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Optimization of a broad-side coupling modal filter by evolutionary strategy algorithm with setting the ranges of the optimization parameters

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Abstract. The paper considers the optimization of a modal filter with broad-side coupling by evolutionary strategy algorithm with limitations (i.e., setting the ranges of the optimization parameters). An improved block diagram of the algorithm with limitations is presented. The sequential optimization that uses the original and improved algorithms with different numbers of computations is performed. The performance of the improved algorithm is demonstrated. The main advantages and disadvantages of this algorithm are shown.

1. Introduction

In modern society, radio-electronic equipment (REE) has become a widespread and integral part of life, and its correct functioning is a key to security and peace. The widespread use of REE has led to the emergence of a new type of threat – electromagnetic terrorism (EMT). The essence of EMT is the destabilization or destruction of REE [1, 2]. Ultrashort pulses (USP) are a special and one of the most dangerous cases of intentional electromagnetic interference that can be used as an EMT tool and affect the REE performance. In general, USPs are pulse signals of large amplitude and short duration, which can penetrate into the REE in various ways, for example, through power circuits [3].

A modal filtration technology has been proposed to protect REE from USPs. The principle of modal filtration consists in decomposing a USP into the sequence of pulses with lower amplitudes, the level of which will not be critical for the protected REE [4]. Devices operating on the principle of modal filtration are called modal filters (MF). When developing MFs, special attention is paid to improving their protective characteristics by ensuring the high values of the mode delay differences and equalizing the amplitudes of the decomposition pulses at the MF output. The first requirement is that it is necessary to increase the duration of the exciting USP that will be fully decomposed into a pulse sequence, and the second is to reduce the amplitudes of the decomposition pulses. The level of electromagnetic coupling between the MF conductors regulated by the parameters of the structure plays an important role in solving these problems.

One of the most important stages in the MF development is optimization. For this, parametric (changing the values of the MF parameters) and/or structural (making changes to the MF structure by changing the number of conductors, dielectric layers, cutouts, etc.) optimizations are applied. Often, structural optimization is performed empirically (using the experience of practical simulation and optimization), while parametric optimization is feasible in various ways: from using heuristic search (manual optimization) to global optimization methods (evolutionary algorithms, deterministic and stochastic methods, etc.).

The general view of optimization problems creates a wide variety of their classes. The choice of the optimization method and, as a consequence, the efficiency of its solution depends on the problem class. The classification of problems is determined by the objective function (OF) and the admissible domain (set by a system of inequalities and equalities or a more complex algorithm) [5]. In accordance with the tasks, optimization methods are classified into global and local. The former deal with multi-extreme OFs. In a global search, the main task is to identify trends in the global OF behavior. The latter converge to some local OF extremum. If the extremum is unique, it will be the global maximum/minimum. A separate class is evolutionary algorithms that work on the principle of natural selection from Darwin's theory. It is often necessary to optimize a number of structure parameters that will affect the final result. Evolutionary algorithms, in particular the genetic algorithm (GA) and evolutionary strategies (ES), perform well in optimization problems with respect to several parameters simultaneously, but the total computation time also increases.

In MF optimization problems, it is the GA that is most frequently used because it can provide multicriteria optimization and rapid value convergence to the global extremum, regardless of the MF configuration. However, its significant drawback is long computation time. Meanwhile, when optimizing the MF using ES, the convergence of the results is also observed, but its results are inferior to the optimization results obtained using GA, which indicates the finding of a local extremum. Nevertheless, the time spent on MF optimization by ES is several times less, compared with the optimization by GA [6]. The user cannot set the necessary limitations (the ranges of the MF optimization parameters) when working with ES. This is one of the reasons for the discrepancy between the two algorithms. The aim of the work is to fill this gap.

2. The main approaches to simulation and optimization

In ES, each individual is characterized by a number of features [7]. The first is a fitness function, which is selected taking into account the specifics of a specific optimization problem. The second is string-chromosome, which includes the vector of some optimization problem solution. The third is the root-mean-square deviation (mutation step), on which the magnitude of the mutation and the rotation angle depend (it is a necessary parameter for the implementation of a correlated mutation, which makes it possible to take into account the OF «landscape»). The adaptation of the values of the mutation step and the rotation angle occurs during the operation of the ES algorithm [8]. The order of the ES algorithm is as follows: initialization; crossover and mutation; calculation of the descendants using the fitness function; selection; checking the ES stopping condition [9]. The main stopping conditions are: the maximum number of iterations (OF calculations), which is defined as 10^3N^2, where N is the size of the search space; the number of generations without changing the best OF value; the small difference between the best and average OF value; the small change in the mutation step, etc.

An MF with broad-side coupling [10] was selected to compare the results of ES optimization without limitations and with them. The MF length (l) was 60 cm. The cross section of the MF is shown in Figure 1, where w is the width of the conductors, s is the separation between the active and reference conductors, t is the thickness of the conductors, h is the thickness of the substrate, d is the distance from the edge of the MF to the active (A) and passive (P) conductors from the left and to the reference (R) on the right side of the MF, and ε_r is the relative permittivity of the substrate. The equivalent circuit of the MF is shown in Figure 2. The following MF parameters are assumed to be unchanged: w=2000 μm and d=w. The parameters to be optimized are h, t, and s. Optimization was carried out according to the criterion of minimizing the maximum value of the output voltage U_{max} (which is possible, as noted earlier, when the amplitudes of the decomposition pulses are equalized). Losses at this stage of the study were not taken into account.

The calculation of the MF time responses was carried out in the TALGAT system [11]. The parameters of the exciting USP were as follows: EMF was 1 V, the duration of the pulse flat top (t_d)

was 50 ps, the durations of the pulse rise (t_r) and fall (t_f) was 50 ps (so that the total duration of the pulse (t_Σ) was 150 ps). The resistances at the MF ends were taken equal to 50 Ohms.

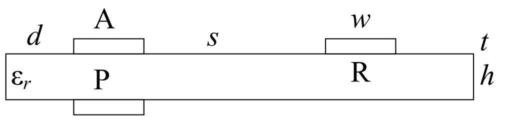

Figure 1. MF cross-section.

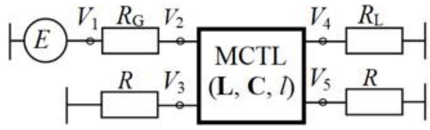

Figure 2. MF equivalent circuit.

When optimizing structures using ES, an open library barecmaes2 with an algorithm in the Python language was used [12]. As input parameters for the algorithm, a list that consists of the initial reference points for each optimized parameter, and the initial step size, which is adapted and changed during the optimization process is used. The initial reference points were chosen h=300 μm, t=30 μm and s=300 μm. As noted earlier, the input parameters do not include range values in which parameters can change during optimization, which, sometimes, leads to a physically unrealizable result. In this paper, a solution to this problem is considered without direct interference with the library but by adding certain conditions when optimizing directly in the executable program file.

The algorithm generates a list of the desired variables beginning with a user-specified starting point and with a step that is changed during the optimization process. Therefore, it is important to eliminate the values that are out of the required range and shift them into the range of the optimized parameters (for example, if the value is negative, shift the search point back). A similar problem can also be solved by excluding values outside the range, but this will lead to errors in the ES operation. In addition, this approach would not solve the problem of shifting to the range of values that went beyond it. Therefore, the problem was solved by replacing the value that was out of the range with a random value in the selected range. It is worth noting that the value that went beyond the range could have been replaced with the starting points that are given above, although this affects all the algorithm performance. Whereas the replacement by a random value in the selected range, in the general case, does not break the algorithm performance. The block diagram of the improved algorithm for ES with limitations (Figure 3) differs from the traditional one by adding elements 1.1 and 1.2, which are responsible for replacing the value that is outside the range with a random value in the selected range.

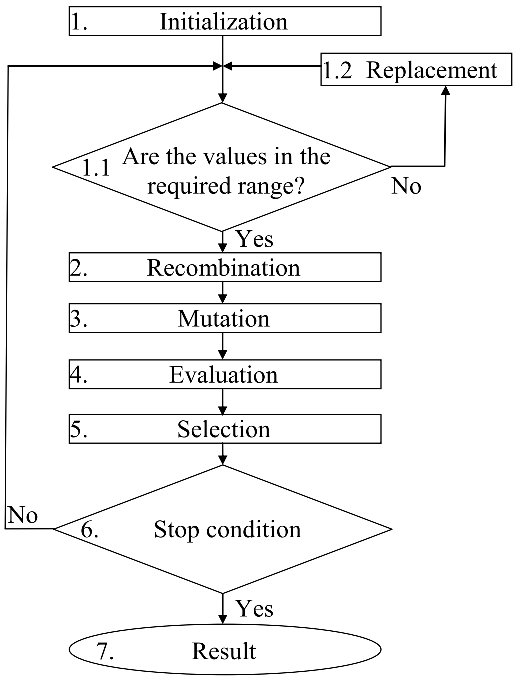

Figure 3. Block diagram of the ES algorithm with limitations.

3. Simulation results

Table 1 shows the optimization results for the MF with broad-side coupling by means of ES without limitations (where N is the number of launches, N_{it} is the number of calculations during one launch of the algorithm, and $N_{\text{it}}^{\max}$ is the number of launches with unspecified number of calculations). The table summarizes the calculation times (time), the $U_{\max}$ values, as well as the values of the optimized parameters. The criteria for stopping the ES (stop) can be different. Criterion I is determined when the maximum calculations are reached. The criterion P means the convergence of the optimized parameters values. Criterion Q means convergence of the OF. Table 2 shows the results of the MF optimization with limitations performed by the method of randomizing the out-of-bounds values in the specified range and with the specified calculation time. The convergence of the parameter t during optimization without limitations is observed at minus 2 µm, which is a non-physical value. Based on this, the starting point of this parameter was changed to 110 µm.

To test the performance of the algorithm, we test it on a narrower range of optimized parameter values. The previous values of the required parameters were in the range of 100–2000 µm for h and s and 18–200 µm for t. We have reduced this range of values to 250–350 µm for h and s and 50–150 µm for t. Table 3 summarizes the results of testing the performance of the algorithm with a narrower search range for values. It is noteworthy that for Table 1, 7-8 launches were performed for each N_{it} value due to the fact that there were 2-3 times, when the values of some optimized parameters went to zero and then to the negative area, which led to non-physical results.

Table 1. Optimization results (where h, t and t parameters are expressed in µm, $U_{\max}$ in mV and time in seconds) for the MF with broad-side coupling according to the algorithm without limitations

N	h	t	s	$U_{\max}$	time	stop	N	h	t	s	$U_{\max}$	time	stop
	N_{it}=500							N_{it}=1000					
1	284.3	126	290.3	144.7	1850	I	1	293	126.1	298.7	144.3	449	Q
2	233.4	123.6	315.2	140.8	1364	Q	2	299.7	125.9	301.5	144.1	720	Q
3	303.8	125.7	296.6	144.7	925	Q	3	289.2	125.6	313.2	142.7	528	Q
4	306.8	125.6	297.4	144.7	807	Q	4	261.3	125.5	301.2	143	713	Q
5	284.9	126.3	341.7	140.3	1166	Q	5	285	126.1	305.7	143.4	559	Q
N	h	t	s	$U_{\max}$	time	stop	N	h	t	s	$U_{\max}$	time	stop
	N_{it}=2500							N_{it}=5000					
1	287	126.2	294.6	144.4	477	Q	1	296.5	126.1	301.1	144.1	1977	Q
2	294.1	126.2	308.3	143.4	978	Q	2	293.8	123	300	143.8	490	Q
3	296	123.5	299.3	144	314	Q	3	300.2	117.9	304.7	142.9	159	Q
4	302.8	125.6	314.3	143.1	231	Q	4	300.6	125.9	293.4	144.9	765	Q
5	278	126	319	142	1112	Q	5	295.7	126.2	303.9	143.9	766	Q

N	h	t	s	$U_{\max}$	time	stop
	$N_{it}^{\max}$					
1	299.6	125.7	284.5	145.7	586	Q
2	297.6	126.2	295.2	144.7	630	Q
3	295.1	125.9	313.7	143	367	Q
4	302.9	126.3	306.9	143.9	808	Q
5	201.3	123.6	323.7	139.5	2532	Q

Table 2. Optimization results (where h, t and t parameters are expressed in µm, $U_{\max}$ in mV and time in seconds) for the MF with broad-side coupling according to the algorithm with limitations

N	h	t	s	$U_{\max}$	time	stop	N	h	t	s	$U_{\max}$	time	stop
	N_{it}=500							N_{it}=1000					
1	132.5	122.8	1820.2	94.5	1863	I	1	111.5	122.5	1791.1	94.6	1719	Q

2	110.4	127.6	1645.6	96.7	1852	I	2	140.1	123	1785.6	95	1257	Q
3	125.3	126.4	1559.5	98.2	1894	I	3	134.1	127.5	1652.7	96.9	2913	Q
4	109.3	128.1	1847.5	94	1859	I	4	311.3	125.4	294	145.2	3850	I
5	131.9	122.5	1169.2	105.2	1881	I	5	110	126.2	512.9	126.6	3003	Q
N	*h*	*t*	*s*	U_{max}	time	stop	*N*	*h*	*t*	*s*	U_{max}	time	stop
	N_{it}=2500							N_{it}=5000					
1	174.2	126.4	572.9	124.4	4524	Q	1	105.9	127.2	1931	92.9	2875	Q
2	287.2	126.4	341.8	140.4	4170	Q	2	116.4	126.3	929.5	111.1	3356	Q
3	317.5	125.6	276	147.2	2562	Q	3	144.1	122.8	1731.5	95.7	6770	Q
4	103.9	127.7	1880.4	93.5	2406	Q	4	130.7	126.3	1616.8	97.4	3628	Q
5	307.8	123.5	323.5	142.2	1785	Q	5	161	127.4	1477	100	3691	Q

N	*h*	*t*	*s*	U_{max}	time	stop
	N_{it}^{max}					
1	101.8	125.3	451.5	130	2343	Q
2	104.1	125.9	928	111	2815	Q
3	303.6	124.4	282.7	145.9	1348	Q
4	119.6	127.4	1989	92.4	3360	Q
5	277.7	126.1	292.4	144.3	6146	Q

Table 3. Optimization results (where *h*, *t* and *t* parameters are expressed in μm, U_{max} in mV and time in seconds) for the MF with broad-side coupling according to the algorithm in the reduced ranges of variation of the optimized parameters at N_{it}^{max}

N	*h*	*t*	*s*	U_{max}	time
1	285	120.7	320.3	141.5	368
2	257.6	121.5	272	145	722
3	281.4	123.3	301	143.3	1336
4	307.7	123.4	319.3	142.6	206
5	256.5	123.3	297.4	142.9	627

In the reduced range of optimized parameter values, the obtained values do not go beyond the specified range, as can be seen in Table 3. Figure 4 shows the voltage waveforms at the MF output for the best optimization result according to the criterion of minimizing the U_{max} value for a different number of calculations.

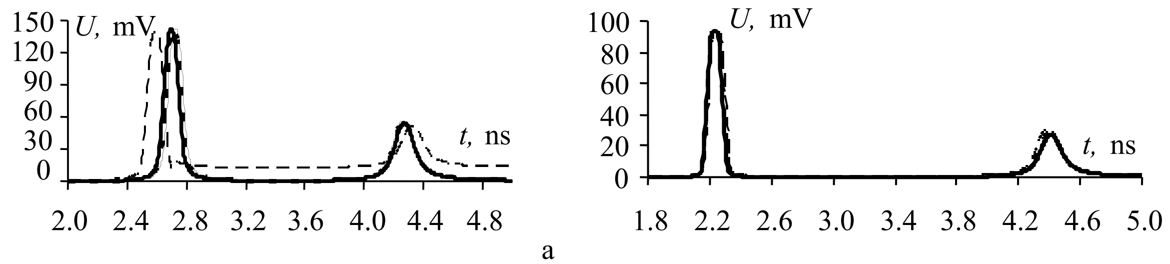

Figure 4. Voltage waveforms at the output with the number of calculations: 500 (—), 1000 (· ·), 2500 (—), 5000 (· ·), no iterations (– –) for optimizations without (a) and with limitations (b).

The convergence of the optimized parameter values during optimization without limitations is observed regardless of the number of calculations (Table 1 and Figure 4a). Despite this, the voltage waveforms at the MF output are represented by two pulses of different amplitudes (0.043 V and 0.139 V). Obviously, the energy of the exciting pulse must be evenly distributed between the decomposition pulses in order to achieve the criterion for minimizing the U_{max} value. This ensures equality of the pulse amplitudes, which does not happen in this case. Meanwhile, the convergence of the optimized parameter values during optimization with limitations is not observed (Table 2 and Figure 4b). However, the voltage waveforms at the MF output show that U_{max} is equal to 0.092 V. In addition, the values obtained during optimization with limitations lie in the required range.

4. Discussion

The calculation time increases after the introduction of limitations. This can be explained by the fact that equating the optimized value to a random number in the specified range slows down the algorithm process. In addition, this equalization introduces additional random variables into the algorithm so the algorithm resumes every time it goes out of the required range. It is worth noting that to find a solution, the algorithm with limitations requires about 1500 calculations and, on average, 3600 seconds (in the algorithm without limitations the time is, on average, 800 seconds). Meanwhile, the convergence to a certain range of values was observed during the optimization without limitations, but with limitations this range became more inaccurate. This is due to the replacement of a value that is out of the required range with a random one. Particularly, since the range of optimized values was quite wide.

As a result of this approach, the U_{max} value is equal to 0.092 V (which is 1.5 times less than the value of 0.139 V obtained during optimization without limitations), with the decomposition pulse amplitudes being close. However, the convergence of the results deteriorates and the calculation time increases. The advantages of ES with limitations include the possibility of optimizing protective devices in the required parameter range and the satisfactory final results that were obtained, among other things, thanks to the introduction of randomness implemented in ES with limitations. The disadvantages include the increased computation time and the lack of results convergence.

5. Conclusion

The ES algorithm has been improved to provide optimization with the specified limitations. The limitations meant the setting of the ranges of the optimized parameter values. It was possible to achieve such optimization approach without interfering with the original library. The sequential optimization using the original and improved algorithms with different numbers of computations was performed. The efficiency of the improved algorithm was demonstrated. Our further efforts will be directed at finding the ways to improve the results of ES optimization with limitations.

Acknowledgments

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