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Modeling of Dielectric Heating in Radio-Frequency Applicator Optimized for Uniform Temperature by Means of Genetic Algorithms

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***Abstract*—**The paper presents an optimization study based on genetic algorithms (GA's) for a radio-frequency applicator used in heating dielectric band products. The weakly coupled electro-thermal problem is analyzed using 2D-FEM. The design variables in the optimization process are: the voltage of a supplementary "guard" electrode and six geometric parameters of the applicator. Two objective functions are used: temperature uniformity and total active power absorbed by the dielectric. Both mono-objective and multi-objective formulations are implemented in GA optimization.

***Keywords*—**Dielectric heating, genetic algorithms, optimization, RF applicators.

I. INTRODUCTION

ELECTROMAGNETIC fields are used for dielectric heating in industrial processes and domestic applications since the early 1960's. Plastics, food, pharmaceutical, textile and wood industries are well established sectors in which operations such as welding, heating, tempering, defrosting, drying, baking, etc. are carried out using radio-frequency (RF) or microwave (MW) heating applicators [1]-[2].

The dielectric heating process represents a coupled electro-thermal problem. According to the classification made by Kumbhar the coupling of electromagnetic and thermal fields is week, due to the large difference in the time constants of the two problems [3]. Thus in modeling and simulation experiments the two problems are treated sequentially, the results of the electric field analysis allowing the determination of the source term for the heat diffusion equation, and the analysis of the temperature distribution in the load enabling a re-evaluation of the physical constants (permittivity, loss angle, etc.) which in turn will modify the electric field distribution.

Many applications require a certain heating pattern, most frequently a uniform temperature field being desired.

Several techniques have been proposed as potential solutions for temperature field uniformization in the dielectric load. These include moving the dielectric [1], surrounding the sample with additional layers that have adequate dielectric parameters [4], or using a pulsed feeding signal for the applicator, thus allowing for heat diffusion during the "off" intervals [5].

One direction of the researches concerning the determination of a configuration that produces a uniform temperature field, both in dielectrics and in semiconductors, is the usage of evolutionary computational techniques, namely genetic algorithms and evolutionary strategies [4], [7]. These stochastic algorithms, inspired from Darwin's evolutionary theory, are suited for solving optimization problems with several design variables, with an objective function that cannot be expressed in compact analytical form and an optimum solution that cannot be anticipated [8]. The coupled electromagnetic-thermal problem encountered in RF or MW dielectric heating and the associated temperature uniformization problem fall in this category.

In our previous studies several applicators for RF heating of lossy dielectrics were analyzed and the usual mechanisms for temperature uniformization, such as translation or rotation of the load and alternating the heating and cooling stages, were investigated [9], [10].

This paper addresses optimization based on genetic algorithms (GA's) of a pulsed staggered through applicator used for heating lossy dielectric band products. The applicator has a supplementary guard electrode, compared to the classical configuration. Previous studies using optimization based on the hill-climbing method (a variant of the direct search method) showed the effect of the guard electrode in increasing the temperature uniformity inside the dielectric [11].

In this paper the finite element method (FEM) is used for the analysis of the electric field, and FEM combined with finite differences, for time discretization, are used for temperature determination. GA optimization is carried out using two objectives: maximization of the temperature uniformity and of the total absorbed power. The results agree with the ones obtained using the classical hill climbing method.

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II. Physical Model of the Applicator and Problem Formulation

Dielectric heating of band products uses stray-field applicators (electrodes placed on one side of the load), mainly for thin products, due to the lower electric fields that they produce, and staggered through-field applicators (electrodes placed on both sides of the dielectric). Within the latter group a special category are pulsed staggered through applicators, with several pairs of electrodes placed at equal distances, forming a periodic structure along the dielectric band.

The physical model of a pulsed staggered through RF applicator for band products is presented in Fig. 1. The word "pulsed" refers to the profile of the active power density in the dielectric band, with peak values in the region of the active electrodes and low values midway between neighbouring pairs of electrodes. The applicator has grounded metal shields (V=0).

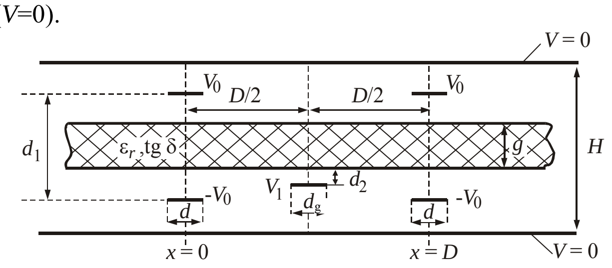

Fig. 1 Physical model of the applicator

If the length of the applicator is much larger than the distance H between the shields and the distance D between successive pairs of electrodes, the analysis of the electric and thermal fields can be reduced to a 2D problem corresponding to the domain $[0, D]\times[0, H]$.

The cuasi-stationary electric field problem may be analyzed solving the Laplace equation:

$$\nabla\cdot(\varepsilon\nabla V(x, y)) = 0 \quad , \quad x\in[0, D],\ y\in[0, H] \tag{1}$$

satisfied by the electric potential V(x,y), with the boundary conditions:

$$V(x,0) = 0,\ x\in[0, D]$$
$$V(x, H) = 0,\ x\in[0, D]$$
$$V\left(x, \frac{H+d_1}{2}\right) = V_0,\ x\in\left[0, \frac{d}{2}\right]\cup\left[D-\frac{d}{2}, D\right]$$
$$V\left(x, \frac{H-d_1}{2}\right) = -V_0,\ x\in\left[0, \frac{d}{2}\right]\cup\left[D-\frac{d}{2}, D\right] \tag{2}$$
$$V\left(x, \frac{H-g}{2}-d_2\right) = V_1,\ x\in\left[\frac{D-d_g}{2}, \frac{D+d_g}{2}\right]$$
$$\frac{\partial V}{\partial x} = 0,\ x\in\{0, D\}$$

The analysis of the temperature evolution in time is realized by solving the equation of heat diffusion:

$$-\rho c_p\frac{\partial T}{\partial t} + \nabla(\lambda\nabla T(x, y, t)) + p_v(x, y) = 0 \tag{3}$$

where $T(x, y, t)$ is the temperature, λ is the thermal conductivity, ρ –density and c_p specific heat of the dielectric. The source term in (3) is represented by the active power density $p_v(x,y)$:

$$p_v(x, y) = 2\pi\ f\ \varepsilon\ \mathrm{tg}\delta\, E^2 \tag{4}$$

where f is the frequency of the applied voltages V_0 and V_1, ε and tgδ are the dielectric permittivity and loss angle, respectively. All the physical constants of the dielectric are temperature dependent.

In this paper the heating uniformity in the dielectric band is appreciated by the function:

$$F_1 = \frac{\max\{T(x, y, t_{\max})\}}{\min\{T(x, y, t_{\max})\}},\ x\in[0, D],\ y\in\left[\frac{H-g}{2}, \frac{H+g}{2}\right] \tag{5}$$

where $t_{\max}$ is the heating time.

Previous studies of this applicator showed that the optimization algorithm using only F_1 as an objective function tends to give designs that have small levels of the total absorbed power. Thus a second indicator of the applicator performance was introduced, namely the total active power absorbed by the dielectric band:

$$F_2 = P = \iiint_V p_v dv = \int_0^D dx\int_0^g p_v(x, y, t_{\max})\, dy\ . \tag{6}$$

In the optimization process F_1 must reach a minimum (ideally F_1=1) and F_2 must reach a maximum.

III. Optimization Using Genetic Algorithm and FEM

GA's represent a non-conventional stochastic optimization method that performs an iterative search for a global extremum of an objective function. The algorithm operates on a population of potential problem solutions using selection, crossover and mutation procedures. Each individual (potential solution) in the population is represented by a chromosome, which is a concatenation of genes, each gene encoding a design variable. The encoding can be binary (using bit strings) or real (using floating point representation of real numbers).

The main stages of the fundamental GA are:

- at t=0, an initial population, $P^0(t)$=P(0) of N_{ind} individuals is created in the allowed search space;
- the objective function is evaluated for each individual;
- a selection procedure based on the fitness of each chromosome is applied to P(t) resulting a subpopulation P'(t); the crossover and mutation procedures are applied to P'(t) leading to a modified subpopulation P"(t). The next generation is formed by the population $(P(t)-P'(t))\cup P''(t)$;
- the generational evolutive process continues until a stopping condition is reached.

In this study the design variables used in the optimization of the applicator in Fig. 1 and their corresponding search intervals are:

H – distance between the shields, $H\in[0.2, 0.5]$ m;

D – distance between successive pairs of active electrodes, $D\in[0.03, 0.1]$ m;

- d_1 vertical distance between two electrodes of opposite polarity, $d_1 \in [0.015, 0.1]$ m;

- d_2 distance between the guard electrode and the dielectric band, $d_2 \in [0.002, 0.05]$ m;

- d width of the guard electrode , $d \in [0.001, 0.01]$ m;

- d_g width of the guard electrode, $d_g \in [0.001, 0.01]$ m;

- V_1 potential of the guard electrode, $V_1 \in [-V_0, 0]$ V.

The search space for the design variables ensures that each potential solution satisfies the condition E_{max}<15kV/cm, where E_{max} is the maximum value of the electric field, in order to avoid arching inside the applicator.

At each iteration, an analysis of the electric field and of the temperature field, based on 2D FEM and using first order triangular elements is performed for each individual.

The temperature dependence of the parameters ε and tgδ for the dielectric, considered to be high density white polyvinylchloride, were previously determined in the laboratory for the frequency f=13.56MHz of the generator. The range of values for the temperature $T \in [24, 110]$ °C were: $\varepsilon_r \in [3.81, 4.34]$ and $tg\delta \in [0.07, 0.14]$ respectively. A linear interpolation was performed in order to determine the values of the physical constants for other temperatures than those used in the experiments. The temperature dependence of the parameters ρ, c_p, λ for PVC and the surrounding air were taken from literature [12].

The duration of the heating process was considered to be t_{max}=60s and the time step used in solving the electro-thermal problem was 10s.

The values of the other parameters used in numerical simulations were: V_0=2000V, g=4mm, $c_{p\mathrm{air}}$=1003 J/(kg·K), ρ_{air}=1.204 kg/m^3, c_{pPVC}=934 J/(kg·K), ρ_{PVC}=1250 kg/m^3, λ_{air}=0.027 W/(m·K), λ_{PVC}=0.164 W/(m·K), T_0=24°C (ambient temperature).

IV. Results and Discussions

The first experiments were carried out considering a simplified mono-objective formulation of the optimization problem. The minimization of F_1 is performed by means of a genetic algorithm based on floating point chromosomal encoding. The generational algorithm works on N_{ind} individuals that directly encode, as float values, all seven decision variables. The initial population is randomly generated within the permitted search space. The distances H, D, d_1, d_2, d and d_g are forced to satisfy some supplementary constraints, i.e. they may encode only multiples of 1mm. These requirements allow an adequate implementation of the device and ensure the compatibility with the finite element method applied for the computation of the electric field. The stochastic universal sampling method is used in order to fill in the recombination pool, and the intermediary arithmetic crossover is applied in order to produce the offspring. Small random variations of the genetic material are generated using uniform mutation. The genetic operators are reconfigured in order to produce offspring that satisfy the imposed constraints. The resulted offspring and the individuals of the current population compete for survival according to a deterministic fitness based insertion. The experiments consider a population of 16 individuals, evolving over 10 generations, a recombination pool with 8 parents, the probability of crossover 0.7 and the probability of mutation 0.2. The best solution achieved during the evolutionary loop (line 1 in Table I) is characterized by a very good objective F_1 value (close to the boundary), but an unsatisfactory corresponding F_2 value, as the algorithm did not improve the performances of the individuals toward that objective direction.

If the problem is formulated as a multi-objective optimization, the case of competitive objectives is addressed, meaning that each objective function has different optimal points. In that situation the problem admits an infinite set of Pareto-optimal solutions, each one indicating a different accepted compromise between the competitive objectives. A solution is Pareto-optimal if no improvement could be obtained subject to an objective direction without reducing the performances toward another objective direction.

As a consequence, the optimization algorithm has to describe the entire Pareto-optimal front, by searching for points situated on the Pareto-optimal front and by preserving an adequate diversity of the population. If no information about the solutions is available, usually a posteriori aggregation between the decision mechanism and the search procedure is preferred. In that context, the optimization algorithm has to obtain a population able to describe the shape of the entire Pareto-optimal front, as a basis for a later selection.

The advantages of the genetic procedures within the framework of multi-objective optimizations are mainly related to the fact that they work on a population of solutions. Consequently, one can expect that, during a single run, the algorithm will be able to find a set of solutions with an acceptable degree of diversity. In the case of single-point algorithms, different convenient solutions are difficult to obtain in sequential runs, because the diversity of the results cannot be simply controlled by setting appropriate values of the algorithm parameters.

In order to solve the multi-objective optimization problem, two different strategies were considered. The first approach is based on a priori articulation between the decision mechanism and the search procedure. In fact, the objectives are aggregated into a single one using predefined weights and the resulted mono-objective optimization problem is solved by means of the genetic procedure described above. In that case, the population-based features of the genetic algorithm are not advantageously exploited. At each run, the algorithm could only search the solutions towards the directions indicated by the specified weights and the final population could only illustrate the shape of the Pareto-front inside a small region. If negative weights are considered, the algorithm will provide the maximization of the corresponding objective function and if positive weights are used, minimization is addressed. Thus a new objective function was evaluated using the relation

$$F = \alpha F_1 + \beta F_2 \, . \tag{7}$$

The performances of the algorithm were tested for three different sets of the weights {α,β}: A = {1, -0.01}, B = {1, -0.001}, C = {1, -0.0001}.

The best achieved solutions are indicated in Table I (lines 2, 3 and 4, respectively). As expected, the best individual, subject to the minimization of F_1, is closest to the solution achieved in case C, which uses the lowest absolute value of the F_2 weight. Also, the maximum value of F_2 is obtained in case A, when the maximization of F_2 gets the highest significance. Fig. 2 and Fig.3 illustrate the performances of the individuals included in the final populations achieved for the mono-objective approach (subject to the minimization of F_1) and for the multi-objective approach solved by means of objective aggregation. All cases are included in Fig. 2 and a zoom is provided in Fig. 3 (case A excluded). In Fig. 2 all individuals are represented with '.'and the best solutions with '◄', while in Fig. 3 the individuals are represented as follows: case B with"*', case C with '.', mono-objective approach with '+' and best solutions with '◄'. Because very important changes of the F_2 weights were considered, the populations obtained in the last generation describe quite different regions of the Pareto-front, but not completely disjoint ones. This result indicates that it would be difficult to control the diversity of the best solutions obtained in successive runs, by means of the F_2 weight.

TABLE I
EXPERIMENTAL RESULTS

No	Optimization method	F_1	F_2	**Best individual *D, H, d_1, d_2, d, d_g*,** [m], ***V_1*** [V]
1.	Mono-objective approach - minimization of F_1	1.0002	1.545	0.0340, 0.3510, 0.0980, 0.0350, 0.0030, 0.0020, - 499.817
2.	Multi-objective approach – aggregation, case A	1.3085	72.32	0.0680, 0.3320, 0.0260, 0.0030, 0.0090, 0.0040, - 1744.6
3.	Multi-objective approach – aggregation, case B	1.0009	3.6511	0.0320, 0.2080 , 0.0720, 0.0320, 0.0050, 0.0050, -1330
4.	Multi-objective approach – aggregation, case C	1.0030	3.71	0.0430, 0.3320, 0.0770, 0.0350, 0.0070, 0.0050, -518.3630
5.	Multi-objective approach – Deb algorithm, case A	1.0021*	3.095*	0.0450, 0.4180, 0.0730, 0.0360, 0.0010, 0.0050, -1356.4
6.	Multi-objective approach – Deb algorithm, case B	1.00062*	3.046*	0.0460, 0.3210, 0.0960, 0.0400, 0.0050, 0.0050, -1362.1

The second multi-objective approach implements the Deb elitist algorithm for providing an efficient search within the admissible space. The optimization method considers an a posteriori articulation between the decision mechanism and the search procedure. The search algorithm considers a ranking based selection, which exploits the results of a Pareto-dominance analysis. Within the context of the present multi-objective optimization problem, an individual X dominates an individual Y if F_1(X)<=F_1(Y) and F_2(X)>=F_2(Y). One can consider that X strongly dominates Y if F_1(X)<F_1(Y) and F_2(X)>F_2(Y). The dominance is a partially ordered relationship. Considering two arbitrary individuals X and Y, one of the following cases could occur: i) X dominates Y; ii) Y dominates X; iii) X does not dominate Y and Y does not dominate X.

The Deb algorithm selects the individuals by determining a sequence of non-dominated fronts of different orders. Firstly, it finds the best non-dominated front, including the individuals that are not dominated by any other chromosomes of the population and it selects this whole front. Then, it removes the best non-dominated individuals from the population and it finds the second non-dominated front, including the individuals that are not dominated by any other chromosomes of the reduced population and it selects this whole front. The procedure continues until the selection pool is filled. If the last non-dominated front is larger then the set of available places, the crowding sort procedure is applied. This procedure computes the crowding distances subject to the objective space. The crowding distance of individual X indicates the maximum radius of the sphere (having the center in X) which does not contain other individuals of the front. The crowding technique permits the survival of the solutions with large crowding distances, in order to preserve an adequate diversity of the population. Usually, this selection is applied for insertion. At each generation, an extended population of N_{ind} parents and N_{ind} offspring is temporarily created. The algorithm selects N_{ind} individuals, that are copied into the recombination pool and produces a new set of N_{ind} offspring, by means of crossover and mutation.

Unfortunately, because the finite element method (called for field computation during the evaluation stage) is an important time-consumer, all experiments consider a small population, evolving during a reduced number of generations. As a consequence, it is expected that the final population will also include several inconvenient solutions, placed quite far from the Pareto optimal front.

The algorithm is applied with flying or fixed goal values. These goal values delimit a preferred region for the individuals. That means the individuals placed inside the region dominate the individuals placed outside the region. Case A considers flying goals that are adjusted at each generation, based on the performances of the parents: the permitted region is 10% larger than the region occupied by the parents in the objective space. Case B works with fixed goals: [1 10] for F_1 and [0 100] for F_2, allowing the survival of offspring having significantly different performances than their parents.

The best solution indicated in Table I (lines 5 and 6, respectively) represents the solution included in the final population having minimum F_1 value, but the decision algorithm can also select another solution. For instance, for case B, on can select an individual characterized by F_1=1.0002, F_2=3.2096 or F_1=1.10122, F_2=8.1505, etc. In a single run, the algorithm was able to produce quite diverse solutions (Fig. 3). The dispersion is better in case B, but because the algorithm works on a reduced set of individuals, during a reduced number of generations, some of the solutions could be dominated by individuals produced by other optimization approaches. However, as illustrated in Fig. 3, almost all the solutions produced by the Deb algorithm dominate those obtained with the aggregation based multi-objective approach.

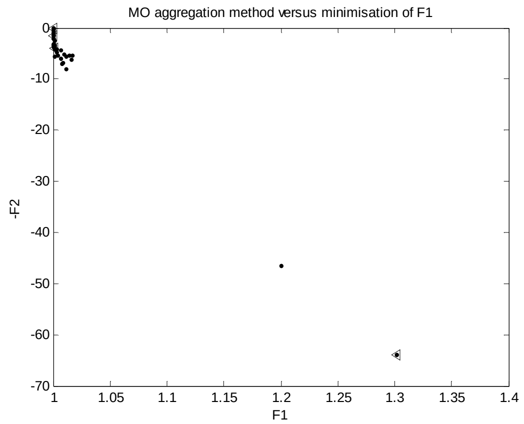

Fig. 2 Final population plot within the objective space for aggregation-based multi-objective optimization

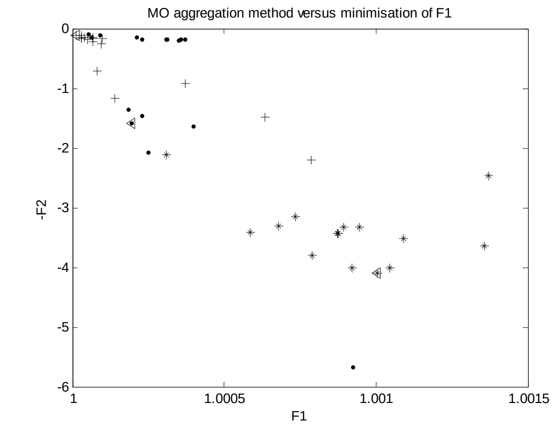

Fig. 3 Aggregation-based multi-objective optimization: the final population plot within the objective space – zoom (case A excluded)

Fig. 4 and Fig. 5 plot the temperature profile in the dielectric after 60 s of field exposure for cases 2 and 3 in Table I, respectively, which achieve higher levels of absorbed power, and thus a higher heating rate. As may be seen, the temperature non-uniformity is rather high in case 2, but the higher value of V_1 and the smaller distance between the active electrodes ensure an acceptable heating rate (mean(T)-T_0)=12.8°C/min.). The configuration obtained in case 3 ensures a very good temperature uniformity, along the dielectric band, but the heating rate is small.

It may be also observed that any modification of the design variables acts in opposite directions on the two objective functions, eg. smaller values of d_1, d_2 and D or higher values of V_1 increase the level of absorbed power, but decrease the temperature uniformity, making the choice of the most acceptable design somewhat difficult.

Fig. 6 presents the temperature profile in the dielectric load after 60s of field exposure for the design corresponding to line 2 in Table I, but without a guard electrode. In this case F_1=1.59, F_2=25.88 W and the heating rate is 5.4°C/min.

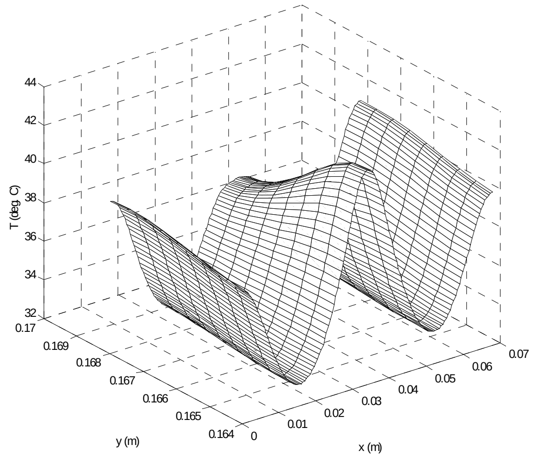

Fig. 4 Temperature in the dielectric after 60 s heating corresponding to case 2 in Table I

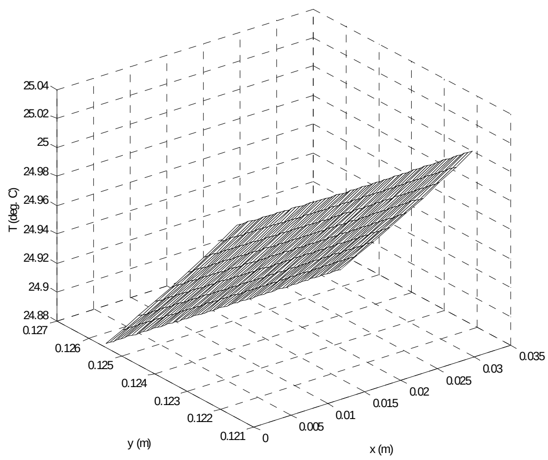

Fig. 5 Temperature in the dielectric after 60 s heating corresponding to case 3 in Table I

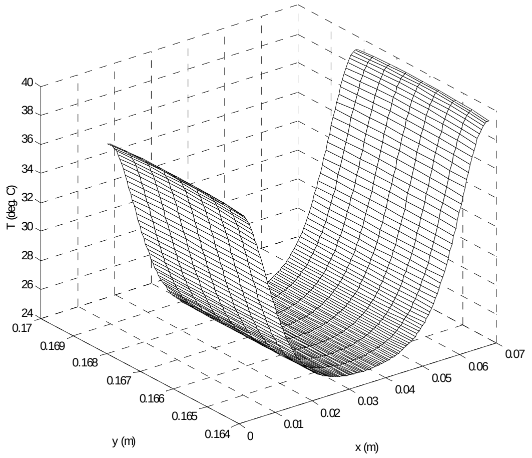

Fig. 6 Temperature in the dielectric after 60 s heating corresponding to case 2 in Table I – configuration without guard electrode

V. Conclusion

The use of a guard electrode in a pulsed staggered through applicator for RF dielectric heating, whose position and voltage are adequately chosen, enhances the temperature uniformity in the load.

GA optimization using real encoding of the design variables (six geometric parameters and the guard electrode voltage) leads to very good designs regarding the level of temperature uniformity (a non-uniformity of 10^{-5} for the best solution). GA optimization using two objective functions, the temperature uniformity and the total active power absorbed by the dielectric, leads to very good solutions regarding the former criterion, but to pourer results regarding the power absorption and the heating rate.

The solution proposed for temperature uniformization in band dielectric products is simple to implement and can indeed achieve an almost uniform heating. If the heating rate is an important criterion, then the solution of shifting the dielectric band must be taken into account.

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