}$, represent the real and imaginary parts of the complex conjugate poles p_n and p_n^*; $\mathrm{Im}\{z_m\}$, $m = \overline{1,M}$ represents the imaginary part of the complex conjugate zeros z_m and z_m^* (for reasons of physical implementation, in our application the zeros are purely imaginary).

First, GA randomly generates the initial population, which then evolves within several generations. New members are born by simulating the specific phenomena of the evolution (crossover and mutation [5], [6]). At the end of a generation, all the possible solutions are sorted in terms of the fitness, evaluated for each individual. The optimal solution is searched among the filters with the same order and same number of singularities, for which the genes have a certain variation Δ around the genes of the specimen. The search area depends on the variation Δ and the length of a gene.

The program developed in Matlab allows the repeating of the searching algorithm several times: the first run starts from the specimen and leads to a first optimal, which can be the starting point for the next cycle, and so on. Moreover, for a finer search, the tests can be run again for the value of Δ decreasing successively by half the initial value for a finer search. In the end, the lower value of the fitness function corresponds to the optimal solution.

IV. SIMULATION RESULTS

The parameters of GA were set up as follows: the size of the initial population of 100, the length of a gene of 8 bits, the crossover rate of 80%, the mutation rate of 20% and the number of generations 100. For each test, the evolutionary cycle of GA was run 3 times, for an elementary variation Δ, $\Delta/2$, and $\Delta/4$ respectively, where $\Delta = 0.01$. For all the tests run for this design example, the specimen was of type II Chebyshev, with 20 dB stop band ripple and the -3 dB cutoff frequency set at 3.325 MHz.

The optimization procedure took place over several series of tests that will be discussed further.

A. The first set of tests

For the first series of tests the effect of changing the test signal from one run to another was investigated. Three orders were considered for the filter transfer function – the 3rd, 4th and 5th – and 60 tests were run for each of these. First a *different* test signal was randomly generated each time; then the same tests were run having the *same* test signal as input. The fitness function resulted in about the same average value in the two cases (see *Figure 2* as an example for the 5th order). Consequently the test signal remained *constant* further in all cases studied in order to reduce the running time.

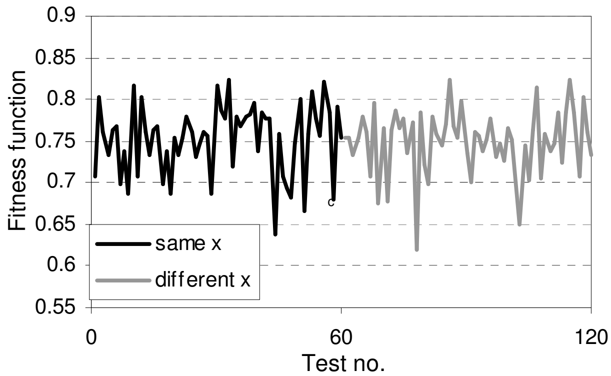

Figure 2. The fitness function for 120 tests when the test signal is the same (black line) and different (grey).

B. The 2nd set of tests

The tests from this set studied the effect of the weights over the fitness function for the 3rd, 4th and 5th orders. The number of tests was 60 of each order, resulting in a total of 180 consecutive tests. *Figure 3* shows the variation of the fitness function resulted from the tests; the settings for the weight vector are detailed in *Table 1*.

For each order, GA started from a specimen of the same order. Each test started from the same specimen, using the same test signal, but different results were obtained due to the fact that GA included random permutations, as it will be discussed later in the paper.

It can be noticed that for any combination of weights the 3rd order has wider variations and a lower mean value for the fitness function than the other two orders. This can be explained by the fact that for the 3rd order GA has more freedom to search for solutions. As the order increases, the transition band is narrower and the probability of finding a better solution decreases.

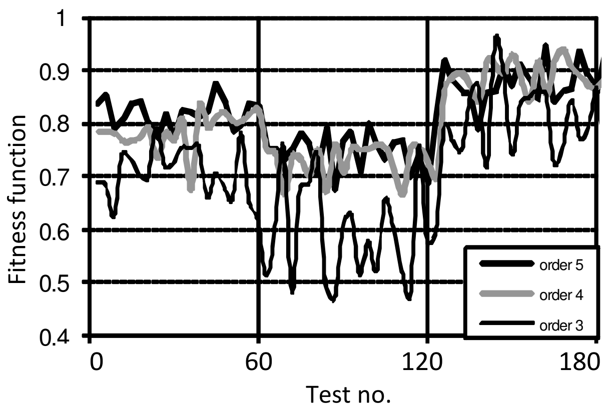

Figure 3. The fitness function for 180 consecutive tests for 3rd, 4th and 5th order filters, respectively.

Table 1. The values of the weights used in 60 tests for the each of the 3rd, 4th and 5th orders.

Test no.	w_R	$w_{\Delta F}$	w_{PR}
1 – 60	0.3	0.1	0.6
61 – 120	0.1	0.1	0.8
121 – 180	0.3	0.3	0.4

One can also observe that for all three orders considered for the filters, the best solutions are obtained for the tests no. 61–120, when the weight w_{PR} was set much higher than the other two weights. This means that the minimization of residual power in the adjacent band is more significant then the other optimization criteria.

The chart from *Figure 4* illustrates the number of cases (tests) and the corresponding ranges of the fitness function, for the combination of weights $w_R = 0.1$, $w_{\Delta F} = 0.1$ and $w_{PR} = 0.8$.

Figure 5 illustrates the spectrum of the test signal (with grey), the gain characteristic of the initial 5th order Chebyshev filter (with dashed black line), and the best solution of 4th order from 40 tests (with continuous black line). The bottom plot in *Figure 5* is a zoom-in of the filter characteristics presented in the upper plot around the cutoff frequency: it can be seen that the cutoff frequency is kept at 3.325 MHz and the maximum attenuation in the pass band is lower than the requirement of 0.5 dB.

C. The 3rd set of tests

The following series of test was run with the purpose to verify if GA can obtain a solution of 4th order which is better than the specimen of 5th order. When using a 5th order specimen as the starting point, GA searched for a 4th order solution during 40 successive tests.

As results to the same series of tests, *Figure 6* illustrates the wanted signal (with grey line) and filter's output signal (bold line). The output of the 4th order solution of the algorithm is with bold black line, and the output of the 5th order initial Chebyshev filter—with simple black line. We mention here that the output were amplified and shifted in order to be aligned to the input, for a better comparison.

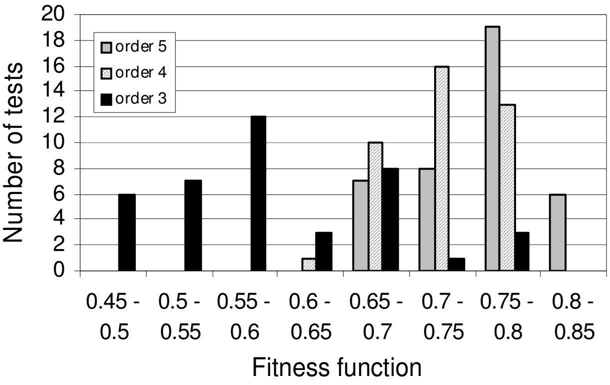

Figure 4. The fitness function for 60 consecutive tests of each order, for $w_R = 0.1$, $w_{\Delta F} = 0.1$ and $w_{PR} = 0.8$.

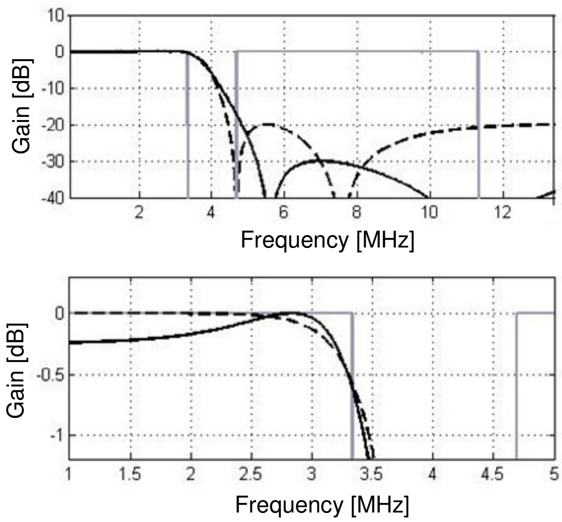

Figure 5. The spectrum of the test signal (grey), the gain of the 5th order specimen (dashed black line), and the gain of the 4th order solution (continuous black line).

In *Figure 5*, one can notice that the 4th order filter does have a ripple in the pass band, but the power-ratio is lower than the specimen's. This fact reflects in *Figure 6* in the curve of the specimen's output, by the presence of oscillations that are higher than the solution's (see the encircled area in *Figure 6*).

The values of the three objective functions and the fitness are shown in *Table 2*. It can be seen that even if the ripple in the pass band is a bit higher for the 4th order filter, its residual power in the adjacent band is highly decreased, and the resulted fitness function is a bit lower than the value obtained when using a 5th order specimen.

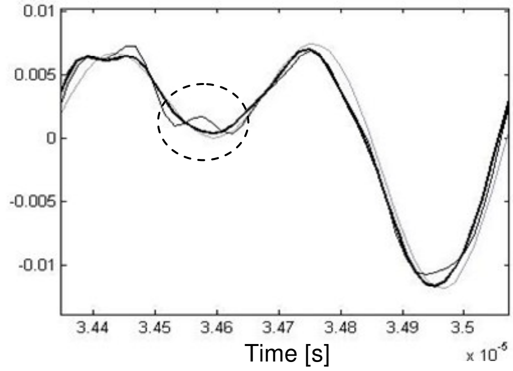

Figure 6. The wanted signal (grey line) and the output signal, when the filter is the 4th order solution (bold line), and the 5th order initial Chebyshev filter respectively (simple line).

Table 2. The objection functions and the fitness function for the 5th order specimen and the 4th order GA filter

Filter	Ripple	Relative error of the cutoff frequency	Power-ratio	Fitness function
5th order (specimen)	0	0.00472	0.006975	1
4th order (solution)	0.2154	0.00472	0.004181	0.8028

D. The 4th set of tests

Another application was the modeling of the filter large-signal behavior by using polynomial transfer functions that describe the filter *nonlinearity* (for 1 dB compression point); this way the inter-modulation products generated by the filter own nonlinearity can be taken into account during the optimization procedure. The nonlinear test signal was also modified so that the power of the adjacent signal was 20dB higher than the power of the wanted signal. *Figure 7* presents the spectrum of the test signal, the gain of the 5th order specimen, and the gain of the 5th order solution given by GA.

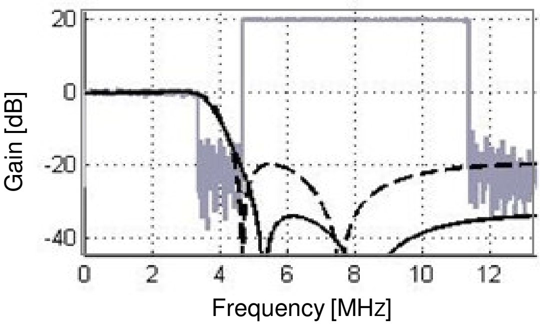

Figure 7. The spectrum of the test signal (grey), the gain of the specimen (dashed black line) and the gain of GA's solution (continuous black line) – when the power of the adjacent signal is 20 dB higher then the power of the wanted signal.

Figure 8 illustrates the filter's output, when the filter is the GA solution (bold line), and the initial Chebyshev filter respectively (grey line). For a better comparison, the two signals were aligned to the wanted signal (simple line).

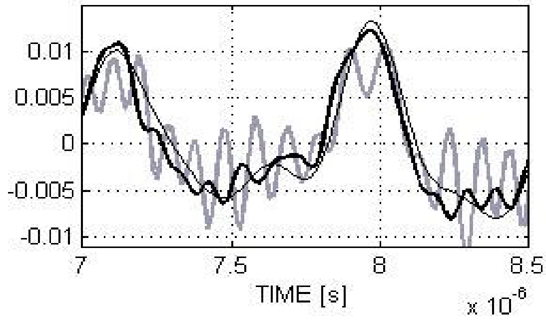

Figure 8. The wanted signal (simple line) and the output signal, when the filter is the GA's solution (bold line) and the initial Chebyshev filter respectively (grey line) – when the power of the adjacent signal is 20 dB higher than the power of the wanted signal.

Figure 9 illustrates the number of tests and the corresponding ranges of the fitness function in the case of the 5th order solutions for linear and nonlinear test signal, when the adjacent ant wanted signals have equal powers.

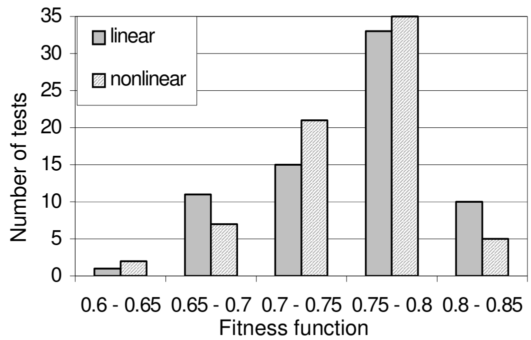

Figure 9. The fitness function for 70 tests for the linear case and the nonlinear case.

The total number of tests was 140 (70 for the linear case, 70 for the nonlinear case). It can be seen that according to this chart the convergence of the algorithm is not influenced by the linearity / nonlinearity of the filter.

V. CONCLUSIONS AND FURTHER WORK

In the context of analog filter optimization by using the genetic algorithms, a particular and practical application has been envisaged in this paper: the optimization of the transfer function of the channel filter for an OFDM DVB-H receiver, starting from type II Chebyshev of 3rd, 4th and 5th order transfer functions. The GA uses only three optimization criteria, which independently control the pass band and the stop band. The feature of employing a "real" OFDM signal generator has been combined with the modeling of the filter large-signal behavior by using polynomial transfer functions that describe the filter nonlinearity; this way the intermodulation products generated by the filter own nonlinearity was taken into account during the optimization procedure.

The solutions provided by the genetic algorithm for the 3^{rd} , 4^{th} and 5^{th} order transfer functions and for different combinations of the weights of the objective functions were analyzed and compared with the classical-approximation counterparts. It was shown that the genetic algorithm can yield a transfer function that fits better the requirements than the solution given by the Matlab function *cheby1* and *cheby2*, even if a higher order is allowed for the classical solution.

Other distinctive feature of this work, in comparison with similar methods proposed in the literature is that the type and order of the transfer function can be changed during the optimization process. Also, the method implies multiple-runs for each set of conditions, so that one can take full advantage of the random permutations the genetic algorithm is based on.

Future work includes the design of active circuits by using the genetic algorithm in component value selection among the commercially available parts, as well as the implementation of other evolutionary algorithm in filter optimization area.

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