Using Genetic Algorithms for Optimization of Magnetic Pulse Forming Installations Based on PSPICE Model

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Abstract *– Genetic algorithms are general-purpose search techniques based on the mechanisms of natural selection and population genetics. They are appealing because of their simplicity, extensibility, easy interfacing possibility and since they need only very little knowledge about the problem. This paper attempts to show how genetic algorithm can be used together with PSPICE simulation program to dynamically implement some optimization problems that can use fitness function derived from a simulation process. Particularly, this optimization technique is applied in the design of a magnetic pulse forming installation.*

Keywords: *magnetic pulse forming, optimal design, genetic algorithms,PSPICE model*

I. INTRODUCTION

Certain classes of engineering design problems are known to respond well to evolutionary techniques, where traditional numerical optimization techniques, such as dynamic programming, become computationally expensive. Although dynamic programming is a popular method for optimization, it is known to break down even in moderately sized problems.

Genetic algorithms (GAs) use only little domain knowledge, make few assumptions about the search space, and use domain independent operators for generating candidate points in the state space.

GAs are powerful search techniques inspired from biological evolution. They were invented by John Holland in the 1970s and are applied to an ever-increasing domain of problems ranging from engineering design, finance, decision support, network design and many combinatorial problems [4].

Their advantage resides in the fact that they use little domain knowledge, make few assumptions about the search space, and use domain independent operators for generating candidate points in a state space.

Genetic algorithms are applied to a variety of problems and becoming an important tool in engineering design.

This paper attempts to show how GAs can be combined with PSPICE program in order to perform optimal design of magnetic pulse forming installation. Your goal is to simulate as closely as possible this sample, which is the usual appearance of typeset papers in the *IEEE Transactions.*

II. THE PSPICE MODEL OF MAGNETIC PULSE FORMING INSTALATIONS

Electromagnetic forming is an unconventional technology of metal working by plastic deformation at room temperature. The principle consists in the deformation of thin metallic pieces by intense impulsive forces acting on the conductor placed in a rapidly varying magnetic field.

The analysis of magnetic pulse forming installations can be performed using model of circuit. The model of circuit takes into account the induction effects with in conductors, the induction effects of work piece motion, and the dynamic behavior of workpiece material.

The PSPICE model of equivalent electrical circuit with concentrated parameters for electromagnetic forming devices obtained in [6] is presented in Fig. 1.

We use voltage and current controlled sources for taking into account the coupling between mechanical and electromagnetic phenomena. The influence of the workpiece deformation is simulated by the voltage sources E1 and E2. The current i_4 represents the electromagnetic pressure on the workpiece walls:

$$i_4 = p_{em} = \frac{\mu_0 \cdot N^2}{2 \cdot h^2} \cdot i_2 \cdot (2 \cdot i_1 - i_2)\,, \qquad (1)$$

and it is simulated by a nonlinear controlled voltage source E3 in series with an equivalent resistor. The motion equations of the workpiece include mechanical equations, which are simulated by the equivalent circuit comprising the sources G1, G2, G3 and I1.

The v_{18} potential represents the radial velocity v of the walls, and the i_6 current represents the radial deformation x. The switch S1 is opened when the stress exceeds the yield point and the total pressure is positive (the elastic properties of the workpiece are negligible).

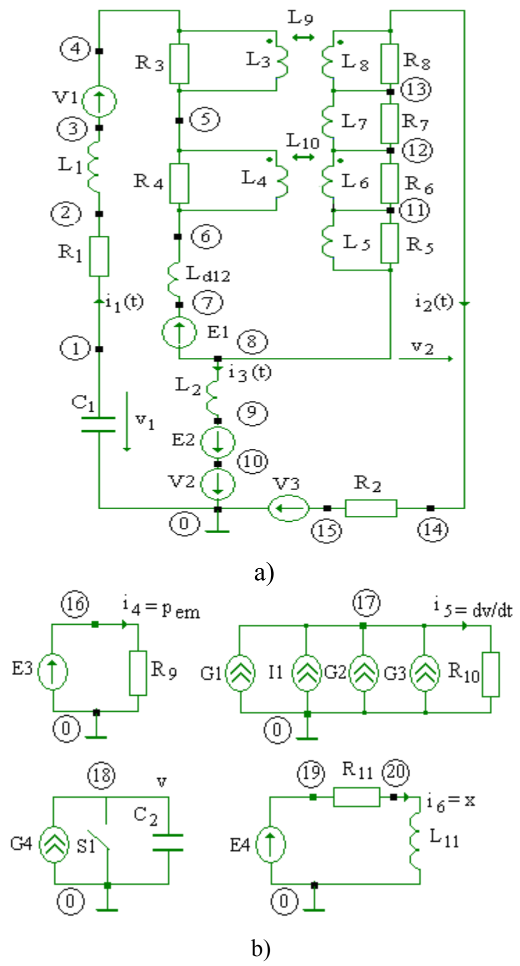

Fig. 1. Implementation of equivalent circuit in PSPICE:
a) Equivalent circuit of electromagnetic phenomenon;
b) Calculus of electromagnetic pressure p_{em}, acceleration a, strain rate v and deformation x.

III. GENETIC ALGORITHMS

GAs are randomized parallel search method that manipulate a population of candidate solutions to an optimization problem, which evolves at each iteration of the algorithm called generation. GAs use probabilistic rules to evolve a population from one generation to another. Each candidate solution for a given problem is encoded as a chromosome also called a genotype or individually, using an alphabet as binary strings, real numbers, vectors. Each chromosome has associated a measure of its quality through a fitness function, which is a scalar value. Evolution is simulated by this function and some genetic operators. The fittest individuals will survive generation after generation while also reproducing and generating off-springs that could be "stronger" then themselves. Meanwhile, the weakest chromosomes disappear from each generation.

In practical genetic algorithms, a population pool of chromosomes must be installed and they can be randomly set initially. In each cycle of genetic evolution, a generation is created from the chromosomes in the current population. Evolutionary cycle is repeated until reaching the termination criterion. This criterion can be set either by the number of cycles of evolution, or a predefined fitness value [1]. A full run of GAs can be divided into a number of successive stages:

Step 1. Create a random population of chromosomes;
Step 2. Evaluate each chromosome assigning a fitness value according to an objective function;
Step 3. Use the selection operator, to form the mating pool;
Step 4. Apply crossover and mutation by randomly choosing a set of parents;
Step 5. Repeat steps 2, 3 and 4 until a termination criterion is met or a fixed number of generations have been completed.

The solution to this problem is the chromosome having the best fitness in all generations. The most used genetic operators are selection, crossover and mutation. Selection determines which chromosomes are copied or selected for the mating pool and how many times they will be selected for mating pool. Higher performers will be copied more often than lower performers. Selection depends on the chromosome's fitness relative to that of other chromosomes in the population. It probabilistically freezes out from the population those points that have relatively low fitness.

Crossover and mutation imitate sexual reproduction. Crossover mates each chromosome at random, using some crossover techniques so it combines genetic information between two parents to produce children. It is a randomized and structured operator that allows information exchange between points in the search space. Crossover is applied with high probability.

Mutation, as in natural systems, is a very low probability operator and it assures that the state space will be fully explored and prevents leading to a local optimal. In GA's literature several implementations for each of these operators can be found [3], [4].

The most important parameters of GA are: population size, the evaluation function, the type of genetic operators, crossover rate and mutation rate.

When used in design, a GAs encodes a candidate design in a binary string, a real number, or another complex data structure. The representation or coding of the variables being optimized has a large impact on search performance, as the optimization is performed on this representation of the variables. The two most common representations, binary and real number coding differ mainly in how the recombination and mutation operators are performed. The more commonly used optimization problems involve real number variables.

A randomly generated set of such candidate forms the initial population from which the genetic algorithm starts it searches. Evaluation of each individual is based on a fitness function that is problem dependent. It determines which of two candidate solutions is better. This corresponds to the environmental determination of survivability in natural selection.

In parameter instantiation tasks, the problem is to find the values of parameters such that a particular design can be instantiated.

IV. USING GAS TO CONTROL SIMULATIONS PERFORMED BY PSPICE PROGRAM

PSPICE is a program widely used to solve various problems in electrical engineering. By combining this program with genetic algorithms, it can operate in the so-called sequential manner in which sequential simulation tasks are run, with the ability to influence the operation, according to the previous simulation results. By performing successive runs of different types of analysis and by modifying the model parameters, simulations can lead to achieve an optimal behavior of the model in terms stated of the user. In this manner, by combining the PSPICE program with GAs optimization tasks can be performed. The control algorithm is defined by the circuit file that is written in accordance with some syntactical rules, that is a source text to generate PSPICE circuits. Commands to define the variables for Pspice analysis should be executed to control PSPICE operation. The results of simulation are received in the out file, and are than processed mathematically.

The conventional method of working with PSPICE is illustrated in Fig. 2.

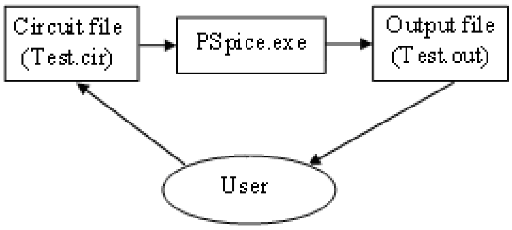

Fig. 2. The conventional method of working with PSPICE

The user can create a model to simulate circuit either directly by writing a PSPICE circuit file or indirectly by trapping scheme. In letter case, the circuit file is established automatically after running one analysis.

The results of tests are available through different data files or through a graphical postprocessor Probe. In such an application, the user analyzes the results and, based on this analysis, manually changes the input data for further consideration

By combining with GAs in a design shown in Fig. 3, the role of the user is replaced by the genetic run.

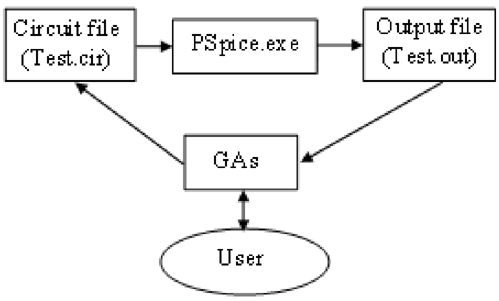

Fig.3. The GAs coupled with the PSPICE method

The user indirectly controls the simulation process by evaluating the results obtained from the out file through some objective functions and by performing a genetic search. The chromosomes that encode the genetic population are exported in the next circuit fileand a new analysis is performed. Thus, GAs control automatically subsequent analysis runs. The operation of the GAs coupled with the PSPICE program is presented in Fig.4 [5]. The design variables are encoded as real numbers and an individual (or chromosome) is represented by a vector of such parameters, as depicted in Fig. 5.

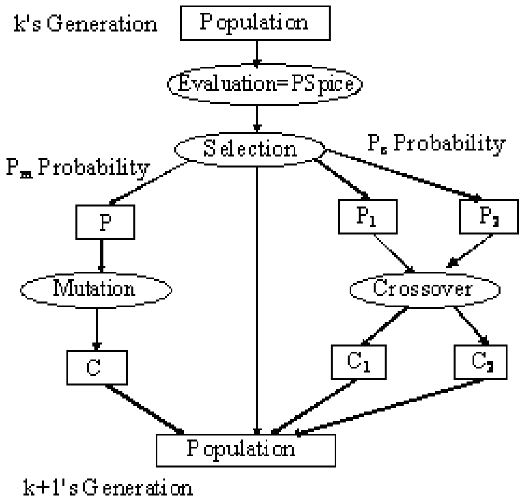

Fig. 4. The mixture of the PSPICE program and the genetic algorithm

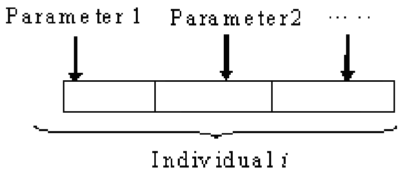

Fig.5. Individual encoding scheme

In the design problem concerned in this paper, only two design parameters were used, namely the U_0 voltage and the C_0 condenser.

These parameters are used in the genetic search and each generation their new values are written in the test.cir file, which is input to PSPICE program.

As objective function, in series the deformation of the tube, later the deformation, together with the efficiency was used. These values are computed based on the results obtained in test.out file.

It has to be noted that in such a case, the optimization problem becomes a multiobjective one, which can be solved by combining the component objective functions using by example the weighted sum approach.

The multiobjective problem can be solved using also other approaches, like Pareto-based approaches, by simply outputting each objective component to the genetic algorithm. Then is the genetic algorithm task to apply a Pareto based ranking to find the Pareto set. [2]

This paper refers only to use weighting coefficients approach.

V. STUDY CASES

All study cases used real value encoded chromosomes, simple GAs, tournament selection with tour factor T=3, Arithmetic crossover with probability 0.80 and Uniform mutation with probability 0.05.

A. Study case 1

The design parameter V_1 in the domain 1000÷7000V was considered, while de capacitor C_1 has the constant value 200µF.

GAs used a population of 50 individuals and were applied for 50 generations. The Fitness function used is given by relation (2):

$$\text{Fitness} = \frac{1}{1+(X_{goal} - X_{max})^2} \quad (2)$$

where X_{goal} is a constant imposed, and X_{max} is the maximum value of the deformation that is found in the PSPICE output file. The obtained results are shown in Table 1

TABLE 1. The solutions for study case 1

Defor-mation	The best solution	Other solutions in roud of the optimal solution finding with AG		
[mm]	V_1 [V]	V_1 [V]		
1	3284.70	3434.20	3175.60	3331.60
2	3999.90	4145.80	4088.10	4054.30
3	4532.10	4580.10	4520.10	4532.10
4	5752.80	5990.80	5624.30	5714.50

B. Study case 2

The following design parameters were considered:

V_1 in the domain 1000÷7000V and C_1 in the domain 100÷400µF.

GAs used a population of 30 individuals and were applied for 25 generations. The Fitness function used was also given by relation (2). An advantage of applying GAs consists in the possibility of finding more solutions from which the designer can later choose the most suitable values related to additional goals. In this case, two close solutions were obtained. They are shown in Table 2.

TABLE. 2. The solutions for study case 2

Defor-mation	The best solution		Other solutions finding with AG	
[mm]	V_1 [V]	C [uF]	V_1 [V]	C [uF]
1	3150.60	291.00	3117.20	304.70
2	3965.40	273.90	3668.20	301.60
3	6284.90	137.40	4142.50	316.40
4	5890.10	189.80	5879.00	190.80

C. Study case 3

The Fitness function used was given by relation (3):

$$\text{Fitness} = \alpha \cdot O_1 + (1-\alpha) \cdot O_2 \quad (3)$$

$$O_1 = \frac{1}{1+(X_{goal} - X_{max})^2} \cdot 1000 \quad (4)$$

$$O_2 = \eta = \frac{W_m}{W_t} \cdot 100 \ [\%] \quad (5)$$

Objective O_2 is referred as Rand in the Table 3, 4 and 5.

The total energy is given by relation (6):

$$W_t = \frac{C_1 \cdot U_0^2}{2} \quad (6)$$

and the mechanical energy is established by using relation (7)

$$W_m = 2\pi \cdot r_{20ext} \cdot h_1 \cdot \int I(E_3) \cdot V(18) \cdot dt \quad (7)$$

I(E3) and V(18) are obtained from the out file produced by PSPICE program.

Since multiple objectives are converted into one objective, the resulting solution to the single objective optimization problem is usually subjective to the parameter settings chosen by the user. Moreover, only one solution can be found in one run.

Accordingly, multiple values in [0.1, … 0.9] interval were considered for α and multiple runs of GAs were performed, with a population of 50 individuals. The GAs evolved for 50 generations. The obtained results for X_{goal} = 3 mm are presented in Table 3 and Fig. 6.

TABLE 3. The solutions for study case 3 (X_{goal} = 3 mm)

	Defor-mation	Capacitor value	Voltage value	Efficiency
No.	x	C_1	U_0	η
	[mm]	[µF]	[V]	[%]
1.	3	124.66	6607.72	6.386
2.	3	145.71	6117.06	6.400
3.	3	161.09	5795.39	6.261
4.	3	163.34	5754.88	6.165
5.	3	169.10	5669.71	6.250
6.	3	188.79	5382.50	6.218
7.	3	189.14	5376.80	6.217
8.	3	232.57	4850.21	6.005
9.	3	278.29	4454.78	5.912
10.	3	380.10	3833.40	5.498

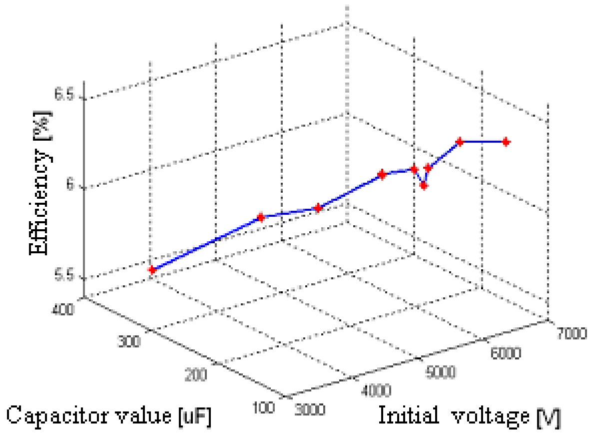

Fig. 6. Reprezentation of efficiency for X_{goal} = 3 mm

The obtained results for X_{goal} = 4 mm are presented in Table 4 and Fig. 7.

TABLE 4. The solutions for study case 3 (X_{goal} = 4 mm)

	Defor-mation	Capacitor value	Voltage value	Efficiency
No.	x	C_1	U_0	η
	[mm]	[µF]	[V]	[%]
1.	4	104.14	6453.59	13.15
2.	4	108.77	6314.35	12.95
3.	4	160.29	5152.11	12.46
4.	4	197.06	4649.30	12.19
5.	4	218.75	4417.21	12.17
6.	4	243.68	4181.76	11.93
7.	4	273.21	3951.99	11.54
8.	4	303.82	3762.84	11.46
9.	4	327.61	3627.09	11,18
10.	4	350.04	3509.25	11.21

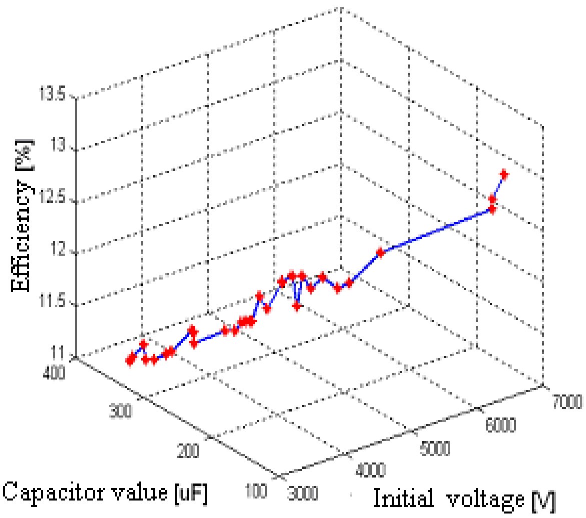

Fig. 7. Reprezentation of efficiency for X_{goal} = 4 mm

The obtained results for X_{goal} = 5 mm are presented in Table 5 and Fig. 8.

TABLE 5. The solutions for study case 3 (X_{goal} = 5 mm)

	Defor-mation	Capacitor value	Voltage value	Efficiency
No.	x	C_1	U_0	η
	[mm]	[µF]	[V]	[%]
1.	5	197.51	6247.90	9.64
2.	5	200.08	6210.02	9.72
3.	5	212.62	6023.77	9.56
4.	5	263.69	5432.41	9.28
5.	5	271.66	5352.02	9.23
6.	5	298.67	5107.45	9.15
7.	5	361.16	4670.19	8.88
8.	5	384.74	4531.72	8.72
9.	5	391.67	4495.70	8.76
10.	5	396.57	4472.72	8.82

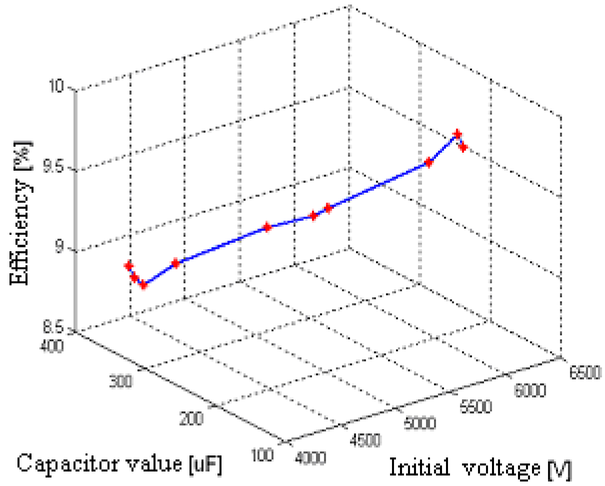

Fig. 8. Reprezentation of efficiency for X_{goal} = 5 mm

VI. CONCLUSIONS

We tried to show how genetic algorithms can be coupled with Orcad PSpice simulation environment to an engineering design optimization problem, which can use a fitness function derived from a simulation process.

This method is easy to implement and simplifies the design process of nonlinear complex systems. We note that the genetic algorithm used was implemented in Matlab, but also can be used other genetic algorithms implemented in different programming languages.

This work will be continued by applying a multiobjective genetic algorithm and also by performing the simulation in Ansys Multiphisics environment.

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