An Experience with Surrogate Functions on the Design of a Transcutaneous Energy Transfer System

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***Abstract*—A transcutaneous Energy Transfer (TET) is a system that uses electromagnetic fields to transfer power from outside the body to an artificial organ (AO) inside the body. In this work a systematic approach to obtain an optimal TET is proposed by using a multi-objective optimization approach that minimizes the volume and the thermal effects of the TET and takes into account the electrical constraints of the device. In order to solve the multi-objective optimization problem a Compromise Programming based criterion was adopted followed by a local constrained optimization. In order to reduce computational time, the device attributes were modeled by an alternative proposed Kriging tree model, which is a class of surrogate functions based on Kriging models from a set of data simulated by Finite Element Methods applications.**

***Index Terms*—** Optimization, Biodevices, Metamodels.

I. INTRODUCTION

A transcutaneous Energy Transfer (TET) is a system that uses electromagnetic fields to transfer power from outside the body to an artificial organ (AO) inside the body. It works similarly to a high frequency transformer, having the skin between the primary (external) and secondary (internal) coils as part of the magnetic coupling. Thus, the external coil is usually excited by an oscillator circuit that transforms the continuous (DC) voltage to high frequency alternating (AC) voltage. This part is known as transmitter system because it transfers energy to an internal system (receiver) containing a coil associated with a rectifier-regulator circuit to supply power to the AO and an internal rechargeable battery [1].

A TET system, when implanted in a patient, should be able to work in different coupling conditions such as different gaps and misalignments between the coils due to tissue thickness of the patient, localization of the surgical implantation and movements from physical activity. The TET size and weight are very important attributes due to body space availability and to minimize the patient discomfort. Finally, the heat generated by the power transfer coils must not cause damage to the surrounding tissues.

The work focused mainly on the optimal size of TET coils bearing in mind the goals and constraints

Brazilian Microwave and Optoelectronics Society-SBMO received March 2015; for review April 2015; accepted June 2015
Brazilian Society of Electromagnetism-SBMag ISSN 2179-1074

mentioned in the last paragraph. With the goal of reducing the computational processing time, a multiresponse optimization method was used together with an alternative proposed Kriging tree model which uses Kriging surrogates of attributes. The Kriging tree models were built with data obtained from simulations performed with Finite Element Method (FEM) applications [2].

The rest of the paper is organized as follows. The next section presents the surrogate modeling with Kriging. In the Section III is presented the multiresponse optimization criterion used in this work, and then Section IV explains the optimization problem and the relationship between the design variables and the attributes as well as how the Kriging tree model approach was used with FEM applications to model the attributes. The obtained results are shown in Section V. The Conclusion, in Section VI, summarizes what has been achieved, and what can be done next.

II. KRIGING

A Kriging model is an interpolation model and can be stated as follows [3]:

$$y(x) = f(x) + Z(x) \tag{1}$$

where $f(x)$, the global model, is a polynomial known function, that can be a constant β, and $Z(x)$ is the realization of a random process with mean zero, variance σ^2 and nonzero covariance to represent a local deviation from the global model. The covariance matrix of $Z(x)$ is:

$$Cov(Z(x_i), Z(x_j)) = \sigma^2 \mathbf{R}\left(R(\theta, x_i, x_j)\right) \qquad i, j = 1,2, \ldots \ldots, n \tag{2}$$

where $\mathbf{R}$ is the correlation matrix, $R(\theta, x_i, x_j)$ is the correlation function and n the number of samples. The correlation function, usually adopted, is related with the distance between the corresponding data points x_i and x_j as:

$$R(\theta, x_i, x_j) = \prod_{k=1}^{d} e^{-\theta_k\left(|x_i - x_j|_k\right)^2} \tag{3}$$

where $|\cdot|_k$ is the distance between x_i and x_j in k direction. The θ_k is the k element of the correlation vector parameter θ, and indicates the correlation between the points on direction k. A large θ_k indicates a low correlation between x_i and x_j in k direction.

The best linear unbiased predictor (BLUP) of x^*, where x^* is a new data point, is given by [3]:

$$y(x^*) = \hat{\beta}(\theta) + \mathbf{r}(x^*, \theta)\mathbf{R}(\theta)^{-1}(\mathbf{y} - \mathbf{f}\hat{\beta}) \tag{4}$$

where $\hat{\beta}$ is the estimated value of β, $\mathbf{y}$ is a $n \times 1$vector of the response sampled values, $\mathbf{f}$ is a $n \times 1$ unit vector, $\mathbf{r}$ is a $1 \times n$ vector of correlations between $x^*$and the n sampled points, whose i_{th}element is $R(x^*, x_i)$

The Maximum Likelihood Estimate (MLE) of β is:

$$\hat{\beta}(\theta) = \left(\mathbf{f}^{\mathbf{T}}\mathbf{R}(\theta)^{-1}\mathbf{f}\right)^{-\mathbf{1}}\left(\mathbf{f}^{\mathbf{T}}\mathbf{R}(\theta)^{-1}\mathbf{y}\right) \tag{5}$$

The accuracy of the prediction in x^* is expressed by the mean squared error of the predictor [4]:

$$\hat{s}^2(x^*) = \hat{\sigma}^2(\theta)\left(1 - \mathbf{r}\mathbf{R}(\theta)^{-1}\mathbf{r}^{\mathbf{T}} + \frac{1 - \mathbf{f}^{\mathbf{T}}\mathbf{R}(\theta)^{-1}\mathbf{r}^{\mathbf{T}}}{\mathbf{f}^{\mathbf{T}}\mathbf{R}(\theta)^{-1}\mathbf{f}}\right) \tag{6}$$

where the MLE of $\sigma^2$is:

  ISSN 2179-1074

$$\hat{\sigma}^2(\theta) = \frac{\left(\mathbf{y} - \mathbf{f}\hat{\beta}\right)^T \mathbf{R}(\theta)^{-1}\left(\mathbf{y} - \mathbf{f}\hat{\beta}\right)}{n} \tag{7}$$

To evaluate (4), for any x^*, is necessary to estimate the correlation parameters θ_k that can be obtained by maximizing the concentrated ln-likelihood function as:

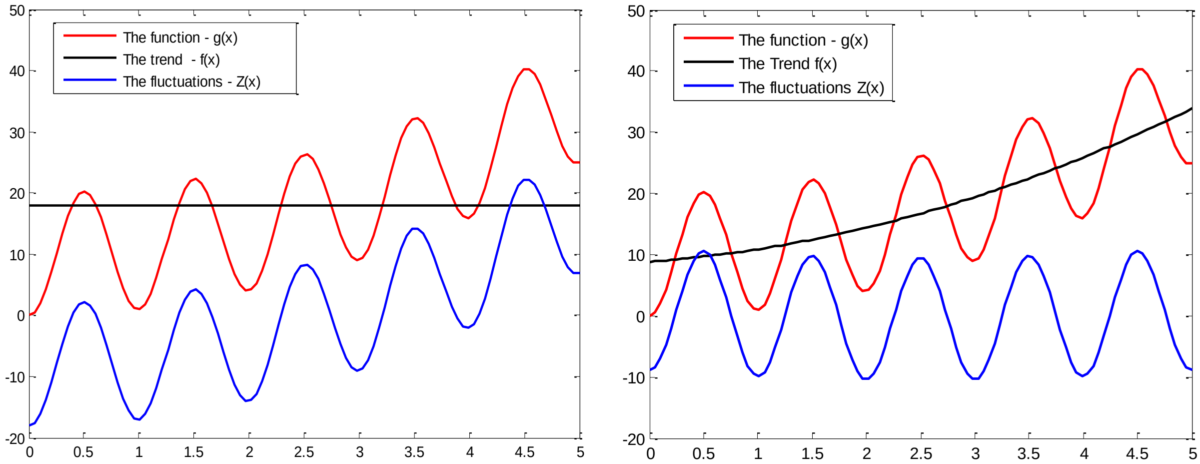
$$\max_{\theta}\left(-\frac{n}{2}\ln(\hat{\sigma}^2) - \frac{1}{2}\ln(|\mathbf{R}|)\right) \tag{8}$$

A. Universal Kriging and Ordinary Kriging

The main difference between Universal Kriging and Ordinary Kriging is in the global model, which is defined in (1) by $f(x)$. In Ordinary Kriging $f(x)$ is a constant and its Maximum Likelihood Estimate (MLE) could be obtained by using (5).

When Universal Kriging is used, the global trend $f(x)$ is a linear combination of known functions (ideally determined by the physics of the problem dealt with). If there is no precise information about this behavior, it is assumed a second order regression. In some cases this change improves the quality of the interpolation, because typically the solution of (8) is not easy. It should be emphasized that the process to determine the Universal Kriging model is straightforward: after obtaining the polynomial *f(x)*, make a Kriging interpolation of the residuals of the regression as is described in the last section.

Fig. 1a) shows the behavior of an Ordinary Kriging for the Rastringin's function in 1D, i.e., $g(x) = 10 + x^2 + 10\cos(2\pi x)$. The behavior of the Universal Kriging is depicted in Fig. 1b). With this function, which has a clear parabolic trend, it could be realized that, with Universal Kriging, it is possible to separate the trend and the fluctuations.



a) b)

Fig. 1. The Kriging for the Rastringin Function: a) Ordinary Kriging; b) Universal Kriging

In electrical engineering, when dealing with power or losses, quantities that are typically square dependents, the adoption of a Universal Kriging model could be a better choice than the Ordinary Kriging model.

III. MULTIRESPONSE OPTIMIZATION

The development of global optimization techniques is an active research field. Indeed various authors have put emphasis on the development of objective functions for multiresponse optimization problems. From methods that require very little preference information from the user, to those mathematically more elaborated that require extensive information on each objective and preferences from the decision-maker (DM), the variety and quantity are large.

The existing multiresponse optimization methods compel the DM to assign preference parameters (weights, cost coefficients, priorities, and/or shape factors) to responses. However, the setting of the values for these preference parameters is not straightforward because it depends on the DM's knowledge and problem context.

To know a priori how the responses will change, varying the preference parameters is not an easy task. However, in order to obtain satisfactory solutions choosing suitable values for these parameters is necessary. Although the DM should express his/her preferences and knowledge, methods that require less cognitive effort from the DM are more attractive.

The next section presents an approach, based on compromise programming method, for optimizing multiple responses that does not require much preference information from the DM.

A. Optimization Criterion

Compromise Programming is a mathematical programming method which has proven to be extremely effective in multiobjective optimization of convex and concave response surfaces [7], and is defined as:

$$min\, L_p = \min\left(\sum_{i=1}^{n}[\lambda_i(\hat{y}_i(x) - u_i)]^w\right)^{1/w} \tag{9}$$

where $\hat{y}_i(x)$ is the estimated response i, u_i is the ideal goal, w is a parameter that specifies a given metric and λ_i represents the priority or the relative weight of the estimated response i.

In [5] a variant of (9) that makes possible the combination of responses with different units, scale and range using a normalization method similar to the upper-lower-bound approach was proposed. In [6], this type of transformation is shown to improve the distribution of optimal solutions, although this type of transformation is not always required to obtain good solutions or to eliminate the possibility of numerical dominance of a particular response. The variant proposed in [5] is:

$$\min CP = \min \sum_{i=1}^{n}\left(\frac{|\hat{y}_i(x) - T_i|}{U_i - L_i}\right)^{w_i} \tag{10}$$

where w_i ($w_i > 0$) are shape factors, T_i is the target value for the estimated response i, and U_i and L_i are product quality control that are usually set equal to the maximum and minimum values of the responses in the experimental region, respectively. In (10), the target values for Larger the Better -type responses are set equal to the upper specification limit, and for Smaller the Better -type responses are set equal to the lower specification limit.

Brazilian Microwave and Optoelectronics Society-SBMO received March 2015; for review April 2015; accepted June 2015
Brazilian Society of Electromagnetism-SBMag ISSN 2179-1074

Using the responses weights $1/(U_i - L_i)$ instead of arbitrary preference parameters λ_i, such as in (9), has a twofold purpose. On one hand, it makes the aggregation of responses possible, which by nature have different units and considers the differences in response properties, such as scale and allowable range. On the other hand, less information is required from the DM.

The Parameters that alter the objective function curvature have a very important function in finding compromise solutions in the multiresponse optimization problems. Rather than using weighting coefficients like those represented by λ_i in (9), Messac et al [7] proved that using exponents to assign priorities to responses is an effective way to capture points in convex and nonconvex regions of Pareto frontiers. Thus, having the required flexibility to capture distributed points along the Pareto frontier is expected by varying w_i values in (10).

In [8], good results usually due to the variation of the shape factors w_i between 0.25 and 3 with increments of 0.25 units were shown for different kind of problems. The increment size and the used limits for the shape factors determine the number and quality of the solutions. Thus a sequential strategy may be adopted to specify the limits and increments for the shape factors.

The choice of the starting point or "initial guess" can affect the ability of the algorithm to find the optimum. Therefore, running the optimization algorithm using multiple starting points of the experimental design is a good practice.

IV. THE OPTIMIZATION PROBLEM

The optimization problem consists in finding the smallest TET coils that supply the required power, with the smallest *thermo factor* at the required voltage limits for a range of specified coupling situations. However, as the coil area decreases, *thermo factor* increases [9]. Thus, the interaction between objectives shows that a significant improvement in one objective may degrade seriously the other. This fact points out the intrinsic objective of multiresponse optimization problems: to identify a compromise solution among the generated responses.

A. The objective functions

The first objective function, computes the smallest TET coils volume. It is defined by the following function:

$$\hat{y}_1 = \sqrt{Vol_1^2 + Vol_2^2} \tag{11}$$

In (11), Vol_i is the volume of coil i and depends on the project variables given by the number of turns (N_i) and the wire gauge in AWG (AWG_i) for $i = 1,2$, respectively the outside coil and inside coil. In the objective function, the same weight was given to both volumes because with this weight choice the volumes will be small and similar.

The other objective function determines the smallest *thermo factor*. It is given by:

$$\hat{y}_2 = \sum_{j=1}^{6} \sqrt{\lambda_{1,j}^2 + \lambda_{2,j}^2} \tag{12}$$

  ISSN 2179-1074

The variable $\lambda_{i,j}$, in (12), is the *thermo factor* of coil *i* and the subscript *j* represents the coil gap given by one of the 6 different gaps at which the TET could be placed (4, 8, 12, 16, 20 and 25 mm).

The *thermo factor* is a ratio between the dissipated power and area of the coil. It depends on all the project variables (source voltage *V*, frequency *Fr*, coils number of turns N_i, and coils gauges AWG_i). It also changes with the gap between the coils:

$$\lambda_{i,j} = \frac{R_i\, I_{i,j}^2}{S_i} \tag{13}$$

where S_i and R_i are respectively the surface area and the Joule loss resistance of the coil *i* (*i* = 1 and 2 for external and internal coil, respectively), and $I_{i,j}$ is the current of the coil *i* when simulated with the coil gap corresponding to *j*. This *thermo factor* represents the temperature increase in the coils, since the computation of the temperature is not an easy task.

In order to obtain the optimum of this multiresponse problem, the responses (11) and (12) were grouped in the *CP* function:

$$CP = \left(\frac{|\hat{y}_1(x) - T_1|}{U_1 - L_1}\right)^{w_1} + \left(\frac{|\hat{y}_2(x) - T_2|}{U_2 - L_2}\right)^{w_2} \tag{14}$$

The maximum and minimum values of the responses in the experimental region were estimated with the following results: $U_1 = 4.7580 \times 10^{-4}$, $L_1 = 4.6580 \times 10^{-7}$, $T_1 = 4.6580 \times 10^{-7}$, $U_2 = 3.1050 \times 10^6$, $L_2 = 0.0059$, $T_2 = 0.0059$.

To provide the power required by the AO, without exceeding the electronic circuit limits, the following constrains must be fulfilled for all the coil gaps, *j* = 1, … , 6:

$$\begin{cases} g_{1,j} = 13 - P_{2,j} < 0 \\ g_{2,j} = \ 8 - V_{2,j} < 0 \\ g_{3,j} = V_{2,j} - 28 < 0 \\ g_{4,j} = V_{0,j} - 30 < 0 \end{cases} \tag{15}$$

The first constraint ($g_{1,j}$) arises from the fact that the load power P_2 must be bigger than the required power (13 W) at any coil gap *j*, because the AO should be driven by a 13 W DC motor that requires constant supply voltage of 15 V. A regulator that has to be inserted between the AO and the internal coil, has an input voltage, V_2, that should be neither less than 8 V nor more than 28 V to maintain the output voltage of 15 V constant, as well as his reliability and durability. That is the reason of the constraints $g_{2,j}$ and $g_{3,j}$. The last constraint ($g_{4,j}$) states that the no-load voltage, V_0, at the output of the internal coil should not exceed the voltage of 30 V, which is the maximum peak voltage that the regulator accepts for very short time.

B. The Responses/Attributes models

Several Kriging surrogate models are adopted to approximate the relationship between the design variables and the attributes/responses that are needed to solve the presented optimization.

The design variables as well as their boundaries are presented in Table I.

TABLE I. DESIGN VARIABLES AND THEIR LIMIT VALUES

Design Variables	Min value	Max value
Frequency - *Fr*	53250 Hz	426000 Hz
External Coil Number of turns - N_1	31 turns	248 turns
External Coil AWG number - AWG_1	16	26
Internal Coil Number of turns - N_2	12 turns	96 turns
Internal Coil AWG number - AWG_2	20	32
Distance between coils	4 mm	25 mm

The source voltage V_1, that could be a variable, was set to 30 V in this study. The distance between coils (coil gaps) will be considered as a perturbation variable.

The **responses/attributes** that are needed for the objective functions and the constraints are:

- Load Power (W) - $P_{2,j}$
- Load Voltage (V) - $V_{2,j}$
- Load Current (A) - $I_{2,j}$
- Source Current (A) - $I_{1,j}$
- No-load Voltage (V) - $V_{0,j}$
- External Joule loss resistance (Ω) - R_1
- Internal Joule loss resistance (Ω) - R_2.

Where once more, the subscript *j* corresponds to the coil gap at which the TET was positioned (4, 8, 12, 16, 20 and 25 mm).

C. Simulation on FEM Software

These responses/attributes change according to the specification of the TET, i.e. they depend on the transmission frequency, gauge of the wire and the number of turns and layers of the external and internal coils.

The FEM software Gmsh [10] and its FEM equations simulated by GetDP [11] allow the connection between the electromagnetic geometry and the electric circuit with an easy interface to Matlab.

These two pieces of FEM software were supplied with coils configurations of different combinations of transmission frequency, gauge of the wire and the number of turns and layers of the external and internal coils.

In order to reduce the simulation time, the homogenization method was used in a 2D axisymmetric problem as proposed in [12] with the geometry shown in Fig. 2. In this figure, the external and internal coils are shown as only a massive box, but the homogenization method ensures that each turn of the each coil is simulated as stranded. The extra lines in the material “Air” in Fig. 2 were inserted only to improve the mesh quality.

Brazilian Microwave and Optoelectronics Society-SBMO received March 2015; for review April 2015; accepted June 2015
Brazilian Society of Electromagnetism-SBMag ISSN 2179-1074

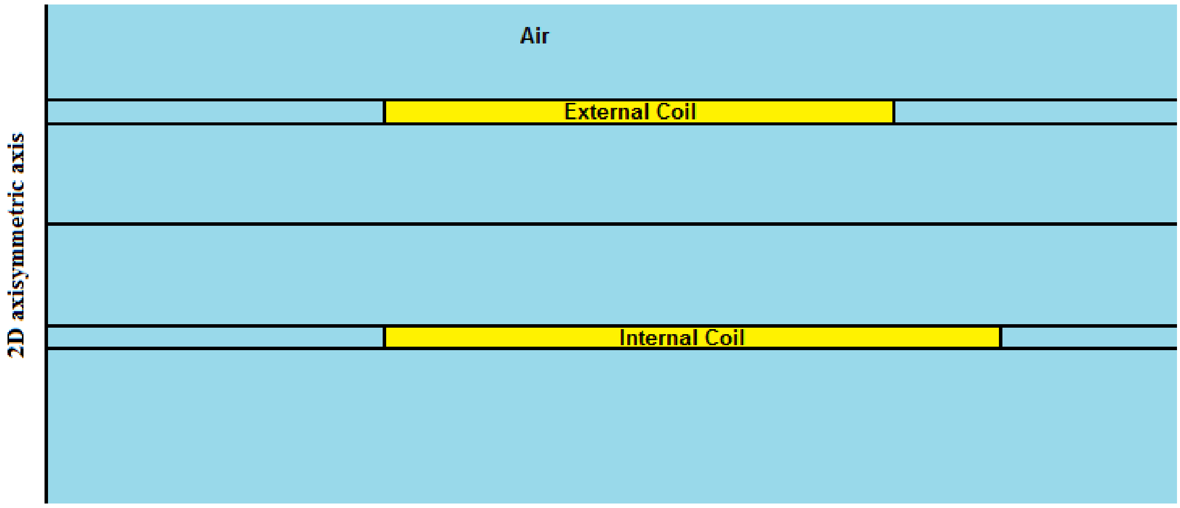


Fig. 2. Geometry used to simulate the TET through MEF.

In this way, for each configuration, the transmission system was modeled by a sinusoidal power supply connected to the external coil. And the behavior of the receiving system composed of the regulator and AO was modeled as a resistance that has its value according to the supplied voltage, consuming always the same power, as proposed in [1].

Then, for each simulated configuration, the external and internal coil Joule loss resistances were collected along with the respective no-load voltage, source current and load power, voltage and current at each coil gap given for the specific load resistance value calculated by the algorithm proposed in [1].

It is noteworthy that not all simulated configurations are able to provide the required power of 13 W. Thus, in case the simulated TET configuration had not enough power to supply the required power, the collected load power, voltage and current and source current were entailed for the resistance value that implies the maximum power that the configuration could supply.

The optimization done in the previous works [1] and [2] (without Kriging models) had to run at least 4105 configurations before getting into the final Pareto optimum. If another optimization process with different constraints or objective functions would be needed, thousands of additional configurations would need to be run again. Running all this configurations with FEM takes a lot of time even using the homogenization method to speed up the process.

Using the Kriging technique also has computational cost, since it involves three different steps:

- first, the pool of data is created through FEM simulations;
- second, the surrogate models are obtained by using the pool of data;
- third, the final solutions are obtained by running the optimization process with the surrogate models.

Even though the Kriging model technique requires an initial computational cost to run the first two steps of the method, these steps are no longer necessary to get additional optimization solutions (third step), e.g. with different constraint values. Then, simulating other configurations with FEM again would not be necessary. For this reason, the use of Kriging models contributes to the optimization process.

D. Modeling the responses and Attributes with Kriging

The TET problem with the Kriging models was similarly approached in [13] using 1024 simulations from FEM applications in its data base input. In order to improve the quality of the model, in this paper, 3125 simulations from FEM applications were used.

Moreover, while analyzing the nature of the TET problem, it was observed that the simulation data contains a set of configurations able to supply the required power that are very well correlated among each other but not as well correlated with the configurations unable to supply the required power. In the same way, the configurations unable to supply the required power have better correlation among each other than with the configurations able to supply the required power. Hence, the TET problems can be divided in two groups with different behaviors depending on the maximum power that the configuration can transmit:

1. Group 1 contains configurations which cannot supply the required power and the result data were given for the maximum power that the configuration could supply;

2. Group 2 contains configurations which can supply the required power and the behavior data are given at this specific power, regardless of the maximum power that they can transmit.

As already mentioned, the load power depends on whether the configuration can supply the required power. In addition, the power that can be supplied is not originally known and thus, it is an output that should be also modeled.

For this reason, an alternative Kriging tree model for TET problems was proposed in this paper. This proposed model uses two sets of Kriging models to create a final model for each response/attribute. In this case, regardless of the attribute that will be modeled, the load power model for Group 1 (P') must be initially calculated. Based on the resulting value of this selection model, either Group 1 or Group 2 is used to compute the final model for the desired variable.

Following this concept, a procedure to create the two sets of Kriging models should be as follows:

1. Divide the simulated data set into the two mentioned groups;

2. Generate Kriging models for load voltage, current, power, source current, no-load voltage and external and internal coil Joule loss resistance for Group 1 ($P_{2,j}'$, $V_{2,j}'$, $I_{2,j}'$, $I_{1,j}'$, $V_{0,j}'$, R_1', R_2') and Group 2 ($P_{2,j}''$, $V_{2,j}''$, $I_{2,j}''$, $I_{1,j}''$, $V_{0,j}''$, R_1'', R_2'');

3. The final Kriging model for load power ($P_{2,j}$) is then created with the two models for load power ($P_{2,j}'$, $P_{2,j}''$) and the required power (P_{req}):

$$P_{2,j} = \begin{cases} P_{2,j}', & P_{2,j}' < P_{req} \\ P_{2,j}'', & P_{2,j}' \geq P_{req} \end{cases} \tag{16}$$

4. The final Kriging models for load voltage and current ($V_{2,j}$, $I_{2,j}$), source current ($I_{1,j}$), no-load voltage ($V_{0,j}$) and external and internal Joule loss resistances (R_1, R_2) are then created for each gap with the two respective models, the estimated power ($P_{2,j}'$) and the required power (P_{req}):

Brazilian Microwave and Optoelectronics Society-SBMO received March 2015; for review April 2015; accepted June 2015
Brazilian Society of Electromagnetism-SBMag *ISSN 2179-1074*

$$V_{2,j} = \begin{cases} V_{2,j}{}' , & P_{2,j}{}' < P_{req} \\ V_{2,j}{}'' , & P_{2,j}{}' \geq P_{req} \end{cases} \tag{17}$$

$$I_{2,j} = \begin{cases} I_{2,j}{}' , & P_{2,j}{}' < P_{req} \\ I_{2,j}{}'' , & P_{2,j}{}' \geq P_{req} \end{cases} \tag{18}$$

$$I_{1,j} = \begin{cases} I_{1,j}{}' , & P_{2,j}{}' < P_{req} \\ I_{1,j}{}'' , & P_{2,j}{}' \geq P_{req} \end{cases} \tag{19}$$

$$V_{0,j} = \begin{cases} V_{0,j}{}' , & P_{2,j}{}' < P_{req} \\ V_{0,j}{}'' , & P_{2,j}{}' \geq P_{req} \end{cases} \tag{20}$$

$$R_1 = \begin{cases} R_1{}' , & P_{2,j}{}' < P_{req} \\ R_1{}'' , & P_{2,j}{}' \geq P_{req} \end{cases} \tag{21}$$

$$R_2 = \begin{cases} R_2{}' , & P_{2,j}{}' < P_{req} \\ R_2{}'' , & P_{2,j}{}' \geq P_{req} \end{cases} \tag{22}$$

Five different values, for each design variable, were used to train the 64 Kriging surrogate models of the responses (32 models for all the attributes at each group 1 and 2). Besides the Max and Min values of the Table I, the other design variable values are: 106500, 160000, 213000 for *Fr*; 62, 93, 124 for N_1; 19, 22, 24 for AWG_1; 24, 36, 48 for N_2; 26, 26, 29 for AWG_2. The responses were generated by the mentioned FEM applications. With the function values of 3125 simulations for each response, the Kriging models were constructed using the isotropic version ($d = 1$) of the correlation function (3).

For further details on the subject of this and of the previous section, please refer to [2].

V. Results

An algorithm was developed to generate compromise solutions with the CP criterion varying the shape factors (w_i) between zero and three in steps of 0.25. This is equivalent to solve several constrained mono-objective problems with 24 different constraints.

The CP criterion is a function of the TET Volume and of the *thermo factor* that is defined in (12). The *thermo factor* is computed using some surrogate functions (resistance and current) at each coil gap. Nevertheless, there are several constraints to take into account: the no-load voltage, the load voltage, and the power on the load. All those Kriging models were aggregated to solve a constrained mono-objective problem with 24 different constraints.

The optimization main challenge is to find a feasible solution that is at the same time a non-dominated one. Fig. 3 shows the obtained non-dominated solutions whose values are reported in Table II.

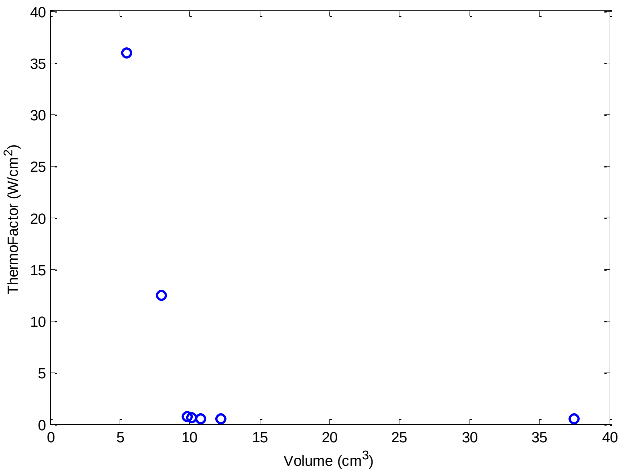


Fig. 3. The Obtained Pareto Set

TABLE II. THE NON-DOMINATED SOLUTIONS AND THE FUNCTION VALUES

N₁ (turns)	***AWG₁*** (AWG)	***N₂*** (turns)	***AWG₂*** (AWG)	***Fr*** (Hz)	***Volume*** (cm^3)	***Thermo Factor*** (W/cm^2)
101	22	22	21	76998	12.19	0.4604
92	22	25	24	80739	10.10	0.5917
90	22	24	24	80908	9.788	0.6526
49	19	14	29	91701	7.936	12.4691
95	22	31	26	81240	10.76	0.5140
67	16	22	24	101305	37.49	0.4596
40	19	13	28	92117	5.474	35.8922

The number of non-dominated solutions is low but this characteristic was also observed in [1] and [2], when a similar problem was solved without the use of surrogate functions.

A. Improving the Thermo Factor

The design of TET System, as proposed here, has a very interesting characteristic: the *thermo factor* depends on all the design variables but the volume is a function of only four design variables. As the frequency does not have an influence on the volume, a sub-problem can be analyzed: for a prescribed volume, i.e., for a prescribed set of values $[N1\ AWG1\ N2\ AWG2]$, is it possible to decrease the *thermo factor*?

Thus, a local constrained optimization was written to minimize the *thermo factor* by varying only the frequency as follows:

$$\begin{cases} \min_{\mathrm{Fr}} \left(\sum_{j=1}^{6} \sqrt{\lambda_{1,j}^2 + \lambda_{2,j}^2} \right) \\ \qquad g_{1,j} = 13 - P_{2,j} < 0 \\ \mathrm{s.t.} \quad g_{2,j} = 8 - V_{2,j} < 0 \\ \qquad g_{3,j} = V_{2,j} - 28 < 0 \\ \qquad g_{4,j} = V_{0,j} - 30 < 0 \end{cases} \tag{23}$$

The volume will not change since the frequency is the only design variable that is used. The constraints of (23) are the same of the original problem. Table III shows the results for some non-dominated solutions.

TABLE III. SOME NON-DOMINATED SOLUTIONS AND THE FUNCTION VALUES AFTER THE LOCAL IMPROVEMENT

N_1 (turns)	AWG_1 (AWG)	N_2 (turns)	AWG_2 (AWG)	*Fr* (Hz)	*Volume* (cm^3)	New *Thermo Factor* (W/cm^2)
92	22	25	24	83286	10.10	0.5266
90	22	24	24	86379	9.788	0.5207
49	19	14	29	98360	7.936	11.3680
95	22	31	26	83416	10.76	0.5042
67	16	22	24	110868	37.49	0.4128

The results show that, with a fine tuning of the frequency value, achieving better *thermo factor* values is possible without penalizing the volume.

VI. CONCLUSION

A transcutaneous Energy Transfer system uses electromagnetic fields to transfer power from outside the body to an artificial organ inside the body. Its main constraints relate with the need to be small, light, and have tolerance to coil misalignments, besides the heat generated by the power transfer coils, which must cause no damage to the surrounding tissue.

A Surrogate Based Optimization was performed in this work to define the smallest TET coils that supply the required power, with the smallest *thermo factor*, at the required voltage limits for a range of specified coil gaps (perturbations to the system). A multiresponse optimization method [5], based in Compromise Programming, was used since the optimization main objectives were in competition. In order to further refine the obtained solutions, a local constrained optimization was used to improve the *thermo factor* without penalize the volume by using only the frequency as a design variable.

Several Kriging surrogates were used to model the relationships between the design variables and the attributes/responses. The Universal Kriging model appears as a good alternative to model a Transcutaneous Energy Transfer system due to its ability to well model the trend of the data. Surrogates functions are welcome to the design of this kind of devices particularly in the first steps of the design process, when many parameters are unknown and they should fulfill several constraints.

Due to the nature of the TET problem, the standard Kriging model was improved by the proposed alternative Kriging tree model that uses two sets of standard Kriging models similarly to a tree with two branches. Thus, 64 Kriging models were created from the configurations simulated by the FEM applications in order to model 32 attributes based on 5 different parameters.

It was observed that, although the optimization based on Kriging models requires an initial computational cost, the proposed technique can be a good option to decrease the computational cost (when compared with optimizations using FEM) mainly when is necessary to test different sets of constraints and of objective functions.

Brazilian Microwave and Optoelectronics Society-SBMO *received March 2015; for review April 2015; accepted June 2015*
Brazilian Society of Electromagnetism-SBMag *ISSN 2179-1074*

ACKNOWLEDGMENT

The authors would like to thank FAPESP under grant 11/18341−3, CNPq under grant 309350/2012 – 3 and Universidade de São Paulo, São Paulo, Brazil, under Grant 2012.1.2384.3.9.

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  ISSN 2179-1074