Improving of 2-D FEM Modeling of a SMES Device Using the Response Surface Methodology Applied on 3-D FEM Modeling

Alin-Iulian Dolan and Florian Stefanescu
University of Craiova, Faculty of Electrical Engineering, Craiova, Romania, adolan@elth.ucv.ro, florian@elth.ucv.ro

***Abstract* — The paper proposes an improving of earlier 2-D FEM modeling of a Superconducting Magnetic Energy Storage (SMES) device with modular toroid coil using the response surface methodology (RSM) applied on 3-D FEM modeling. Usually, RSM problems use polynomial models of first- or second-order (regressions) that approximates the value of response for any combination of the influencing factors. The earlier 2-D model of SMES device created in FEMM software is based on the assumption of the equality between the inductances of the complete circular cross section toroid and of the rectangular cross section toroid, providing an approximation for the depth of planar model which does not take into account the leakage magnetic flux. Therefore a 3-D model of real geometry was realized using ANSYS software to improve this approximation. Imposing the equality of the magnetic field energies in 2-D and 3-D simulations, a new value for depth of 2-D planar model is derived for which are proposed two polynomial models of first order without interactions and with interactions based on two factors characterizing the geometric torus shape: the coil inner diameter ratio and the coil thickness ratio. The results based on a few 3-D numerical experiments show that using a model with interactions is justified. The application of analysis of variance (ANOVA) and the computation of some adjusting coefficients prove that the both models can be considered of best quality, since there is more than 99% chance that they explain the variations in the response. The models indicate an underestimation of the depth of the 2-D planar modeling in the old approximation and consequently, of the magnetic field energy, for SMES devices of great dimensions, when the leakage magnetic flux increases.**

Keywords—SMES; FEM; DOE; RSM; ANOVA

I. INTRODUCTION

The design and the optimization of the Superconducting Magnetic Energy Storage (SMES) devices is a topic of permanent interest [5] - [15].

The numerical simulations help to preview the best solutions with minimum costs. In [13] and [16] were created 2-D and 3-D numerical models of a 21 kJ modular toroid coil system, using finite element method (FEM) in FEMM and ANSYS software. The results shown that a 2-D model under well-chosen assumptions can be as accurate as a 3-D model of the real geometry, which is much more expensive in terms of work time and hardware resources.

In [15] was established a geometric criteria for pre-sizing of toroidal coil for magnetic energy storage in order to optimize the storage capacity, choosing two geometric parameters. Based on analytical calculation, correlations between different dimensions have been derived.

In [17] and [18] are proposed optimized solutions of modular toroid coil geometry of a 21 kJ SMES device using design of experiments (DOE) and FEM.

In this paper is proposed an improving of the earlier 2-D FEM modeling of the SMES device with modular toroid coil using the response surface methodology (RSM) applied on 3-D FEM modeling.

In the first part is presented some basic concepts in RSM concerning the first degree polynomial models, the ways of estimation of their coefficients and the technique of analysis of variance (ANOVA) with adjusting coefficients as tools for testing of the validity of the models and for appreciating their quality.

In the second part, two polynomial models of first-degree are proposed for the depth of 2-D planar model, based on equivalence of magnetic field energies between 2-D and 3-D models. The ANOVA is applied and some adjusting coefficients are computed for statistical tests of the models.

II. RESPONSE SURFACE METHODOLOGY

A. Basic Concepts in RSM

The response surface methodology (RSM) is a useful technique for modeling and analysis of the response of a system influenced by a set of independent factors. The design of experiments (DOE) is essentially based on the creation and exploitation of the models of the response consisting of analytical relationship describing the variations of the response versus to the variation of the factors. [1] - [4].

Usually, the RSM problems use polynomial models of first- or second-order derived as results of a series of experiments with different values for the factors. For a set of k factors, the model function (called regression) Y_{mod} approximates the value of response Y for any combination of the factors by matrix-form relationship

$$Y_{\mathrm{mod}}(\boldsymbol{x}) = f(\boldsymbol{x}) \cdot \boldsymbol{\beta}\,, \quad (1)$$

where $$\boldsymbol{x} = (x_1 \; x_2 \; \dots \; x_k)^{\mathrm{T}} \quad (2)$$

is the coordinates vector of an experience point P,

$$f(\boldsymbol{x}) = (1 \; x_1 \dots x_k \;\; x_1 x_2 \dots x_1 x_k \dots x_2 x_k \dots x_1^{\;2} \dots x_k^{\;2}) \quad (3)$$

is a line vector whose elements contain the values of the k factors and theirs possible combinations by mutual multiplications up to second order and

$$\boldsymbol{\beta} = (b_0\ b_1 \dots b_k\ b_{12} \dots b_{1k} \dots b_{2k} \dots b_{11} \dots b_{kk})^{\mathrm{T}} \quad (4)$$

is the vector of the correspondents coefficients, with p elements.

1) The first-order model without interactions does not take into account the interaction between the factors. For two factors denoted $x_1 = x$ and $x_2 = y$, we have $p = 3$ and

$$\boldsymbol{x} = (x\ y)^{\mathrm{T}}, \quad f(\boldsymbol{x}) = (1\ x\ y), \quad \boldsymbol{\beta} = (b_0\ b_1\ b_2)^{\mathrm{T}}. \quad (5)$$

The values of the model function can be also written as

$$Y_{\mathrm{mod}}(\boldsymbol{x}) = b_0 + \boldsymbol{x}^{\mathrm{T}} \cdot \boldsymbol{b}, \quad \boldsymbol{b} = (b_1\ b_2)^{\mathrm{T}}. \quad (6)$$

The coefficient b_0 is the value of model function in the origin point $(0\ 0\ \dots\ 0)^{\mathrm{T}}$ and the vector $\boldsymbol{b}$ indicates the direction of the greatest increase of the model function.

2) The first-order model with interactions takes into account the interactions between the factors. For two factors in this case $p = 4$ and

$$f(\boldsymbol{x}) = (1\ x\ y\ xy), \quad \boldsymbol{\beta} = (b_0\ b_1\ b_2\ b_{12})^{\mathrm{T}}. \quad (7)$$

B. Estimation of Coefficients of Polynomial Models

For a series of N experiments, the value of the model function in any experience point $\mathrm{P}_i(\boldsymbol{x}_i) = \mathrm{P}_i(x_i, y_i)$ is

$$Y_{\mathrm{mod}}(\boldsymbol{x}_i) = f(\boldsymbol{x}_i) \cdot \boldsymbol{\beta}, \quad 1 \le i \le N. \quad (8)$$

The vectors $\boldsymbol{Y}$ and $\boldsymbol{Y}_{\boldsymbol{mod}}$ bring together all the responses respectively their models and a new matrix form relationship can be written [4]

$$\boldsymbol{Y} = \left(Y(\boldsymbol{x}_1) \dots Y(\boldsymbol{x}_N)\right)^{\mathrm{T}}, \quad (9)$$

$$\boldsymbol{Y}_{\boldsymbol{mod}} = \left(Y_{\mathrm{mod}}(\boldsymbol{x}_1) \dots Y_{\mathrm{mod}}(\boldsymbol{x}_N)\right)^{\mathrm{T}} = \boldsymbol{X} \cdot \boldsymbol{\beta}, \quad (10)$$

where $$\boldsymbol{X} = \left(f(\boldsymbol{x}_1) \dots f(\boldsymbol{x}_N)\right)^{\mathrm{T}} \quad (11)$$

is the design matrix built from the N experience points.

If $N = p$ experiences are performed, all the p coefficients can be uniquely determined by the system of linear equations

$$\boldsymbol{Y} = \boldsymbol{X} \cdot \boldsymbol{\beta}. \quad (12)$$

The model passes exactly through the experience points and the matrix $\boldsymbol{X}$ is saturated (square).

If $N < p$, the above system is underdetermined, so one must always have $N \ge p$.

For the most common situations where $N > p$, the system (12) is overdetermined and there is enough information in the experimental data to estimate a unique value for $\boldsymbol{\beta}$ such that the model best fits the response. In this case the model cannot pass exactly through the experience points, but it commits an adjustment error in each of these points.

So there is an error vector $\boldsymbol{\varepsilon}$ (residue) nonzero. The coefficients must be estimated by the minimization a given criterion. The method of least squares is the best known and most used in the polynomial approximation.

The matrix-form relationship linking the response and the model function based on the estimation vector $\hat{\boldsymbol{\beta}}$ is

$$\boldsymbol{Y} = \boldsymbol{X} \cdot \hat{\boldsymbol{\beta}} + \boldsymbol{\varepsilon}. \quad (13)$$

The objective is the calculation of vector $\hat{\boldsymbol{\beta}}$ such that the vector $\boldsymbol{\varepsilon}$ to be minimized. The least squares criterion translates this requirement by an equivalent objective

$$\sum_{i=1}^{N} \varepsilon_i^{\,2} = \sum_{i=1}^{N} \left(Y(\boldsymbol{x}_i) - Y_{\mathrm{mod}}(\boldsymbol{x}_i)\right)^2 \to \min \quad (14)$$

The estimation vector $\hat{\boldsymbol{\beta}}$ results

$$\hat{\boldsymbol{\beta}} = \left(\boldsymbol{X}^{\mathrm{T}} \cdot \boldsymbol{X}\right)^{-1} \cdot \boldsymbol{X}^{\mathrm{T}} \cdot \boldsymbol{Y} \quad (15)$$

C. Analysis of Variance of the Model and Adjustement Coefficients

The ANOVA can be used to test the validity of the model function based on the relationship [4]

$$\boldsymbol{Y}^{\mathrm{T}} \cdot \boldsymbol{Y} = \boldsymbol{Y}_{\boldsymbol{mod}}^{\ \mathrm{T}} \cdot \boldsymbol{Y}_{\boldsymbol{mod}} + \boldsymbol{\varepsilon}^{\mathrm{T}} \cdot \boldsymbol{\varepsilon}. \quad (16)$$

The left terms, called the total sum of the squares (*SST*), is composed of the sum of squares due to regression (*SSR*) and of the sum of errors squares (*SSE*), so

$$SST = SSR + SSE. \quad (17)$$

The variances (the mean squares) of the responses, regression and residues are deducted dividing the sums of squares by the corresponding degrees of freedom (DOF)

$$MST = \frac{SST}{N}, \quad MSR = \frac{SSR}{p}, \quad MSE = \frac{SSE}{N - p}. \quad (18)$$

In about all cases, the model contains a constant term which corresponds to coefficient b_0, which is the average of responses

$$b_0 = \frac{1}{N} \sum_{i=1}^{N} Y(\boldsymbol{x}_i) = \bar{Y}, \quad \bar{\boldsymbol{Y}} = \left(\bar{Y} \dots \bar{Y}\right)^{\mathrm{T}} \quad (19)$$

Since this component is of no interest in ANOVA, it is usually suppressed. Consequently, the regression DOFs and total DOFs decrease by 1. Thus

$$MST_{-0} = \frac{SST}{N - 1}, \quad MSR_{-0} = \frac{SSR}{p - 1}. \quad (20)$$

Is then performed the Fisher-Snedecor test by calculating the ratio F_{obs}:

$$F_{\mathrm{obs}} = \frac{MSR}{MSE} \quad \text{or} \quad F_{\mathrm{obs}} = \frac{MSR_{-0}}{MSE_{-0}}. \quad (21)$$

The *MSR* (or MSR_{-0}) can be considered of the same order as the *MSE* (or MSE_{-0}) if the ratio F_{obs} is less than a statistical threshold. The null hypothesis H_0 means that $\boldsymbol{\beta} = \boldsymbol{0}$. Under this assumption, F_{obs} is an observed value of a variable F of Fisher-Snedecor type, with p (or $p - 1$) and

($N-p$) DOFs. The hypothesis H_0 must be rejected at level λ when the probability $P(F \geq F_{obs}) \leq \lambda$.

The quality of a model can be evaluated by adjustments coefficients:

1) Global variance of regression (σ^2) can be estimated by *MSE.* The model is the better fit to the experimental data as *MSE* is low

$$\hat{\sigma}^2 = MSE\,. \tag{22}$$

2) Coefficient of determination (R^2) is the ratio of the variance explained by the regression and the variance of responses, both corrected by the average value $\overline{Y}$.

$$R^2 = \frac{\boldsymbol{Y}_{mod}^{\mathrm{T}} \cdot \boldsymbol{Y}_{mod} - \overline{\boldsymbol{Y}}^{\mathrm{T}} \cdot \overline{\boldsymbol{Y}}}{\boldsymbol{Y}^{\mathrm{T}} \cdot \boldsymbol{Y} - \overline{\boldsymbol{Y}}^{\mathrm{T}} \cdot \overline{\boldsymbol{Y}}} = \frac{SSR_{-\mathrm{m}}}{SST_{-\mathrm{m}}} = \frac{SST_{-\mathrm{m}} - SSE_{-\mathrm{m}}}{SST_{-\mathrm{m}}}\,. \tag{23}$$

This coefficient takes values between 0 and 1. A value close to 1 indicates a good model with a very good predictive power.

3) Adjusted coefficient of determination (R_a^2) has the same signification as R^2 but it is defined in relation to corresponding DOFs

$$R_a^{\,2} = \frac{\dfrac{SST_{-\mathrm{m}}}{N-1} - \dfrac{SSE_{-\mathrm{m}}}{N-p}}{\dfrac{SST_{-\mathrm{m}}}{N-1}}\,. \tag{24}$$

It can take negative values if the R^2 is close to 0. Due to the consideration of DOFs one always has $R_a^2 < R^2$.

The ANOVA and the adjustment coefficients allow evaluating the quality of the model. These tools require an additional cost of ($N-p$) experiments compared to the calculation of a model requiring p experiments. There is therefore a compromise: possibility to evaluate the quality of the model or minimization of the effort for model calculation.

III. RSM Applied on SMES Device Modeling

A. SMES Geometry Description and Loads

The analyzed SMES device is shown in Fig. 1 [18]. For the shape of the coil, a modular toroid coil was chosen, consisting of solenoids connected in series and symmetrically arranged.

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 [13], [15].

The basic dimensions are the mean diameter of modular toroid D = 142 mm, the coil inner diameter d and the coil thickness g. The number of solenoid modules is n = 8 and the cross section of the coil is 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.

The current density in superconductor 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.

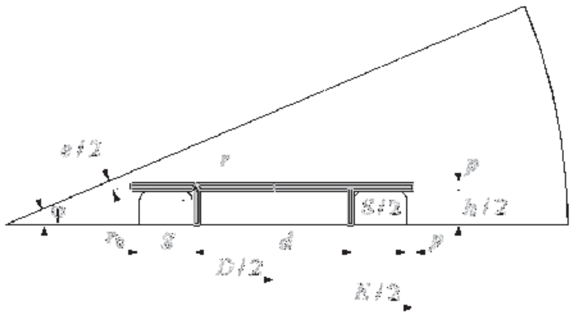

Fig. 1. Geometry of modular toroid coil [18].

Two main parameters characterize the geometric torus shape: the coil inner diameter ratio α and the coil thickness ratio β.

They were chosen in [15] to optimize the storage capacity of a SMES device with toroidal coil

$$\alpha = \frac{d}{D}, \quad \beta = \frac{g}{D}\,. \tag{25}$$

The study domain is limited by a few constraints on position (Fig. 2).

$$\begin{cases} \alpha_{\min} \leq \alpha \leq \alpha_{\max} \\ \beta_{\min} \leq \beta \leq \beta_{\max} \\ g_{\mathrm{dist}}(\alpha,\beta) \leq 0 \\ g_{\mathrm{diam}}(\alpha,\beta) \leq 0 \end{cases}, \tag{26}$$

where
$$\alpha_{\min} = 0.035 \leq \alpha \tag{27}$$

is in accord with manufacturing possibilities [14], ($\alpha_{\max}$, $\beta_{\min}$ and $\beta_{\max}$ are free),

$$g_{\mathrm{dist}}(\alpha,\beta) = e_{\min} - e(\alpha,\beta) \tag{28}$$

does not allow a distance e between two carcasses of solenoids less than $e_{\min}$ = 5.425 mm and

$$g_{\mathrm{diam}}(\alpha,\beta) = E(\alpha,\beta) - D_{\max} \tag{29}$$

that does not allow a total diameter of the modular toroid coil greater than $D_{\max}$ = 230 mm [14]

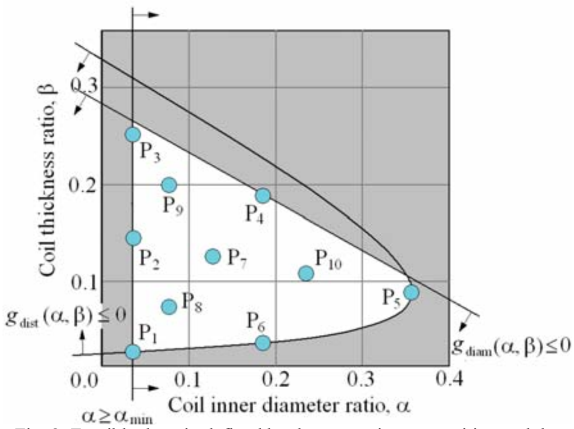

Fig. 2. Feasible domain defined by the constraints on position and the experience points (blue).

$$e(\alpha,\beta) = 2\cdot\sin\frac{\varphi}{2}\cdot\left(r_0 - p - \frac{\frac{h}{2}+p}{\tan\frac{\varphi}{2}}\right), \quad (30)$$

$$r_0 = \frac{D-d}{2} - g = D\cdot\left(\frac{1-\alpha}{2}-\beta\right),\quad h = \frac{S}{g} = \frac{S}{\beta D},\quad \varphi = \frac{2\pi}{n}, \quad (31)$$

$$E(\alpha,\beta) = D + d + 2g + p = D\cdot(1+\alpha+2\beta) + p\,. \quad (32)$$

B. Modeling of depth of 2-D Planar Model by RSM

The numerical simulations can be considered virtual experiments in which the studied object does not physically exist but its physical properties can be numerically calculated. The virtual experiments are exempted from measurement errors being governed only by numerical errors (type of solving method, mesh characteristics, mathematical formulation, accuracy of numerical data).

The earlier 2-D model created 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 describing the depth of the planar model was derived as

$$depth = 0.766\cdot d = 108.772\cdot\alpha\,. \quad (33)$$

The equivalence of the inductances does not take into account the leakage flux. Therefore a 3-D model of real geometry (Fig. 4) was realized using ANSYS software to improve the approximation (33).

The magnetic field energy as result of 2-D simulation $W_{m\_2\text{-}D}$ is computed by multiplying the magnetic field energy per depth unity $w_{m\_2\text{-}D}$ by the parameter *depth*

$$W_{m\_2\text{-}D} = w_{m\_2\text{-}D}\cdot depth\,. \quad (34)$$

Imposing the equality of the magnetic field energies in 2-D and 3-D simulations, a new value *depth'* for depth of 2-D planar model parameter can be derived

$$W_{m\_3\text{-}D} = w_{m\_2\text{-}D}\cdot depth' = \frac{W_{m\_2\text{-}D}}{depth}\cdot depth'\,, \quad (35)$$

$$depth' = \frac{W_{m\_3\text{-}D}\cdot depth}{W_{m\_2\text{-}D}}\,. \quad (36)$$

Two polynomial models of first order (linear regressions) without interactions and with interactions are proposed for *depth'* parameter based on factors α and β

$$depth'_1(\alpha,\beta) = b_0 + b_1\alpha + b_2\beta\,, \quad (37)$$

$$depth'_2(\alpha,\beta) = b_0 + b_1\alpha + b_2\beta + b_{12}\alpha\beta\,. \quad (38)$$

Given the breadth of 3-D simulation, reaching to a working time up to hours compared to a working time of seconds order, the number of the numerical experiments was limited to $N = 10$ for different levels of the factors α and β. The set of chosen experiments form a Simplex Lattice Design ($P_1 - P_6$) augmented with the axial points ($P_7 - P_{10}$) [1] for a better coverage of the study domain (Fig. 2).

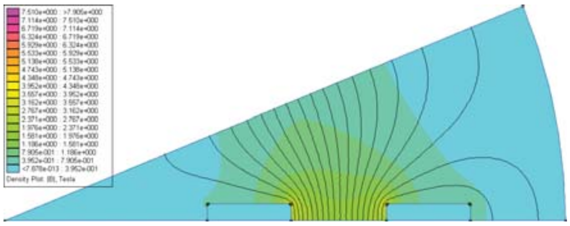

Fig. 3. Distribution of magnetic flux density for experience point P_7, 2-D FEMM, α = 0.142558, β = 0.125433.

C. Numerical simulations

The perfect diamagnetism was simulated by considering the value of relative permeability of the superconductor close to zero [13]. The value $\mu_r = 10^{-7}$ is enough small for expulsion of magnetic field from superconducting domain (Fig. 3). Based on the symmetries, the sixteen-th part of the geometry was modeled to increasing the accuracy of the results. The mesh was realized using about 30000 nodes and 60000 triangular elements.

Commands files have been created using LUA scripting language. The zero tangential component of magnetic field strength was considered for the edges forming a sharp angle and zero magnetic vector potential, for the curve edge.

The MVP-edge based formulation has been employed for the analysis of static magnetic field of the 3-D coil, using the same simulated diamagnetism. Based on the symmetries, the thirty-two-th part of the geometry was modeled [16]. Commands files have been created using APDL (ANSYS Parameter Design Language). The mesh was realized using about 500000 nodes and 400000 tetrahedral elements, being limited by hardware resources. The flux normal conditions have been considered for the sides forming a sharp angle and the flux parallel conditions, for the others (Fig. 4).

IV. Results and Conclusions

The results of the N numerical experiments are presented in Table I. The estimations of the vectors of coefficients for the two models are $\hat{\boldsymbol{\beta}}_1$ and $\hat{\boldsymbol{\beta}}_2$ (39). The results of ANOVA and the adjustment coefficients are presented in the Tables II–IV.

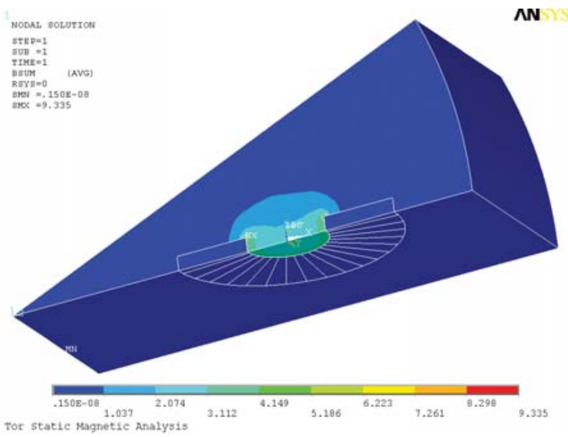

Fig. 4. Distribution of magnetic flux density for experience point P_7, 3-D ANSYS, α = 0.142558, β = 0.125433.

TABLE I.
RESULTS OF 3-D NUMERICAL EXPERIMENTS

Experience points	α	β	*depth'* [mm]
P_1	0.035000	0.024573	4.304607
P_2	0.035000	0.140000	6.332778
P_3	0.035000	0.250000	7.400906
P_4	0.196337	0.183522	32.354933
P_5	0.357674	0.087537	48.457262
P_6	0.196337	0.034660	24.789312
P_7	0.142558	0.125433	23.737578
P_8	0.088779	0.077000	13.320104
P_9	0.088779	0.187680	16.763830
P_{10}	0.250116	0.106485	36.884541

TABLE II.
ADJUSTMENT COEFFICIENTS

	Model 1	Model 2
R^2	0.987379	0.996445
R_a^2	0.983773	0.994668
$\hat{\sigma}$ [mm]	1.856123	1.063967

TABLE III.
RESULTS OF ANOVA FOR THE MODEL 1 (WITHOUT INTERACTIONS)

Source of variation	DOFs	Sum of squares [mm^2]	Mean sum of squares [mm^2]	F_{obs}
Regression	3-1=2	1886.728	943.364	273.820
Residue	10-3=7	24.116	3.445	Probability
Total	10-1=9	1910.844	212.316	0.99999977

TABLE IV.
RESULTS OF ANOVA FOR THE MODEL 2 (WITH INTERACTIONS)

Source of variation	DOFs	Sum of squares [mm^2]	Mean sum of squares [mm^2]	F_{obs}
Regression	4-1=3	1904.052	634.684	560.662
Residue	10-4=6	6.792	1.132	Probability
Total	10-1=9	1910.844	212.316	0.99999990

$$\hat{\boldsymbol{\beta}}_1 = \begin{pmatrix} -1.402 \\ 137.797 \\ 26.237 \end{pmatrix}, \quad \hat{\boldsymbol{\beta}}_2 = \begin{pmatrix} 1.093 \\ 109.919 \\ 2.816 \\ 276.340 \end{pmatrix} \tag{39}$$

In Fig. 5 and Fig. 6 are presented the linear regressions without and with interactions for depth of 2-D planar model compared to (33) and to numerical experiments. It is found that in the both cases the factor α has an important influence, as the approximation (33) suggests. The model 2 indicates a strong interaction between the factors, expecting significant variations in the directions α and β in the same time, so that using a model with interactions is justified.

The same conclusion would be given by the study of the variation of R^2 between the modes.

The probability that the variance due to the regression will be significantly different from the residues is 0.99999977 for the first model and it increases to 0.99999990 for the second. The models can be considered of best quality, since there is more than 99% chance that they explain the variations in the response.

The both models indicate an underestimation of the depth of the 2-D planar modeling and consequently, of the magnetic field energy, for SMES devices of great dimensions, when the leakage flux increases.

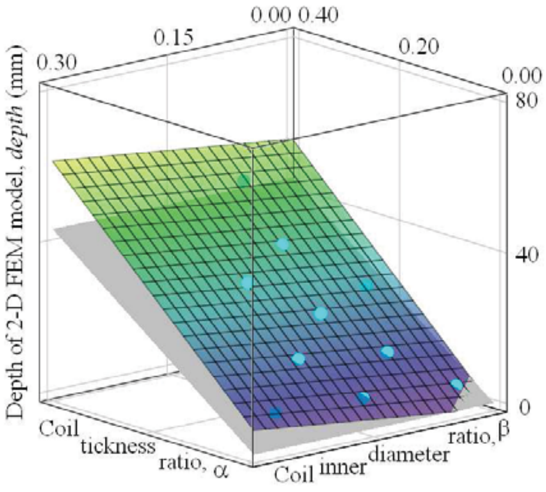

Fig.5. Depth of 2-D planar model: (33) (gray), 3-D numerical experiments (blue points) and linear regression without interactions (color).

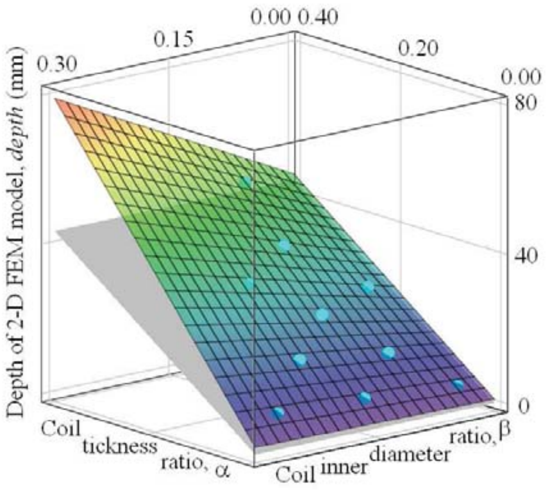

Fig.6. Depth of 2-D planar model: (33) (gray), 3-D numerical experiments (blue points) and linear regression with interactions (color).

For the lowest values of the factor α or of the factor β, the model with interactions agrees enough well with (33). The lowest values for α imply the invariance of depth parameter regardless the values of β. That means that the magnetic field energy of SMES devices of little dimensions do not depend on the coil thickness.

ACKNOWLEDGMENT

The authors thank to the Electrical Engineering Faculty of University of Craiova for the financial support.

REFERENCES

[1] D. Montgomery, "*Design and Analysis of Experiment*," 5-th Edition, Arizona State University, 2000.

[2] F. Gillon, "Modelisation et optimisation par plans d'experiences d'un moteur a commutations electronique," Ph-D Thesis, Lille, 1997.

[3] M. Caldora-Costa, "Optimisation de dispositifs electromagnetiques dans un contexte d'analyse par la methode des elements finis," Ph-D Thesis, Grenoble, 2001.

[4] S. Vivier, “Strategies d’optimisation par la methode des plans d’experiences et applications aux dispositives electrotechniques modelise par elements finis,” Ph-D Thesis, Lille, 2002.

[5] M. Shimizu, Y. Tanabe, T. Yoshioka, K. Takeda, T. Hamajima, N. Miki, Y. Nakayama, M. Udo, N. Takeda, H. Miyazaki, K. Kamemura and M. Yamamoto, “Feasibility study of a 10-GWh toroidal superconductive magnetic energy storage system 1. System design,” Physics Journal, 8th International Conference on Magnet Technology, vol. 45 (C1), pp. 581-585, 1984.

[6] Floch, A. Lacaze, Y. Laumond, J. M. Kauffmann and P. Hiebel, “Dimensionnement et réalisation d'un SMES impulsionnel de 500J,” Eur. Physical Journal Applied Physics, vol. 2, no. 1, pp. 17-25, 1998.

[7] P. Alotto, B. Brandstatter, G. Fuerntratt, Ch. Magele, G. Molinari, M. Nervi, M. Repetto and K. R. Richter, “Some Results On a SMES Device Optimization Benchmark Problem,” International Journal of Applied Electromagnetics and Mechanics, pp. 315-324, 1998.

[8] C. A. Borghi, M. Fabbri and P. L. Ribani, “Design optimisation of a microsuperconducting magnetic energy storage system,” IEEE Transaction on Magnetics, vol. 35, no.5, pp. 4275-4284, 1999.

[9] R. L. Causley, C. Cook and S. A. Gower, “Design of a high temperature superconductor magnetic energy storage system,” Proceedings of the Australasian Universities Power Engineering Conference (AUPEC-2001) – Perth, September 23 – 26, pp. 322-325, 2001.

[10] J. H. Kim, S. Y. Hahn, C. H. Im, J. K. Kim, H. K. Jung and S. Y. Hahn, “Design of 200 kJ HTS SMES system,” IEEE Transactions on Applied Superconductivity, vol. 12, no. 1, pp. 774–777, 2002.

[11] F. Stefanescu, “Systemes de Stokage de l’energy electrique,” 9th International Conference on Applied and Theoretical Electricity and 11th Symposium on Cryoelectrotechnics and Cryogenics, Craiova, October, 08-10, 2008, Annals of the University of Craiova, Series: Electrical Engineering, no.32, pp. 337-341, 2008.

[12] S. Nomura, H. Tsutsui, S. Tsuji-Iio, H. Chikaraishi and R. Shimada, “Feasibility study on high field magnets using stress-minimized helical coils,” Proceedings of the Fifteenth International toki Conference on "Fusion and Advanced Technology", vol. 81, no. 20-22, pp. 2535-2539, 2006.

[13] F. Stefanescu and A. I. Dolan, “Conceptual design of 21 kJ superconducting magnetic energy storage device,” Annals of the Univ. of Craiova, Series: El. Eng., no. 34, pp. 109-112, 2010.

[14] F. Stefanescu, “Technical and scientific report,” 4-th part of Project “Sistem supraconductor pentru stocarea energiei electrice sub formă magnetică,” PNCDI II 22113, Univ. of Craiova, 2011.

[15] F. Stefanescu, “Geometry optimization of SMES coil,” Annals of the Univ. of Craiova, Series: El. Eng., no. 35, pp. 214-218, 2011.

[16] A. I. Dolan and F. Stefanescu, “Three Dimensional Numerical Solution for Maximum Magnetic Field of 21 kJ Superconducting Magnetic Energy Storage Device,” Annals of the University of Craiova, Series: Electrical Engineering, No. 37, pp. 73-77, 2013.

[17] A. I. Dolan and F. Stefanescu, “Optimization of Modular Toroid Coil Geometry of a Superconducting Magnetic Energy Storage Device Using Design of Experiments and FEM,” 12-th International Conference on Applied and Theoretical Electricity – ICATE 2014, Craiova, October 23-25, 2014.

[18] A. I. Dolan and F. Stefanescu, “Application of two direct optimization methods on a SMES device by DOE and FEM: method by zooms and method by slidings of plans,” Annals of the University of Craiova, Series: El. Engineering, No. 38, pp. 78-85, 2014.