Application of Two Direct Optimization Methods on a SMES Device by DOE and FEM: Method by Zooms and Method by Slidings of Plans

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Abstract— **The Design of Experiments (DOE) applied to electrical systems modeled by the finite element method (FEM) has become a useful strategy to solve many optimization problems. In this paper, two direct optimization methods by DOE and 2-D FEM were applied on a Superconducting Magnetic Energy Storage (SMES) device with modular toroid coil, in order to optimize its storage capacity: the method by zooms without computation of models and the method by slidings of plans without computation of models. Two parameters that characterize the geometric torus shape were chosen to minimize the volume of the superconducting material with a maximum stored magnetic energy: the coil inner diameter ratio and the coil thickness ratio. The 2-D FEM implementation uses an equivalent rectangular cross section toroid, conserving the inductance of the system. The optimization results by the two methods are obtained with less than 2% error of objective function value and they are comparable between them and better than previous approximate values determined by simple numerical tests.**

I. Introduction

The Design of Experiments (DOE) is an old methodology of analysis of behavior of a system subject to various external influences [1]. Applied to electrical systems modeled by the finite element method (FEM), it has become a useful strategy to solve many optimization problems [2] - [4].

The Superconducting Magnetic Energy Storage (SMES) system is a modern and expensive technique for direct storage of electricity through the magnetic energy in superconducting short-circuited coil. The design and the optimization of the SMES devices is a topic of permanent interest [5] - [15]. An optimized configuration must reduce as much as possible the volume of the superconducting material and thus, the cost of device, respecting the critical limit of magnetic field of the superconducting material.

In this paper, two direct optimization methods by DOE and 2-D FEM were applied on a 21 kJ SMES device in order to optimize its storage capacity: the method by zooms without computation of models and the method by slidings of plans without computation of models.

Previous 2-D and 3-D numerical models of the coil of the SMES device were created using FEM in FEMM [13] and ANSYS software [16]. For the shape of the coil, a

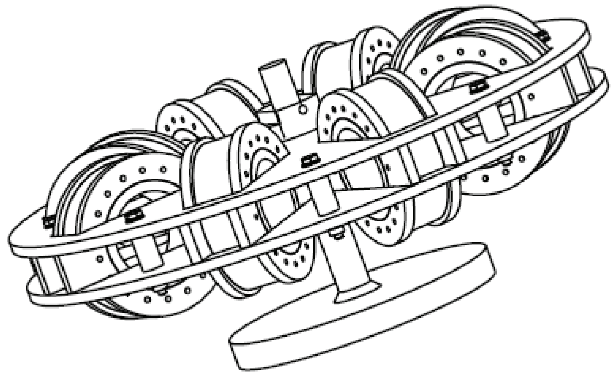

Fig. 1. Modular toroid coil 3-D view [18].

modular toroid was chosen, consisting of eight solenoids connected in series and symmetrically arranged (Fig. 1) [18]. Each solenoidal coil is realized by NbTi superconductor (with Cu matrix) whose operating temperature is low (4.2 K), using the liquid helium with all the implications of this extremely low temperature.

Two parameters that characterize the geometric torus shape were chosen to minimize the volume of the superconducting material with a maximum stored magnetic energy: the coil inner diameter ratio and the coil thickness ratio. These are the same parameters chosen in [15] to optimize the storage capacity of a SMES device with toroidal coil.

The results of the application of two optimization methods are compared with ones determined by simple numerical tests [13].

II. Optimization by Design of Experiments

The concept of DOE refers a complete methodology for behavioral characterization of a system, analyzing the variation of the response at the variation of a set of factors. The method of DOE is a rational realization of a series of real experiments (plan) a priori expensive in time and material resources. A plan includes many points, that is, many configurations with different values for the factors. The result is a model consisting of analytical relationships linking the response and the factors. The realization of an experiment may be impeded by constraints on position acting on the factors and participating in definition of the study domain and by constraints on reached values involving the response. The screening technique allows determining the influencing elements. If 2 levels are taken into account for each of k

factors, can be performed a full or a fractional factorial design, that is a number of 2^k experiments or less.

The DOE fits to the special case of electromagnetic simulations which can be considered virtual experiments, often requiring important calculations. Applied to the electrical systems modeled by the FEM, it has become a basic tool for solving optimization problems [2] - [4].

The optimization methods based on DOE are classified into three classes, although they are not distinct from each other:

- methods by slidings of plans;
- methods by zooms;
- exhaustive methods.

The first class defines the methods by performing successive slidings of identical plans. These are relatively small to the feasible domain. Their positionings are deduced from each other by exploiting the calculated models or by examining the raw values from experiments.

The second class includes algorithms using plans of the same type, but whose sizes are successively reduced, from an iteration to another. The initial plan typically covers the great part of the study domain.

Finally, the exhaustive methods form the third class. They proceed to a complete and systematic analysis of the study domain. This operation consists in partitioning the study domain in subdomains, performing an experimental plan in each of them and then, deducing a local responses modeling.

A. Zooms without computation of models

The principle of this optimization algorithm was given in [2]. It was modified and supplemented [4] in order to extend its operations to multidimensional spaces and to take into account some specific configurations. It is a simplified version of the algorithm "Zooms – Rotations – Translations", where the rotation operation is not applied.

This algorithm does not require the calculation of models of the response, but directly uses the values of the response in the experience points. These are located on the vertices and on the center of each hyper-rectangular plan.

The first hyper-rectangular plan must be chosen inside of the feasible domain, so that all experiments can be performed (Fig. 4). At each iteration, a full factorial design is performed adding a new one in the center, that is $2^k + 1$ experiments. Among these points, we accept the point in which the response is better, in the sense of desired optimality. The new domain is defined with the same or lower volume compared to the previous, in an area encompassing the best point.

When the response is the best in the central points of the plan, the new plan keeps this point as center and its dimensions are those of the current domain divided by a reduction ratio τ, so the new domain is inside of the current domain for $\tau > 1$. When the best response is not found at the center point, the new domain is centered on the best point and it has the same dimensions as the current domain. Therefore, the new domain may not be fully included in the study domain. Only the valid area must be considered. In the best case, it is possible to recuperate two points from the previous plan (the center point and a point on a corner), only if τ is 1.

At each iteration are made $N = 2^k + 1$ experiments (without considering the recuperate points). Among these N points can be identified the extreme values of the response function: $y_{\min}$ and $y_{\max}$. Considering all the response values obtained during the application of the algorithm, it can be noted in the same way the extreme points $Y_{\min}$ and $Y_{\max}$. Since $Y_{\min} = y_{\min}$ and $Y_{\max} = y_{\max}$ at the first iteration, the stopping test is made only from the second iteration. This involves testing if

$$\varepsilon\,[\%] = \frac{y_{\max} - y_{\min}}{Y_{\max} - Y_{\min}} \cdot 100 \le \varepsilon_{\max}\,[\%] \qquad (1)$$

If the optimum sought is a maximum, then $Y_{\max} = y_{\max}$; in the case of a minimum, $Y_{\min} = y_{\min}$. A stop criteria [17] can be also, the relative error of the objective function value at the last iteration (t) compared to the previous iteration (m) with different value ($1 \le m \le t - 1$)

$$\varepsilon_F\,[\%] = \frac{F^{(t)} - F^{(m)}}{F^{(m)}} \cdot 100 \le \varepsilon_{F\max}\,[\%] \qquad (2)$$

B. Slidings of plans without computation of models

For this optimization algorithm [4], the factors are assumed to be discrete, taking a finite set of values. Thus, a grid of points (preferably regular) is defined which will be support for the optimization process (Fig. 6). Often, the grid is determined by the number of the intermediate values N_{ivk} of the k factors, which influence the accuracy of the result.

The algorithm starts with a point P'_0 necessarily inside the study domain. At each iteration the value of the response in the points around it is studied. The point with better value of the response than the origin point, in the sense of desired optimality, is considered as a new origin point and the algorithm restarts. No mathematical model of the response is calculated.

In the realization of a plan, an important parameter is the step $s \ge 1$ that is the number of crossed grid nods, on a given direction, between the current origin point and the points of the plan. Whatever the number k of factors, there are 2^k diagonal points and $2k$ axial points related to the current origin point. The value of this parameter may be set arbitrarily but it may be correlated to the number of the intermediate values N_{ivk}.

At first, the algorithm performs $N = 2^k$ experiments in the diagonal points related to the origin point P'_0. This is equivalent to calculating a full factorial design on a domain whose dimensions are imposed by the parameter s. If there is a diagonal point in which the response is better than in P'_0, this point becomes the origin for the next iteration.

Otherwise, the algorithm performs $N = 2k$ experiments in the axial points. If there is an axial point in which the response is better than in P'_0, this point becomes the origin for the next iteration.

Otherwise, the current value of the step s is decremented by 1, if it is possible.

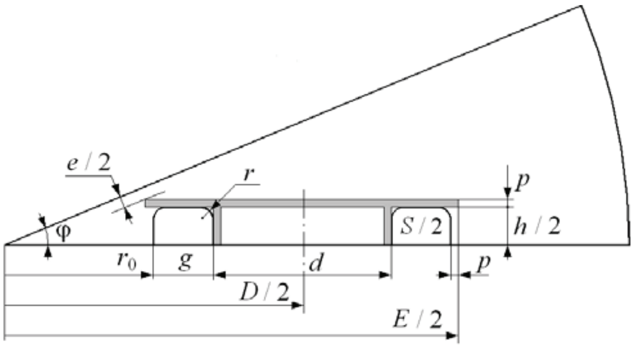

Fig. 2. Geometry of modular toroid coil [18].

All the above operations are then resumed. All the new plans derive from the previous by sliding them on diagonal or axial direction with different values of the step *s* (Fig. 6).

The constraints are taken into account during the determination of the points around the origin point. The diagonal or axial points excluded by the constraints correspond to unrealizable experiences.

The algorithm stops when the step is $s = 1$ and there is no point (diagonal and axial) around the current origin point, whose response is better than in this point. Another stop criteria can be (2).

The step *s* allows managing the speed of the algorithm, which is the speed of slidings of plans in the feasible domain to search the optimum point. Higher step may increase the speed but it may reduce the probability of reaching the optimal point. A compromise is necessary, depending on the encountered conditions.

The strong points of the both optimization algorithms are theirs robustness by simplicity of calculations and the limited number of experiments to be performed at each iteration for small values of *k*. The shortcomings are that the founded optimum is local and that it cannot use economic designs for $k > 2$ (fractional factorial designs, for example).

III. Optimization Problem

The analyzed modular toroid coil with continuous winding is shown in Fig. 2 [18]. The basic dimensions are the mean diameter of modular toroid $D = 142$ mm, the coil inner diameter d and the coil thickness g. The volume of superconducting material depends on the basic dimensions

$$V = n \cdot S \cdot \pi \cdot (d + g) \tag{3}$$

where the number of solenoid modules $n = 8$ and the cross section of the coil $S = 128$ mm^2. According to specifications presented in [14], the radius of superconducting wire $r = 0.2$ mm and the thickness of carcass $p = 4$ mm.

To optimize the storage capacity, two parameters were introduced [15] characterizing the geometric torus shape: the coil inner diameter ratio α and the coil thickness ratio β, defined by relations

$$\alpha = \frac{d}{D} < 1, \quad \beta = \frac{g}{D} < 1 \tag{4}$$

The stored magnetic energy W_m depends also on the basic dimensions and on the current density j in superconductor, that was taken $j = 381.548$ MA/m^2, corresponding to a current $I = 75$ A. According to specifications presented in [11], the critical current density of NbTi superconductor at $T = 4.2$ K and $B_{lim} = 7$ T is $j_c = 530$ MA/m^2.

An optimized storage capacity means a maximum stored magnetic energy with a minimum volume of superconducting material, that is the maximum of the function [15]

$$F(\alpha, \beta) = c \frac{W_m(\alpha, \beta)}{V(\alpha, \beta)} = c \frac{W_m(\alpha, \beta)}{n \cdot S \cdot \pi \cdot D \cdot (\alpha + \beta)} \tag{5}$$

where c is an additional factor to obtain F values around unity. This is a 2-D nonlinear optimization problem (P) with constraints on position and on reached value.

$$\mathrm{P}: \begin{cases} \max F(\alpha, \beta) \\ \alpha_{min} \le \alpha \le \alpha_{max} \\ \beta_{min} \le \beta \le \beta_{max} \\ g_{dist}(\alpha, \beta) \le 0 \\ g_{diam}(\alpha, \beta) \le 0 \\ g_{B\max}(\alpha, \beta) \le 0 \end{cases} \tag{6}$$

where $$\alpha_{min} = 0.035 \le \alpha \tag{7}$$

is a constraint on position, according to manufacturing possibilities [14], (α_{max}, β_{min} and β_{max} are free),

$$g_{dist}(\alpha, \beta) = e_{min} - e(\alpha, \beta) \tag{8}$$

is a constraint on position that does not allow a distance e between two carcasses of solenoids less than $e_{min} = 5.425$ mm,

$$g_{diam}(\alpha, \beta) = E(\alpha, \beta) - D_{max} \tag{9}$$

is another constraint on position that does not allow a total diameter of the modular toroid coil greater than $D_{max} = 230$ mm [14] and

$$g_{B\max}(\alpha, \beta) = B_{max}(\alpha, \beta) - B_{lim} \tag{10}$$

is a constraint on reached value that does not allow exceeding the limit value $B_{lim} = 7$ T. Unlike the constraints on position, this magnetic constraint is not known a priori, but it can be highlighted during the application of optimization algorithm.

$$e(\alpha, \beta) = 2 \cdot \sin\frac{\varphi}{2} \cdot \left(r_0 - p - \frac{\frac{h}{2} + p}{\tan\frac{\varphi}{2}} \right) \tag{11}$$

$$r_0 = \frac{D - d}{2} - g = D \cdot \left(\frac{1 - \alpha}{2} - \beta \right), \quad h = \frac{S}{g} = \frac{S}{\beta D}, \quad \varphi = \frac{2\pi}{n} \tag{12}$$

$$E(\alpha, \beta) = D + d + 2g + p = D \cdot (1 + \alpha + 2\beta) + p \tag{13}$$

The feasible domain defined by the constraints on position can be seen in Fig. 3. Both, the objective function values and the maximum magnetic flux density values are numerically determined using FEM.

IV. 2-D Numerical Simulation

An earlier 2-D planar model used in FEMM software describes a rectangular cross section toroid [13], [16]. Under the assumption of the equality between the inductances of the complete circular cross section toroid and of the rectangular cross section toroid, the *depth* parameter of the planar model was derived as

$$depth = 0.766 \cdot d \tag{14}$$

The same model is used to perform the numerical simulations. The perfect diamagnetism was simulated by considering the value of relative permeability of the superconductor close to zero. The value $\mu_r = 10^{-7}$ is enough small for expulsion of magnetic field from superconducting domain (Fig. 8) [18]. Commands files have been created using LUA scripting language. The mesh was realized using about 30000 nodes and 60000 triangular elements.

V. Optimization Algorithms

To solve the optimization problem (6), the method of zooms without computation of models and the method of slidings of plans without computation of models were used. The solution was obtained in two steps, consisting in solving of two optimization problems:

- The first (P_1) aims to minimize the maximum magnetic field density $B_{max}(\alpha,\beta)$, starting with an arbitrary plans in the feasible domain, centered in the point P_0 (Fig. 3) and having as stop criteria the magnetic constraint, that is the algorithm stops when B_{max} decreases under the limit value B_{lim} = 7 T. Results the start point for the second step

$$P_1 : \begin{cases} \min B_{max}(\alpha,\beta) \\ \alpha_{min} \le \alpha \le \alpha_{max} \\ \beta_{min} \le \beta \le \beta_{max} \\ g_{dist}(\alpha,\beta) \le 0 \\ g_{diam}(\alpha,\beta) \le 0 \end{cases} \tag{15}$$

- The second (P_2) is the optimization problem itself (P), starting with the best point of the previous step. At each iteration, the optimal point are chosen from a total of N points of the current plan, in the sense of increases of $F(\alpha,\beta)$, under condition of $B_{max}(\alpha,\beta) \le 7$ T.

A. Optimization by zooms without computation of models

In this case each iteration uses a plan counting $N = 2^2 + 1 = 5$ points [18]. The reduction ratio τ was chosen to be 4 (Fig. 4, a, c), 2 (Fig. 4, b), or 1, depending on specific conditions. The evolution of the algorithm can be seen in Fig. 5 and the computed values are written in Table I. After one iteration the first step offers the point P_1 with B_{max} = 6.376 T < 7 T, that is the starts point for the second step.

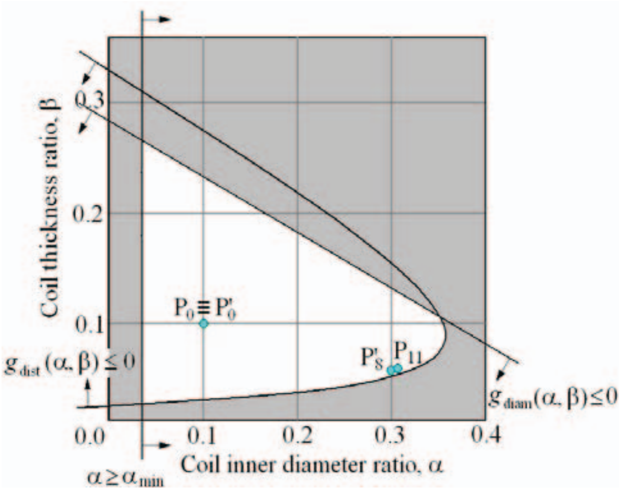

Fig. 3. Feasible domain defined by the constraints on position.

The threshold in the stop criteria (1) of the second step was chosen ε_{max} = 1 %.

After 11 iterations, the algorithm offers the optimal solution α = 0.3125 and β = 0.0533203125, corresponding to the best ratio F = 2.4277 of the stored magnetic energy W_m = 405.689 J and the superconductor material volume $V = 1.671 \cdot 10^{-4}$ m^3, d = 44.38 mm and g = 7.57 mm. The error on objective function value results ε_F < 0.1 % but a relative stabilization can be observed even from the 8-th iteration.

The total number of the necessary experiments during the application of the optimization algorithm is N_{tot} = 55, but, taking into account the number of the recuperate points N_{rec} = 20, results 35 numerical experiments. In Fig. 9 and Fig. 10 [18] are presented the values of objective function, of the maximum magnetic flux density and the magnetic constraint (the limit level B_{lim} = 7 T) in all the points of this algorithm.

B. Optimization by slidings of plans without computation of models

In this case each iteration uses a plan counting $N = 2^2 = 4$ points. A grid with $N_{iv\alpha} \times N_{iv\beta} = 31 \times 127$ intermediate values related to the initial range [0÷ 0.4] of the factors α and β was chosen. The considered step at the beginning of the algorithm was set s = 8. The evolution of the algorithm can be seen in Fig. 7 and the computed values are written in Table II.

After two iterations the first step offers the point P'$_2$ with B_{max} = 6.987 T < 7 T, that is the starts point for the second step. After 8 iterations, the algorithm offers the optimal solution α = 0.30 and β = 0.05, corresponding to F = 2.317, W_m = 370.403 J, $V = 1.559 \cdot 10^{-4}$ m^3, d = 42.60 mm and g = 7.10 mm. The error on objective function value is ε_F < 2 %. The result is comparable to the previous.

The total number of the necessary experiments during the application of the optimization algorithm is N_{tot} = 32, but, taking into account the number of the recuperate points N_{rec} = 4, results 28 numerical experiments. In Fig. 11 and Fig. 12 are presented the values of objective function, of the maximum magnetic flux density and the magnetic constraint in all the points of this algorithm.

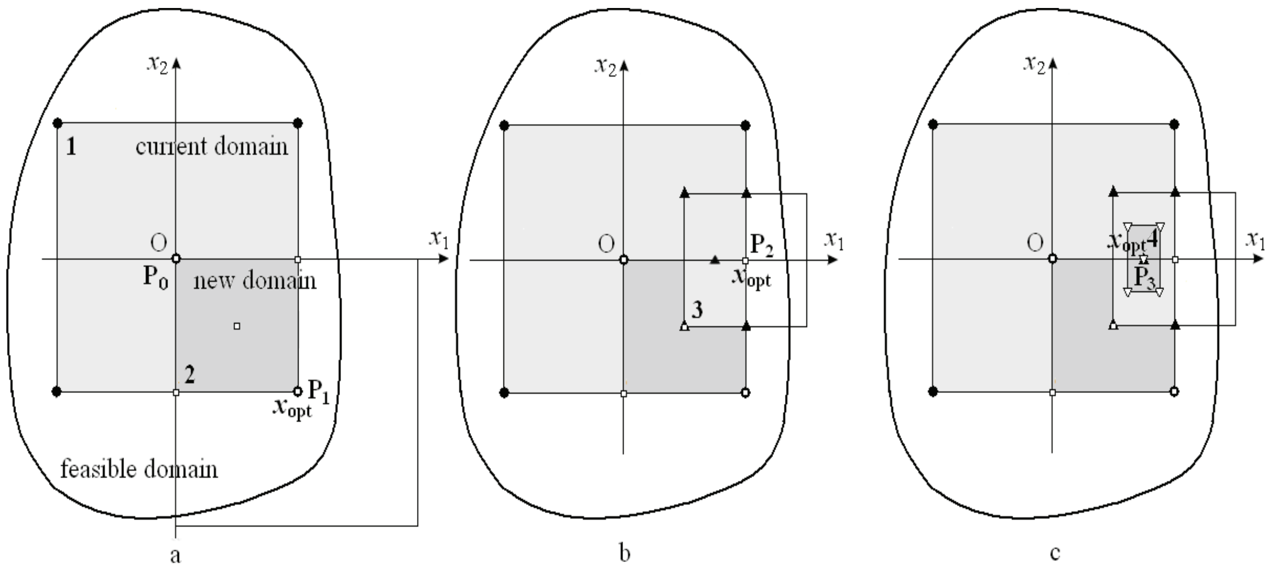

Fig. 4. Graphical illustration of the application of optimization algorithm by zooms [18].

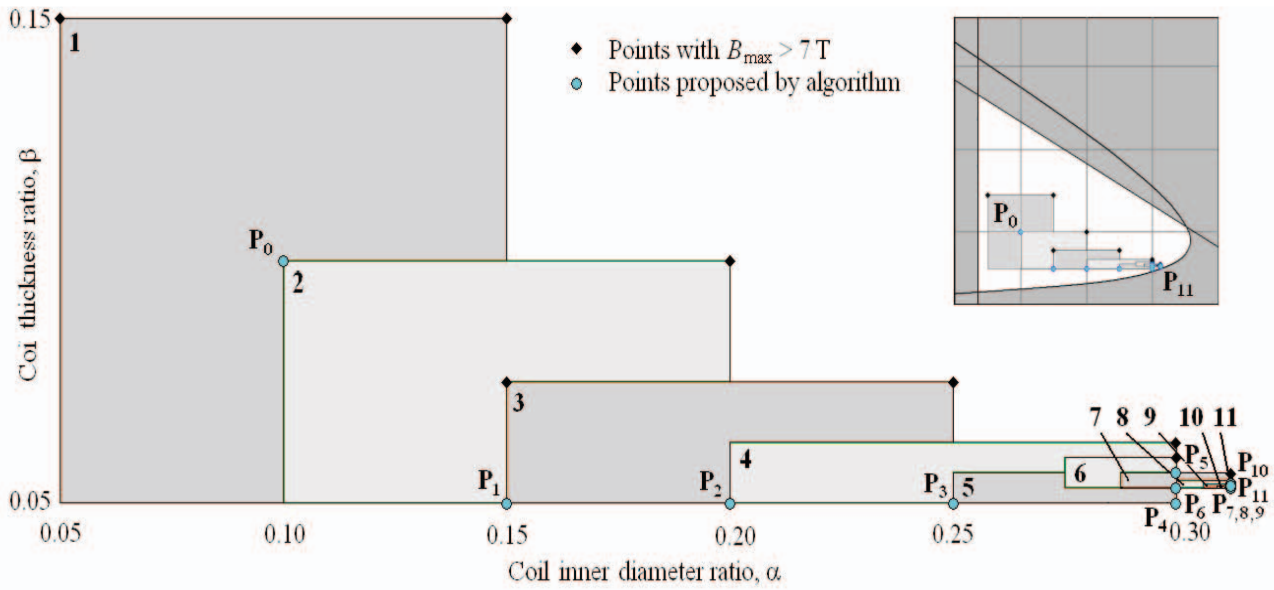

Fig. 5. Graphical illustration of the application of optimization algorithm by zooms [18].

TABLE I.
OPTIMIZATION PROCESS EVOLUTION: FEM BASED VALUES OF OBJECTIV FUNCTION F AND OF B_{MAX} FOR THE METHOD BY ZOOMS [18]

Iterations	N_{tot}	N_{rec}	α	β	F	B_{max} [T]	ε [%]	ε_F [%]	d [mm]	g [mm]
1	5	1	0.1500	0.0500000000	1.1636	6.376	-	-	21.30	7.10
2	5	1	0.2000	0.0500000000	1.5505	6.421	65.07%	33.250%	28.40	7.10
3	5	2	0.2500	0.0500000000	1.9341	6.609	48.28%	24.740%	35.50	7.10
4	5	2	0.3000	0.0500000000	2.3167	6.779	38.78%	19.782%	42.60	7.10
5	5	2	0.3000	0.0562500000	2.3321	6.799	19.97%	0.665%	42.60	7.99
6	5	1	0.3000	0.0531250000	2.3254	6.869	9.88%	-0.287%	42.60	7.54
7	5	2	0.3125	0.0531250000	2.4229	6.951	9.21%	4.193%	44.38	7.54
8	5	3	0.3125	0.0531250000	2.4229	6.951	4.70%	0.000%	44.38	7.54
9	5	2	0.3125	0.0531250000	2.4229	6.951	2.35%	0.000%	44.38	7.54
10	5	2	0.3125	0.0535156250	2.4275	6.931	1.22%	0.190%	44.38	7.60
11	5	2	0.3125	0.0533203125	2.4277	6.934	0.61%	0.008%	44.38	7.57
TOTAL	55	20								

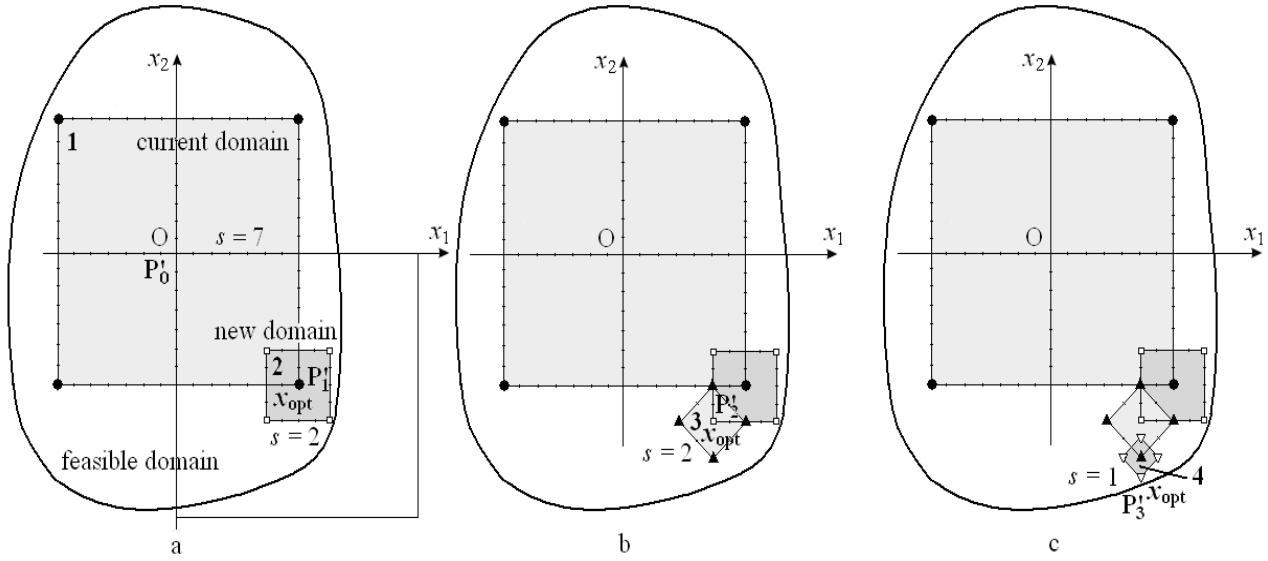

Fig. 6. Graphical illustration of the application of optimization algorithm by slidings of plans.

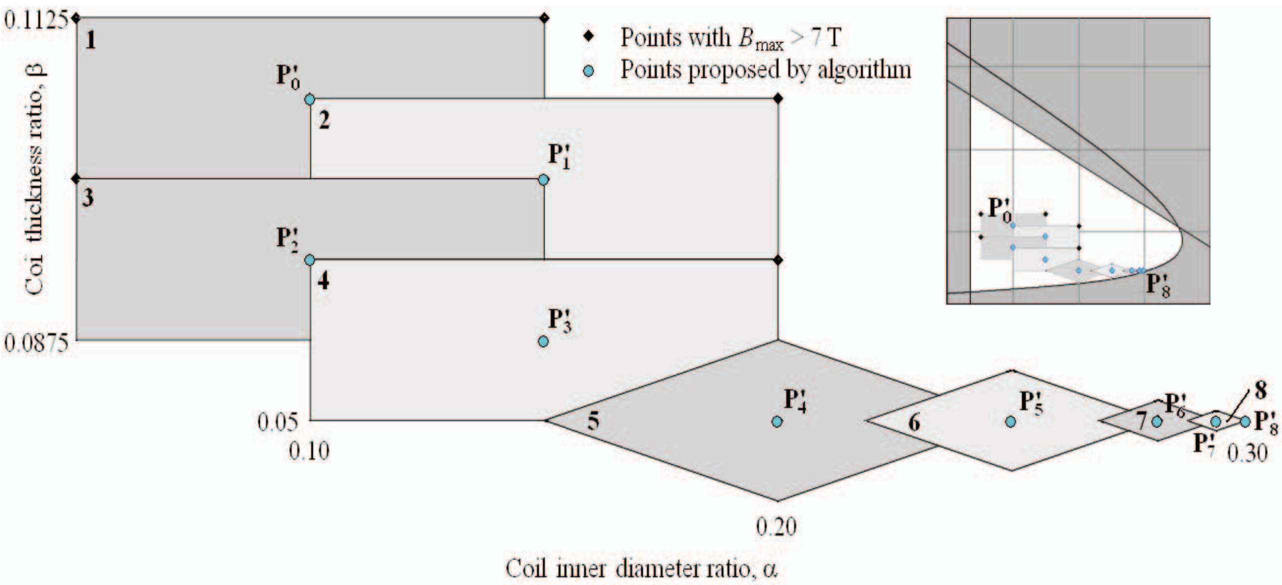

Fig. 7. Graphical illustration of the application of optimization algorithm by slidings of plans.

TABLE II.
OPTIMIZATION PROCESS EVOLUTION: FEM BASED VALUES OF OBJECTIV FUNCTION F AND OF B_{MAX} FOR THE METHOD BY SLIDINGS OF PLANS

Iterations	N_{tot}	N_{rec}	α	β	F	B_{max} [T]	s	ε_F [%]	d [mm]	g [mm]
1	4	2	0.15000	0.0875	1.137	7.330	8	-	21.30	12.43
2	4	2	0.10000	0.0750	0.755	6.987	8	-33.60%	14.20	10.65
3	4	0	0.15000	0.0625	1.172	6.709	8	55.23%	21.30	8.88
4	4	0	0.20000	0.0500	1.550	6.421	8	32.25%	28.40	7.10
5	4	0	0.25000	0.0500	1.934	6.609	8	24.77%	35.50	7.10
6	4	0	0.28125	0.0500	2.177	6.697	5	12.57%	39.94	7.10
7	4	0	0.29375	0.0500	2.274	6.732	2	4.46%	41.71	7.10
8	4	0	0.30000	0.0500	2.317	6.779	1	1.89%	42.60	7.10
TOTAL	32	4								

The results are compared with previous approximate values determined by simple numerical tests [13] and they are written in Table III. In all the cases, the magnetic constraint is accomplished.

VI. CONCLUSIONS

Two direct optimization methods by DOE and 2-D FEM were applied on the configuration of modular toroid coil geometry of a SMES device in order to optimize the storage capacity respecting the critical limit of magnetic field of the superconducting material: the method by zooms without computation of models and the method by slidings of plans without computation of models.

The optimization problem was to find the maximum ratio of the stored magnetic energy and the volume of superconducting material, depending on two geometric parameters characterizing the torus shape: the coil inner diameter ratio and the coil thickness ratio. Constraints on position and constraints on reached value (magnetic constraint) were taken into account.

TABLE III.
RESULTS OF THE OPTIMIZATION BY THE METHODS BY ZOOMS AND BY SLIDINGS OF PLANS

	Simple numerical tests	Method by zooms	Method by slidings of plans
W_m [J]	338.063	405.689	370.403
V [m^3]	$1.544 \cdot 10^{-4}$	$1.671 \cdot 10^{-4}$	$1.559 \cdot 10^{-4}$
F	2.1895	2.4277	2.3167
α	0.2816901409	0.3125	0.30
β	0.0563380282	0.0533203125	0.05
d [mm]	40.00	44.38	42.60
g [mm]	8.00	7.57	7.10
B_{max} [T]	6.914	6.934	6.779

The results obtained by the two optimization methods are comparable between them and better than previous approximate values determined by simple numerical tests.

Other optimization algorithms based on DOE will be used to solve the same problem. The variation of the number of solenoid modules can influence the maximum

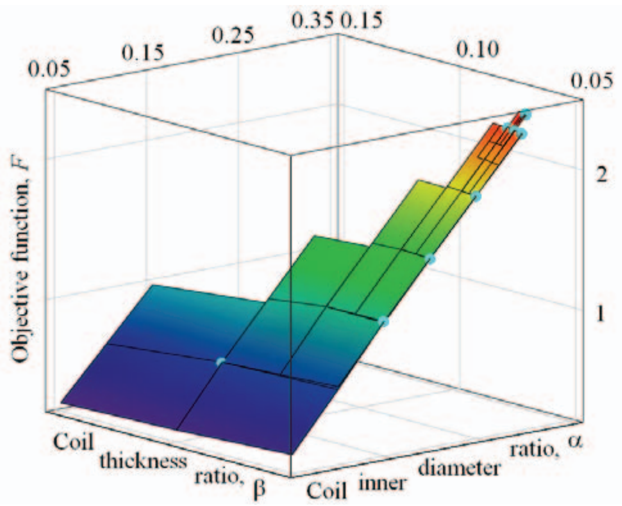

Fig. 8. Objective function values in all the points of the optimization algorithm by zooms [18].

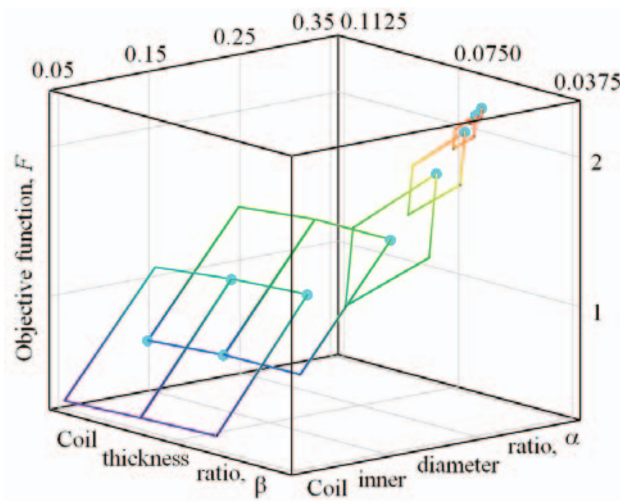

Fig. 10. Objective function values in all the points of the optimization algorithm by slidings of plans.

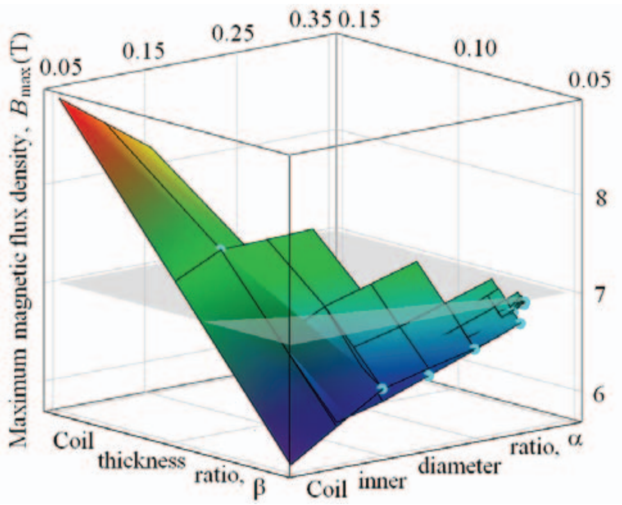

Fig. 9. Maximum magnetic flux density values in all the points of algorithm by zooms and magnetic constraint B_{lim} = 7 T [18].

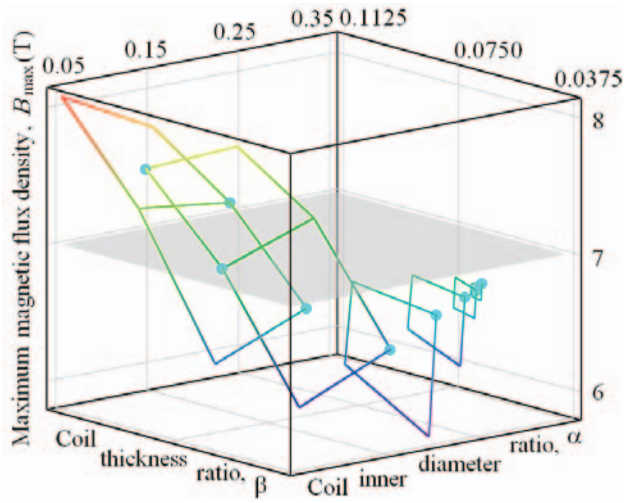

Fig. 11. Maximum magnetic flux density values in all the points of algorithm by slidings of plans, magnetic constraint B_{lim} = 7T.

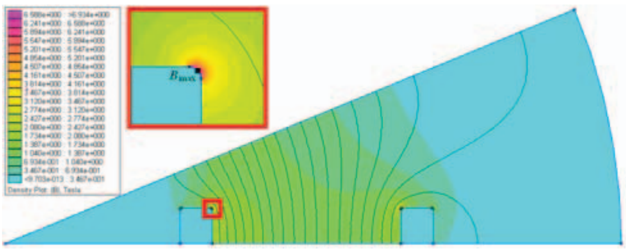

Fig. 12. Magnetic flux density distribution for the optimal solution obtained by the method by zooms [18].

value of the magnetic flux density, so, an optimization problem taking into account also this factor can be solved. Similar parameters can be used to optimize the coil geometry basing on other criteria.

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