Optimal Design of a SMC Cylindrical Transformer by Stochastic Methods

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Abstract: - This paper deals with optimal design of a SMC Cylindrical transformer by stochastic methods were using simulated annealing and genetic algorithm. This methods are used for design of a new structure of transformer (pot-core) using a Soft Magnetic Composite (SMC) material.

Key-Words: - SMC; Simulated Annealing; Genetic algorithm Design, Optimization, Transformer.

1 Introduction

The application of stochastic optimization procedures for design problems in electrical engineering has become very well-liked in the last few years, because they are fairly simple to implement, stable in convergence, and able to find the desired region with quite a good probability.

In this paper, the study of convergence to the optimal solution using two stochastic methods (simulated annealing and genetic algorithm) are considered when optimizing the design of a new structure of transformer (pot-core) using a Soft Magnetic Composite (SMC) materials**.**

2 Design Problem Definition

Generally, the design of any device is guided by a schedule of conditions. In our work, the device to be conceived is a transformer using SMC fed by 120V/60Hz. It must output, under a resistive load, 100VA and a voltage of 12.5V. The temperatures T_1 and T_2 of the primary and secondary coils should not exceed 120°C and the temperature of the magnetic circuit T_c must be lower than 60°C. The efficiency of the transformer must be at least equal to 0.7.

3 Optimization Problem Formulation

To formulate the optimization problems, it is necessary to define the objective function to be optimized. In this case, we have considered the weight of the transformer. The remainder of the criteria of the schedule conditions will be used like constraints of equalities and inequalities.

The resolution of the design problem will be equivalent to the resolution of the optimization problem defined as follows: To determine the unknown vector X: X=(x1, x2... x9) (fig. 1) which minimizes the objective function weight (X): Min weight (X) Subjugated with:

Constraints of inequalities

$T_1(X) \leq 120$

$T_2(X) \leq 120$

$T_c(X) \leq 60$

Efficiency(X)>0.7

Constraints of equalities:

$U_2(X)=12.5 \pm 5\%$

$S_2(X)=100 \pm 5\%$

Thrusts fixing the acceptable field:

$X_{max} \leq X \leq X_{min}$

$X=(x_1, x_2. x_7, N_1, a=N_1/N_2)$, N_1 and N_2 are respectively the numbers of turns of primary and secondary coils and a the transformer ratio.

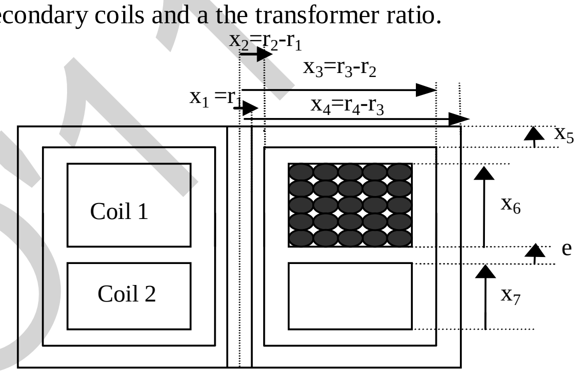

Fig. 1 Geometry of the Transformer Vector unknown X

4 Procedures of Optimization

The adopted procedure is schematized on fig. 2. It uses, the magnetic and thermal models, defining the device operation to be conceived [2]. A nonlinear optimization method with constraints is used to reach the optimal solution (minimizing the weight and satisfying the constraints of the schedule conditions).

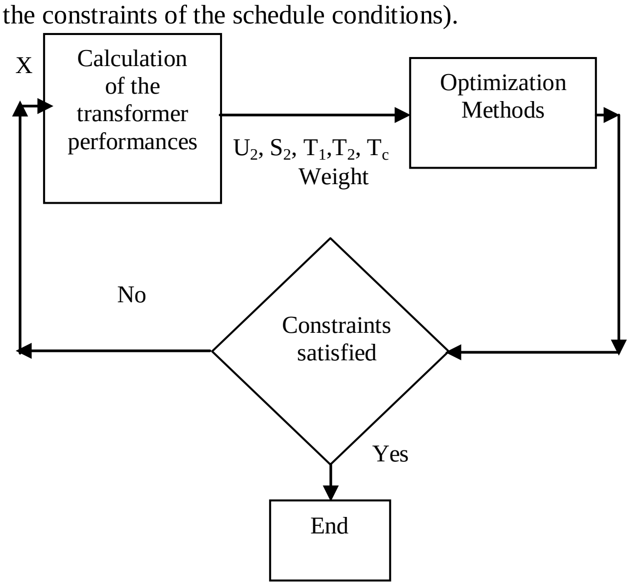

Fig.2 Optimization Procedure for Design Problem

5 Simulated Annealing Method

The method of simulated annealing was proposed in 1983 by Kirkpatrick, Gelatt and Vecchi; it finds its origins in thermodynamics [3]. This method is based on slow cooling of a material at state fusion, which leads, it to a solid state with low energy.

The same basic principle can be used in an optimization algorithm. The objective function to be minimised, can be considered as the system energy while the different combinations of the optimization of freedom degrees are its configurations. The probability that a particular configuration, even a worst one, is accepted, and ruled by a Boltzmann-like equation.

5.1 Description of the Algorithm

Simulated annealing is a well established stochastic technique originally developed to model the natural process of crystallization and later adopted to solve optimization problems [3].
One of the most characteristic features of SA algorithm is criterion of the acceptance which is usually the metropolis criterion and which states that a configuration has a probabilistic chance to be accepted even if it is worse than the previous one. This selection is usually done according to a configuration given by [3]:

$$P = e^{(-\Delta E)/T} \tag{1}$$

Simulated annealing, in fact, chooses his path through the parameter space using some random factors. An important feature of them is that they accept deterioration in the objective function during the iteration process. This fact enables them to find the region of the global optimum with a high probability. Fig. 3 illustrates the research process of the global optimum of a function by simulated annealing method.

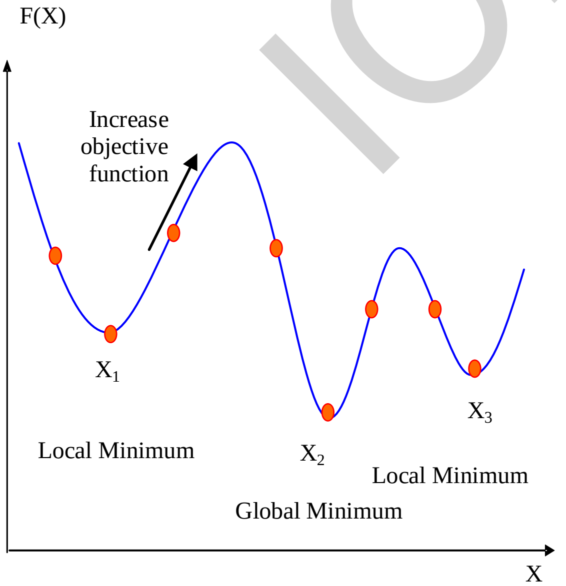

Fig.3 Illustration of the process of Research of the global Optimum of a Function by Simulated Annealing Method

Where:

W(X): Objective function

W_0 : Initial value of objective function

W_{opt} : Optimal Value of objective function

T: Control parameter (temperature)

5.2Initial Temperature Determination

For the determination of the initial temperature, several methods are proposed in the literature.

The method used in this paper consists to generate a certain number of random configurations X, for which is evaluates the objective function and calculate their average value $.M$. This average value shares the distribution in to two parts of witch the probability is equals to a 0.5. Finally, one deduces the initial temperature starting from the criterion of Métropolis given by [3]:

$$P = e^{-M/T_0} = 0.5$$

$$\log p = -\frac{M}{T_0}$$

$$T_0 = \frac{M}{\log p}$$

So

$$T_0 \approx 1.44.M \tag{2}$$

For the parameter decrease of the temperature, one can take a geometrical decrease as the following form:

$$T_{k+1} = \lambda . T_k \tag{3}$$

Where:

T_{k+1} : The current temperature,

T_k : The previous temperature,

λ : Reduction factor ($0 < \lambda < 1$).

For the change of stage of temperature, one can simply specify a number of transformations, accepted or not, with the end of which the temperature is lowered.

Fig.4 presented below, shows the flowchart of simulated annealing method.

6. Genetic Algorithm Method

The genetic algorithms rest on the analogy between the natural evolution of Darwin and optimization. According to the theory of Darwin, the individuals of a population best adapted to their environment have a great probability of surviving and to reproduce, by giving descendants adapted still better. As in the natural mechanism of the reproduction the main operators who affect the constitution of a chromozome, which codes the characteristics of the individuals are the crossing and the change.
The characteristics of AG are
1 - They use a coding of the parameters and not the parameters themselves
2 - They work on a population of points instead of a single point

3 - They use only the value of the studied function and not its derivative or knowledge auxiliary

4 - They use probabilistic and nondeterministic rules of transition

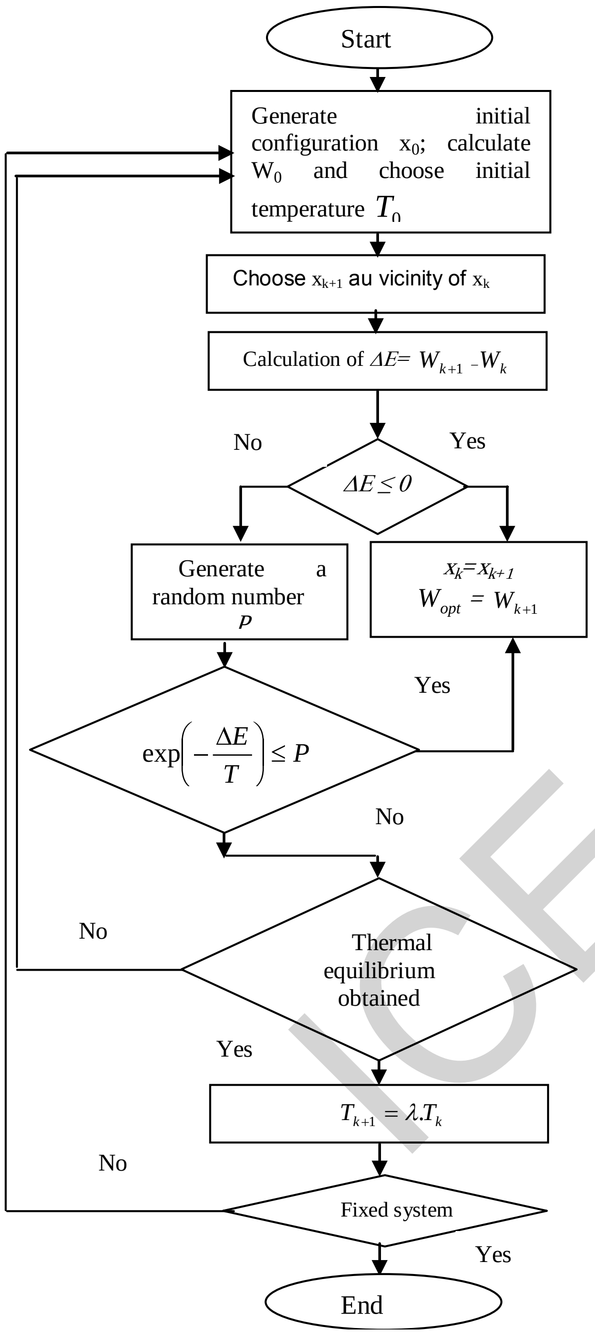

Fig.4 Flowchart of simulated annealing

7 Accounting of the Constraint in Stochastic Method

As all stochastic strategies are rather simple to implement, stable in convergence, and able to find desired region with quite good probability. it usually suffers from a high number of function evaluations.

The accounting of the constraints in a method of optimization stochastic is often obtained by using a function of penalty associated with the objective function. Classically, one uses a function of external penalty [5], according to which the function to be minimized becomes equal to:

$$W(X) = f(X) + r\sum_{i=1}^{m}\left[\max\left[0, g_i(X)\right]\right]^2 \qquad (5)$$

Where:

$f(x)$: Objective function without constraints;

$g_i(X)$: Constraints function;

r: Penalty coefficient .

Contrary to the deterministic methods of optimization, the value of (r) remains constant during the process of optimization stochastic [5]. The previous work suggests that r=0.1 may be suitable.

8. Results

In this section, Tables 2 and 3 show the results of transformer Performances and Solution Vector obtained by genetic algorithm (AG) method and Simulated annealing (RS).

Table 2
Transformer Performances

	RS	AG
U2 (V)	12.74	12.76
S2 (VA)	103.98	105.66
T1 (°c)	86.93	65.82
T2 (°c)	86.12	66.12
Tc (°c)	63.72	56.54
η	79.12	85.12
W(X) (Kg)	1.78	1.76
Time (s)	356.42	217.84

Table 3
Solution Vector

	RS	AG
x_1	0.0036	0.0034
x_2	0.0154	0.0196
x_3	0.0166	0.0186
X_4	0.0077	0.0042
X_5	0.0071	0.0040
X_6	0.0176	0.0304
X_7	0.0152	0.0097
X_8	556.91	358.48
X_9	7.81	8.42

9. Analysis of the Results

When comparing the two used methods, for optimal design of a SMC Cylindrical transformer by stochastic methods were using simulated annealing and genetic algorithm. Genetic algorithm has shown a good convergence to the optimal point and a good reproducibility of the results.

10. Conclusion

The optimization stochastic methods are based on probabilistic and random mechanisms of search.

The two most promising stochastic methods: genetic algorithm and simulated annealing, have been programmed, and tested. These methods have a great capability to find the global optimum of a problem. Contrary to the most deterministic methods, they require neither a starting point, nor the knowledge of the objective function derivatives to reach the optimal solution.

In this paper, we have presented an optimal design of a SMC cylindrical transformer by stochastic methods. Were using simulated annealing ,and genetic algorithm. The comparison between the tow méthods show that, the GA gnerates better solution than the simulated anneling .

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