Fast Parameter Optimization of Large-Scale Electromagnetic Objects Using DIRECT with Kriging Metamodelling

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Abstract—With the advent of fast methods to significantly speed up numerical computation of large-scale realistic electromagnetic (EM) structures, EM design and optimization is becoming increasingly attractive. In recent years, genetic algorithms, neural network and evolutionary optimization methods have become increasingly popular for EM optimization. However, these methods are usually associated with a slow convergence bound and, furthermore, may not yield a deterministic optimal solution. In this paper, a new hybrid method using Kriging metamodelling in conjunction with the divided rectangles (DIRECT) global-optimization algorithm is used to yield a globally optimal solution efficiently. The latter yields a deterministic answer with fast convergence bounds and inherits both local and global-optimization properties. Three examples are given to illustrate the applicability of the method, i.e., shape optimization for a slot-array frequency-selective surface, antenna location optimization to minimize EM coupling from the antenna to RF devices in automobile structures, and multisensor optimization to satisfy RF coupling constraints on a vehicular chassis in the presence of a wire harness. In the first example, DIRECT with Kriging surrogate modeling was employed. In the latter two examples, the adaptive hybrid optimizer, superEGO, was used. In all three examples, emphasis is placed on the speed of convergence, as well as on the flexibility of the optimization algorithms.

Index Terms—Coupling, DIRECT optimization algorithm, electromagnetic compatibility (EMC), electromagnetic interference (EMI), finite element boundary integral (FE–BI), frequency-selective surface (FSS), Kriging metamodeling, Kriging surrogate modeling, multilevel fast multipole moment method (MLFMM), superEGO.

I. INTRODUCTION

RECENT developments on fast algorithms, such as the multilevel fast multipole method (MLFMM) [15]–[17] and the hybrid finite-element boundary-integral method [18], [19], have allowed for significant reduction in CPU time while retaining geometrical adaptability and material generality. This makes the application of design optimization a realistic possibility. Previous work in RF design (antennas, RF circuits, etc.) has primarily focused on optimizing specific problems [2] and involved the use of evolutionary schemes, like genetic algorithms (GAs) [1]–[3], least squares optimization, and physically modeled processes like simulated annealing (SA) [4], [5].

The GA is a relatively robust stochastic global-optimization algorithm modeled after the Darwinian process of natural selection to produce the best-fit design. As such, it lacks efficiency in its optimization routine and requires typically hundreds or thousands of solver evaluations. In addition, the tuning parameters involved in using a GA, such as population size, crossover, mutation operators, and the fundamental aspects of natural selection (by using random numbers to do the mutation crossovers), causes GAs to yield possibly nonconclusive solutions. This is not necessarily bad, as it may allow the GA to find an acceptable solution, albeit within a longer time frame. In practice, different runs with a GA would yield different answers and a measure of luck is involved in producing the optimal solution.

SA is also a stochastic global-optimization algorithm that models the physical process of annealing, defined as a thermal process for obtaining low-energy states of a solid in a heat bath. In SA, the objective function is analogous to temperature. The solid is heated until it begins to melt (a high objective function) to a liquid. Following this, the temperature is allowed to cool and the particles in the liquid arrange themselves randomly. In SA, crystallization of the liquid occurs when the temperature is sufficiently cool and this is referred to as the ground state of the solid. The ground state is analogous to the global minimum solution and the current state of the thermodynamic system is analogous to the current iterate. To achieve the ground state (the optimum solution), the starting temperature must be sufficiently high (large objective function) and cooling has to be sufficiently slow. Thus, SA suffers from the same drawbacks as the GA in that convergence is slow and the optimized solution is not always repeatable. In addition, the performance of SA depends

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on proper initialization of program parameters used within SA. The difficulty of finding suitable parameters values is a weakness of the GA and SA.

In this paper, we propose two hybrid global-optimization schemes that converge quickly and yield a deterministic optimized solution. The first method involves use of the DIRECT global optimizer in conjunction with Kriging surrogate modeling. In comparison, the second method (i.e., superEGO) uses the DIRECT global optimizer to predict a candidate optimal solution by solving an auxiliary problem based on a Kriging metamodel. In the second method, the Kriging metamodel is adaptively improved and updated by each simulation iteration that does not meet the termination criteria according to some infill sampling criteria (ISC). Both of these hybrid schemes involve use of Kriging [8]–[12] to interpolate between data points and employ the divided rectangles (DIRECT) as the global optimizer. The DIRECT algorithm [13], [14] is a derivative-free global algorithm that reaches a deterministic solution and does not require selecting values for any parameters. In addition, DIRECT has the added benefit of possessing both local and global-optimization properties. Hybridizing the DIRECT search algorithm with Kriging metamodel parameters produces an efficient global optimizer that converges quickly. These attributes make the proposed hybrid optimizer ideal for optimizing complex large-scale electromagnetic (EM) structures within an acceptable time frame.

The theory and pertinent aspects of Kriging metamodeling and the DIRECT optimizer are explained in Section II. In Section III, we apply the proposed hybrid optimizer consisting of DIRECT with Kriging surrogate modeling to optimize the size of a slot-array frequency-selective surface (FSS) with respect to a pre-specified reflection coefficient and bandwidth. For this example, Kriging surrogate modeling is applied to the problem whereby the entire design space is split into a finely sampled mesh and the analyzer code is applied to each separate point to create the Kriging model. In this instance, the EM modeling tool is the hybrid FE–BI method. In Section IV, we employ the adaptive hybrid optimizer algorithm to solve an auxiliary problem, constructed with Kriging metamodeling in conjunction with the DIRECT global optimizer (superEGO). For this example, the Kriging metamodel is initially created using a sparse number of points. Furthermore, this metamodel is continually updated using the current data point for each optimization iteration that does not satisfy the termination criteria. Also, the flexibility of the hybrid optimizer is improved by allowing DIRECT to optimize on other ISC. This allows the user to change the emphasis the optimizer places on a local versus global search. As an application, this hybrid optimizer is used to optimize the antenna position on an automobile (Section V). The antenna location on the automobile is selected to minimize EM coupling on the chip pins housed within a resonant cavity in the automobile. In Section VI, the same optimization scheme is applied to determine the maximum allowed excitations that can be applied at ports of a harness (running over the floor of the automobile body) given the maximum allowable interference to an FM antenna printed on the back glass of the automobile.

II. OPTIMIZATION METHODS—KRIING AND DIRECT

Gradient-based optimization algorithms such as sequential quadratic programming (SQP) and generalized reduced gradient (GRG) have fast convergence rates. However, they require information on the gradients of the objective functions with respect to all design variables at each iteration step. For a large problem with many variables, the process of evaluating these gradients numerically at each iteration step is computationally expensive. Furthermore, gradient-based algorithms find only local minima within the problem domain and the final optimized solution may depend on the starting point specified for the search process if multiple optima exist. On the other hand, gradient-free optimization methods rely primarily on the objective function values and are suitable for problem domains either with many design variables or fewer design variables, but with computationally expensive objective functions. Some of these algorithms have the desirable properties of being able to sift through multiple local minima to achieve a more optimal solution. However, since global algorithms sift the entire search space, their convergence rate tends to be rather slow, usually in the hundreds or thousands of solver iterations. Also, they cannot deal with a large number of design variables efficiently.

The interaction between the optimizer and EM analyzer code can be seen in Fig. 1. Overall convergence depends on both the convergence rates of the optimizer, as well as the analyzer. Our aim in this paper is to use an efficient global optimizer that utilizes a statistical model in its search for a global minimum solution and is also capable of exhibiting local searching properties. As is essential, a fast EM solver is employed to design large-scale EM structures. The statistical model is derived from Kriging interpolation metamodeling and DIRECT is used as the global-optimization algorithm.
A. Kriging Interpolation Metamodeling

Interpolation among the sampled data points can be accomplished using polynomial fitting or least squares fit. However, for a relatively higher order polynomial, this method exhibits a highly oscillatory curve-fitting function at some locations between the sampled data points. This may manifest itself if there is a large number of data points available for fitting. On the other hand, Kriging interpolation functions and neural networks exhibit much less oscillation and have been shown to provide better fitting in multidimensional domains. Kriging is a special form of interpolation function that employs the correlation between neighboring points to determine the overall function at an arbitrary point. The concept of utilizing Kriging as interpolation functions originated in the 1950s, where it was first used to analyze mining data [10]. Consider the following decomposition for a single dimension:

\[ Y(x) = f(x) + \varepsilon(x) \]  

where \( Y(x) \) is a random variable on the \( x \)-parameter. \( Y(x) \) is the interpolated point via Kriging corresponding to the true function \( f(x) \) with \( \varepsilon(x) \) denoting the error deviation of the predicted value \( Y(x) \) from the true function \( f(x) \). Polynomial and least squares interpolation function regards \( \varepsilon(x) \) as independent. However, Kriging metamodels consider the errors in the predicted values as dependent values and are modeled as a zero-mean Gaussian process. With this in mind, for a \( k \)-th dimension problem, (1) can be written as

\[ Y(\mathbf{x}) = f(\mathbf{x}) + \varepsilon(\mathbf{x}) = \sum_{j=1}^{k} \beta_j f_j(\mathbf{x}) + Z(\mathbf{x}) \]

where \( f_j(\mathbf{x}) \) are the basis functions, \( \beta_j \) are the corresponding coefficients, and \( Z(\mathbf{x}) \) is the zero-mean Gaussian-distributed error function that models the deviation from \( Y(\mathbf{x}) \). The covariance of the error function is, in turn, modeled as

\[ \text{Cov}(Z(\mathbf{w}), Z(\mathbf{x})) = \sigma^2 \ R(\mathbf{w}, \mathbf{x}) \]

\[ R(\mathbf{w}, \mathbf{x}) = \prod_{d=1}^{k} e^{-\theta_d |w_d - x_d|^p} \]

in which \( \sigma^2 \) is a scale factor known as the process variance that can be tuned to fit the given data and \( R(\mathbf{w}, \mathbf{x}) \) is the spatial correlation function (SCF). The vector \( \mathbf{w} \) refers to the vector of given neighboring data points with respect to the vector \( \mathbf{x} \), which refers to the stationary data point in the \( k \)-th dimension. The value of \( \theta^p \) in (4) relates to the influence of the surrounding data points on the predicted point, with larger values indicating a smaller degree of influence and, thus, a weaker covariance value. Finally, the \( p \)-parameter in (4) determines the continuity of the function and the superscripts \( d \) in (4) refers to one of the \( k \) dimensions in the multidimensional model. The covariance and SCF \( R \) increases in complexity with respect to the number of design variables. The basis functions \( f_j(\mathbf{x}) \) are chosen to be an \( n \)-th order polynomial function and by default are set to a linear function. Before the application of the Kriging algorithm, the values of \( \sigma^2, \theta, \beta_j, \) and \( p \) are determined from an auxiliary optimization problem where the difference between the function values of the predicted and the given data points is minimized (maximum-likelihood estimation). For this, gradient-based SQP, sequential linear programming (SLP), and any other optimization algorithms can be used. The DIRECT algorithm is employed in our implementation. This process is referred to as “fitting” and is essential for constructing the Kriging metamodel. An example comparing a Kriging approximated function with that of the true function for a specified number of data points for a well and badly fitted model is shown in Fig. 2. In the case of sample A, either a better fit of the Kriging parameters has to be obtained or more data samples are required. The reader interested in more details of Kriging is referred to the literature [8]–[10].

B. DIRECT Algorithm

The DIRECT optimization algorithm is a derivative-free global algorithm that yields a deterministic and unique solution. Its attribute of possessing both local and global properties makes it ideal for fast convergence. An essential aspect of the DIRECT algorithm is the subdivision of the entire design space into hyper-rectangles or hyper-cubes for multidimensional problems. The iteration starts by choosing the center of the design space as the starting point. Subsequently, at each iteration step, DIRECT selects and subdivides the set of hyper-cubes that are most likely to produce the lowest objective function. This decision is based upon the Lipschitzian optimization theory, specifically the manipulation of the Lipschitzian constant. Mathematically, the Lipschitzian constant \( K \) satisfies the relation

\[ |f(x_1) - f(x_2)| \leq K ||x_1 - x_2||, \quad x_1, x_2 \in \text{domain } R \]

where \( x_1 \) and \( x_2 \) lie within the entire design space and \( f(x) \) refers to the objective function for the optimization problem. The Lipschitzian function finds the global minimum point provided the constant \( K \) is specified to be greater than the largest rate of change of the objective function within the design space and that the objective function value is continuous. Within DIRECT, all possible values of the Lipschitzian constant \( K \) are
used with the larger values of $K$ chosen for global optimization (to find the basin of convergence of the optimum) followed by smaller values of $K$ for local optimizations within this basin of convergence. As mentioned above, DIRECT divides the domain into multiple rectangles at each iteration. Thus, the convergence process is greatly sped up and the optimization algorithm achieves both local and global searching properties.

An illustration of a one-dimensional optimization by DIRECT is shown in Fig. 3. At the first iteration, DIRECT samples the center of the design space, subdivides the domain into two, and samples at the centers of the sub-domains during the next iteration. The domain with the lower sampled objective function value is further subdivided and the center points within the new sub-domains are further sampled. This is repeated until the termination criterion (usually the maximum number of iterations) has been met. Such a global process of subdividing the domains and sampling at their centers is mathematically guaranteed to obtain the optimum solution in the limit provided the Lipschitzian constant is chosen to be greater than the largest gradient of the objective function. In choosing from all possible values for this constant, DIRECT has sufficient resolution to capture the largest change of the objective function gradient to obtain the most optimal point. The multidimensional optimization process of the DIRECT algorithm can be easily extended from this one-dimensional example. Fig. 4 shows DIRECT optimization in two dimensions. This is summarized by the following steps.

Step 1) Begin at center of the user-supplied bounds of design space.
Step 2) Divide the design space (into three rectangles in Fig. 4).
Step 3) Evaluate the centers of new rectangles.
Step 4) Use the Lipschitz constant to select which boxes will be further divided.
Step 5) Go back to Step 2 until the maximum number of function evaluations is reached or the termination criterion has been met.

For further information on DIRECT, the reader is referred to the literature [13], [14].

III. APPLICATION 1—FSS OPTIMIZATION

As a first application, the hybrid DIRECT optimizer (with Kriging surrogate modeling) is applied to optimize the size of the slot-array FSS to achieve a pre-specified reflection coefficient passband. For this example, a design of experiments is carried out over the entire design space (evaluated with small perturbations in the variables) to create the Kriging surrogate model. This Kriging model approximation then replaces the analyzer code to obtain a good design efficiently. The Kriging surrogate model is, in turn, applied to both the DIRECT global optimizer and to the gradient-based SQP. The analysis code, for this example, is a well-validated hybrid FE–BI solver algorithm and the overall objective function $F$ is defined as

$$F = \sum_{i=1}^{N} w_i |\Gamma_{in,i}|^2 + \sum_{j=1}^{M} w_j |\Gamma_{in,j} - 1|^2.$$  (6)

This objective function $F$ is a sum of the 10-dB reflection coefficients of the FSS both within ($|\Gamma_{in,i}|$) and outside ($|\Gamma_{in,j} - 1|$) the passband region, where $w_i$ and $w_j$ refer to the weights for the $i$th in-band and $j$th out-of-band frequency components, respectively.

The geometry for the slot-array FSS is given in Fig. 5. For this optimization problem, there are four design variables, two of which pertain to the size of the unit cell for the FSS and...
two other variables relating to the physical size of the slot. In addition, the optimization process must satisfy four inequality constraints, which relate to the physical constraints of the slot-array FSS. These are

\[ g(1) = \text{unit } x - 1.2 \leq 0 \]  
\[ g(2) = \text{unit } y - 1.2 \leq 0 \]  
\[ g(3) = x - \text{unit } x + \text{FEM}_\text{mesh}_\text{size} \leq 0 \]  
\[ g(4) = y - \text{unit } y + \text{FEM}_\text{mesh}_\text{size} \leq 0. \]

The variables unit \( x \) and unit \( y \) relate to the size of the unit cell of the FSS. The thickness of the FSS substrate \( t \) is fixed at 1.0 cm and the size of the unit cell for the FSS is limited to within 1.2 cm. The designed 10-dB reflection-coefficient bandwidth of the FSS is from 10.7 to 11.3 GHz centered at 11.0 GHz.

Surface mapping of the objective function \( F \) via Kriging with respect to the two variables pertaining to the size of the slot (the other variables held constant) is shown in Fig. 6. This is a highly wrinkled surface with the presence of multiple local minima. As can be expected, the presence of the valley of local minima causes gradient-based algorithms to perform poorly. Indeed, when SQP was applied to this Kriging surrogate model, a large number of local optima were obtained for different starting points. Different starting points characterized by gradient-based SQP algorithms.

Fig. 6. Residual surface mapping of the Kriging metamodel with two variables.

In contrast, when DIRECT is applied to this Kriging surrogate model, after 112 iterations, the following optimized variables were obtained: \( x = 0.0995 \) cm, \( y = 0.9243 \) cm, unit \( x = 1.1 \) cm, and unit \( y = 1.1 \) cm. To verify the acceptability of this design, a final simulation using these optimized parameters with the hybrid FE–BI algorithm yields the reflection coefficient plot shown in Fig. 8. This indicates a 10 dB or less return loss from 10.65 to 11.33 GHz centered at 11 GHz. Clearly, this performance is close to the predefined return-loss bandwidth and center frequency stated earlier.

IV. SUPEREGO HYBRID OPTIMIZER

The concept of creating a design of experiments [20] on the entire design space of the optimization problem, as done with the previous example, may be inefficient since it maps both potentially good, as well as bad domains within the design space exhaustively. For the implementation of the hybrid superEGO optimizer, an initial sparse sample is used to map the design space for creating and fitting the Kriging metamodel. To ensure that only the more promising design domains are searched, one approach is to use the information of the current iterate to update the Kriging metamodel. In this manner, it endows the Kriging metamodel to have an adaptively improving characteristic and, thus, reduce the number of iterations required before convergence can be found. The program flow of this improved hybrid optimization algorithm is shown in Fig. 9 and is referred to as the superEGO hybrid optimizer.

The flexibility of the hybrid optimizer is further improved by defining the ISC. The ISC determines which location in the design space to investigate at each iteration. In the previous version, the hybrid optimizer typically optimizes for the minimum
objective function. Here, we will define two different sampling criteria: the regional extreme sampling criteria and the minimum objective function criteria. The regional extreme criterion [21] is mathematically defined as

\[ \hat{y} + (f_{\min} - \hat{y}) \Phi \left( \frac{f_{\min} - \hat{y}}{S} \right) + \sigma \phi \left( \frac{f_{\min} - \hat{y}}{S} \right). \] (11)

In (11), \( \Phi \) is defined as the cumulative distribution function and \( \phi \) refers to the probability distribution function of the Kriging model shown in (3) and (4). Also, \( f_{\min} \) is the current minimum objective function value, \( \hat{y} \) refers to the predicted value of the objective function, and \( \sigma \) refers to the variance in the Kriging model. For this infill sampling criterion, the hybrid superEGO optimizer minimizes both objective function values, as well as the uncertainty in the Kriging model, giving a user-defined emphasis on the local searching properties in addition to the local properties of the DIRECT algorithm. The minimum objective function sampling criterion simply allows DIRECT to search for the minimum of the Kriging model approximation without utilizing the statistical property of the Kriging metamodel.

In essence, the superEGO hybrid optimizer starts off with a very sparse sampling of the design domain and fits this model to derive the Kriging metamodel using the DIRECT global optimizer. It then proceeds to solve an auxiliary problem based on the optimization of the chosen ISC. The relationship between the Kriging metamodel and ISC parameters is displayed in Fig. 10. In this instance, DIRECT is used (within this auxiliary optimization) to predict the next iterate. This is, in turn, used by the fast analyzer code to carry out an expensive computational evaluation of the objective function. At the end of each optimization iteration, the predicted point is used to update the Kriging metamodel. This continuous update of the Kriging metamodels at every iteration adaptively improves the Kriging metamodel for fast convergence. The process is summarized as follows (also refer to Fig. 10).

Step 1) Fit Kriging model to the given data sample.
Step 2) Locate optimum of ISC.
Step 3) Add point from Step 2 to data sample.
Step 4) Go back to Step 1 until convergence is achieved.

V. APPLICATION 2—ANTENNA POSITION OPTIMIZATION

As an example of the hybrid superEGO optimizer, we optimize the antenna location on the rear of an automobile subject to minimal EM coupling at the 40 pins around the peripheral chip circumference located within a resonant enclosed cavity at 700 MHz, as shown in Fig. 11. The antenna field consists of a pair of crossed magnetic slots with orthogonal phase excitation to generate a circularly polarized field at a frequency corresponding to the cavity resonance. Consequently, a significant amplification of the incident antenna field within the cavity may occur. The overall objective function is defined as the ratio of the equally weighted sum of the total fields at the 40 pins to the incident field at the same 40 locations. Specifically,

\[ F(x; y, z) = \frac{\sum_{i=1}^{40} |E_{L_{\text{total}}}|^2}{\sum_{i=1}^{40} |E_{L_{\text{inc}}}|^2} \] (12)

where \( E_{L_{\text{total}}} \) refers to the total field measured in the presence of the automobile and cavity at the \( i \)th pin location, while \( E_{L_{\text{inc}}} \) refers to the incident field in the absence of these structures at the \( i \)th pin location.

For this optimization problem, there are three variables and six inequality constraints pertaining to planes confining the spatial volume at the rear of the automobile (which defines the design domain for the problem). The analyzer code used for this problem employs the MLFMM with curvilinear basis functions.
[15]–[17] over the method of moments. The automobile is modeled with curvilinear biquadratic elements to reduce geometry error and problem size. An initial mesh of the automobile with the former elements is shown in Fig. 12. The automobile model has approximately 36,000 unknowns solved in approximately 2 h on a Silicon Graphic Inc. (SGI) computer platform. Due to high computational expense, it was necessary to use function evaluations very judiciously. Hence, superEGO was much better suited to this problem than SQP, a GA, or SA. SuperEGO is started with a very sparse initial sample of 18 points located randomly within the design domain. The objective function value and the SCF covariance of the Kriging metamodel for the initial 18 sampled points over the $x$--$y$-plane with $z$ at the middle of the design volume is shown in Fig. 12. Again, surface mapping shows multiple local minima making gradient-based algorithms unsuitable. The final plots of the Kriging metamodel after convergence are given in Fig. 13.

The convergence history for the hybrid optimizer is shown in Fig. 14 and it can be seen that this optimizer achieved convergence within 30 iterations. During the first segment of the optimization history, the regional extreme sampling criterion is used (within the auxiliary optimization problem). As can be seen from Fig. 14, this additional local search property can cause the optimizer to be trapped within a local minimum point. Changing the sampling criterion to the minimum objective function (so that the hybrid optimizer has a reduced emphasis on local searching) resulted in the hybrid optimizer searching through other local minimum points. Thus, convergence is achieved within tens of iterations. This is in contrast to the GA and SA, which may take hundreds of iterations to converge.
The final objective function value is $F(x, y, z) = 0.122057$ corresponding to the antenna position $x = 24.19753$ mm, $y = -121.773$ mm, and $z = -34.6448$ mm. We remark that the value of the objective function $F$ for the antenna located at the center of the design space is 13.3025. Thus, the hybrid optimizer has yielded a satisfactory solution that reduced coupling by as much as 20.37 dB, as compared to the antenna located at the center of the vehicle. Moreover, the optimal solution for this optimizer is a deterministic answer. Further, we remark that the optimal locations correspond to an objective function behavior (see Fig. 13) whose derivatives are rather small. Consequently, small changes to the antenna locations would result in little change in the value of the objective function and the solution is robust.

VI. APPLICATION 3—OPTIMIZING ANTENNA-HARNESS COUPLING

In the third example, we optimize the coupling from a wire harness located within an automobile onto a printed antenna at the rear of an automobile to within a certain range of values. Constraints are imposed on four sources (sensors) located at the end of the wire harness. Fig. 15 shows the computer-aided design (CAD) model of the automobile in the presence of the wire harness. For our analysis, a pseudoharness was placed just above the floor of the car as shown. Each port on the harness is independently driven by a sensor. Here, the goal is to optimize the complex amplitude of each sensor output voltage so that the resulting average field magnitude along the length of the FM antenna (printed on the back glass) receives a maximum field intensity on the order of 9.7–9.8 $\mu$V/m. The problem has four

The hybrid superEGO optimizer in the previous example was used here as well. The corresponding convergence history is shown in Fig. 16. The optimization converged within 20 iterations yielding a good solution. The resulting optimal driving voltages are $V_1 = 69.53e^{0}$ $\mu$V, $V_2 = 22.58e^{18.08}$ $\mu$V, $V_3 = 174.10e^{15.13}$ $\mu$V, and $V_4 = 157.01e^{15.02}$ $\mu$V. For this example, we did not consider harness relocation that could cause additional parameters within the optimization loop. As expected, the sensors at locations 1 and 2 must keep their output voltages to low values since they are exposed toward the antenna (even though they are physically further). Sensors 3 and 4 are allowed to have greater output voltage values since they have a lesser influence on the field values at the printed antenna location. Part of this optimization exercise is to give

$$
\langle F \rangle = \left| \sum_{j=1}^{4} \sum_{i=1}^{M} \frac{E_{ij}^{\text{ANT}}}{M} \right| - 9.75 \times 10^{-6} \quad (13)
$$

where $E_{ij}^{\text{ANT}}$ are the complex electric field amplitudes at the $i$th sample point on the antenna location and $M = 16$.

Fig. 14. Convergence curve of the hybrid optimization algorithm.

Fig. 15. Geometry of the harness-antenna coupling reduction problem.

Fig. 16. Convergence data for the harness-antenna coupling reduction optimization problem.
some guidance on the various maximum sensor outputs and, thus, avoid excessive interference by these sensors on the printed antenna.

VII. CONCLUSIONS

We have demonstrated that the recently proposed hybrid optimizer, with DIRECT global optimizers in conjunction with Kriging metamodeling (superEGO) and surrogate modeling, is capable of performing rapidly converging global optimization. This alleviates the slow convergence experienced with other global optimizers like GAs and SA. The new superEGO hybrid optimizer has the additional flexibility of allowing the user to change the emphasis of local searching upon the backdrop of global searching within the design space. This hybrid optimizer was applied in conjunction with general purpose tools for: 1) shape optimization of a slot-array FSS subject to a predefined reflection coefficient bandwidth; 2) antenna location optimization to minimize EM coupling to a device located within an automobile; and 3) optimization of multisensor voltages subject to a specified field coupling criteria between the wire harness and antenna on an automobile. Of particular importance was the speed of the hybrid optimizer. The demonstration with three complex EM examples showed that convergence occurs within tens of iterations and yields a deterministic solution. These characteristics make the new hybrid optimizer ideal for large-scale complex EM problems.

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