Sample Movement Optimisation for Uniform Heating in Microwave Heating Ovens

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ABSTRACT: A technique for improving the uniformity of heating patterns of dielectric samples in a multimode cavity is presented based on a strategic movement of the sample inside the microwave applicator. Different optimisation algorithms are compared to determine the best microwave irradiation period for each sample position. A new optimisation procedure that minimizes electric field variance is also presented and assessed.

Keywords: optimisation procedure; uniform microwave-assisted heating, multimode oven, sample movement.

I. INTRODUCTION

Microwave heating systems must provide uniform heating in order to obtain high quality products and avoid the so-called hot spots within the irradiated materials [1]. Traditionally, the temperature uniformity is accomplished by moving or rotating the sample within the applicator [2], using mode stirrers [3-4], employing multiple feed systems [5] or a combination of these techniques. Recently, several works have shown that it is possible to predict microwave-heating patterns for dielectric samples within microwave applicators when sample rotation [2] or mode stirrers are employed [3,4]. In these works, an average electric field pattern is computed by taking into account the individual electric field contributions for each sample or mode stirrer position. Additionally, several mode stirrers' configurations are assessed in [4] to obtain uniform electric field patterns. The obtained results show that, despite the employment of these techniques, uneven electric field distributions can appear within dielectric samples. Therefore, it seems necessary to find alternatives that provide uniform microwave heating.

In this work, we present a new strategy for achieving uniform electric field spatial distributions and we compare this novel technique to constant sample movement which is usually used in industrial microwave applicators. This method uses an intelligent combination of the individual electric field patterns obtained during the linear sample movement to synthesise uniform average electric field distributions within dielectric objects. Several conventional optimisation techniques are used and evaluated by using both statistic indicators and electric field pattern visualisation. Additionally, we present and assess a new optimisation procedure that minimizes electric field variance throughout the dielectric sample. Finally, materials such as rubber, polyester and epoxy resins [6], whose dielectric characteristics are within the range of the permittivity values considered in this work, could be used for the application of this optimisation technique.

II. ELECTRIC FIELD COMPUTATION

Figure I shows the 50x50 cm^2 two-dimensional (2-D) multimode applicator used for all simulations. A standard WR-340 waveguide centred at the upper wall of the oven has been used as the feeding system. The operating frequency has been set to 2.45GHz (ISM band) and the TE_{10} mode has been excited in the waveguide with a normalised amplitude of 1 V/m (peak value). The boundary condition at the waveguide allows taking into account the potential power reflections. The dielectric sample has been placed on a 1-cm thick PTFE sheet and moved along the x-axis. The continuous sample movement has been discretized into N sequential positions, and the module of the electric field spatial distribution has been obtained for each position. For the k_{th} sample position, the electric field has been obtained in the frequency domain with the aid of the vector wave equation:

$$\nabla^2 E_k(x,y) + \omega^2 \mu \varepsilon E_k(x,y) = 0 \qquad (1)$$

with $E_k\,(x,y)$ being the electric field distribution in the multimode cavity for the k_{th} sample position, ω the angular frequency, μ the permeability and ε the permittivity of the medium. It must be pointed out that low values for k indicate that the sample is near the left side of the oven and high values are used for positions around its right side.

In this study, we consider non-magnetic materials characterised solely by its complex relative permittivity:

$$\varepsilon_r = \varepsilon' - j\varepsilon'' \qquad (2)$$

where ε' is the dielectric constant and ε'' the loss factor of the medium.

The Finite Element Method (FEM) has been used to solve (1) by using the variational formulation as indicated in [3]. MatlabTM Partial Differential Equation (PDE) Toolbox has been used to mesh the two-dimensional domain and to obtain electric field patterns for this partially filled multimode cavity [7]. FEM can be applied to samples with any shape, size or composition, but it requires relatively long analysis times, compared to other numerical methods.

Indeed, the particular structure of the heating problem described in this work, where sample have rectangular cross sections, permits the implementation of faster techniques, such as mode matching. This could improve the computational times, for the considered scenario, by speeding up the simulation of the electric filed patterns for each sample position.

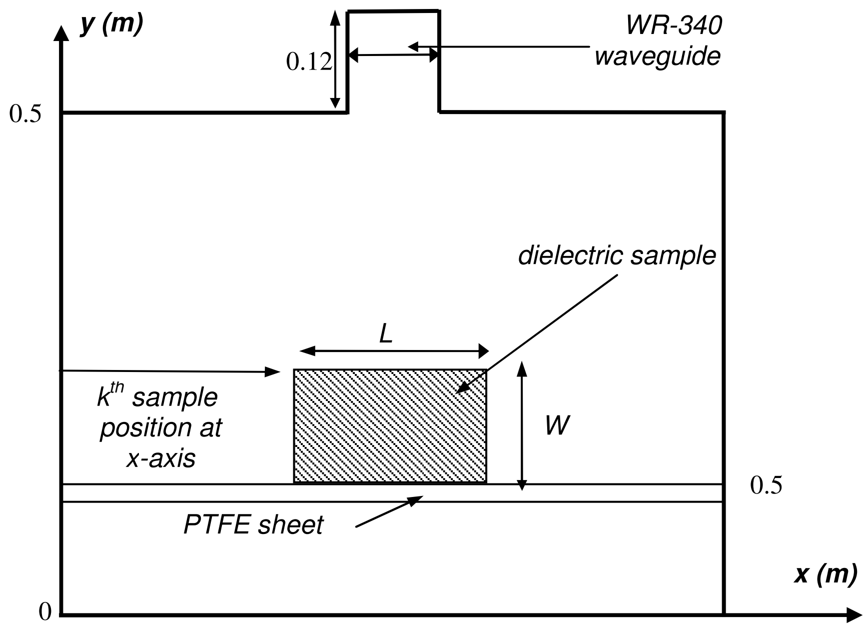


Figure 1. Two-dimensional scheme for the microwave oven used for electric field simulations.

III. OPTIMISATION PROCEDURES

The main objective of this work is to find an optimisation method that provides a uniform average electric field pattern within the irradiated dielectric samples. For this purpose, we use several conventional optimisation algorithms such as Method of Steepest Descent (MSD) [8] or Levenberg-Marquardt (LM) [9] in order to achieve a desired constant pattern with the highest convergence velocity. Additionally, a new method based on the MSD algorithm but modified for variance control (MSD-VC), which involves in the same cost function the quadratic error and the electric field variance, has been designed in order to achieve the proposed objective and compared to MSD and LM optimisation procedures. The obtained results are also compared to the constant sample movement method, which carries out a linear average of the absorbed power within the sample for each sample position.

Let $E(x,y)^{(k)}$ be the 2-D spatial distribution of the electric field within the sample for the k^{th} sample position within the multimode applicator and N be the maximum number of sample positions along the x-axis. The temperature increment for the k^{th} sample position is given by the so-called heat equation [1,4]

$$\rho c_p \Delta T_k(x,y,t) = \Delta t_k \left[k_t \cdot \nabla^2 T(x,y) + 2\pi f \varepsilon_0 \varepsilon'' \left|E(x,y,t)\right|_k^2\right] \tag{3}$$

where ρ is the material's density, c_p its specific heat, k_t its thermal conductivity, ε'' its loss factor, f the operating frequency, $\Delta T_k(x,y)$ the temperature increment distribution at the k^{th} sample position and Δt_k the irradiation interval at that position.

From (3), one can conclude that the temperature evolution within the sample depends linearly on both $\left|E(x,y,t)\right|_{(k)}^2$ and Δt_k. In order to simplify the notation, let $P(x,y)$ and W_k be:

$$P^{(k)} = \left|E(x,y,t)\right|_{(k)}^2 \qquad\qquad W_k = A_k^2 = \Delta t_k \tag{4}$$

where $P^{(k)}$ is a matrix that provides information about the absorbed power pattern deposition and W_k is a positive defined coefficient equal to the sample irradiation time at position k.

By taking into account that the dielectric materials usually show low thermal conductivity values, which leads to a negligible effect of thermal conduction versus microwave heating, and assuming a sample movement faster than the thermal conduction effect, an average electric field spatial distribution, $E_{av}(x,y)$, can be obtained from a weighted lineal combination of $P(x,y)^{(k)}$:

$$P_{av}(x,y) = E_{av}^2(x,y) = \sum_{k=1}^{N} W_k \cdot P^{(k)} = \sum_{k=1}^{N} A_k^2 \cdot P^{(k)} \tag{5}$$

By considering the quadratic error between the average and the desired pattern, the optimisation procedures in this work must obtain the coefficients W_k that minimise the 2-D Error matrix, *Err*:

$$Err = P_D^2 - \left| \sum_{k=1}^{N} W_k \cdot P^{(k)} \right|^2 = P_D^2 - \left| \sum_{k=1}^{N} A_k^2 \cdot P^{(k)} \right|^2 \quad (6)$$

where the desired average power absorption distribution, P_D, is a constant 2-D matrix that must be set before applying the optimisation algorithms. The optimum values for the W_k coefficients correspond to the sample irradiation times at the k^{th} position.

Equation (6) shows the cost function of a conventional optimisation procedure, based on the quadratic error. However, in this case, that final result for W_k coefficients can not be optimal, because one important restriction is imposed to this problem: the W_k coefficient can not be negative, since they correspond to irradiation intervals. Considering that no restrictions can been imposed on the W_k obtained values during the optimisation process, we have replaced the W_k coefficients with A_k^2 and optimised the A_k coefficients instead. Once the optimisation problem has been described in terms of error minimization, the constant movement, MSD, LM and MSD-VC algorithms are described in detail.

A. Traditional Algorithm for Temperature Levelling

The traditional method in industrial microwave applicators for achieving even temperature distributions during microwave heating involves a constant movement of the sample inside the multimode cavity. In this case, since the sample stays the same time in each position, the average pattern matrix, $P_{av}(x,y)$, is obtained by linearly averaging the $k=1\ldots N$ patterns, $P^{(k)}(x,y)$, obtained during sample movement [3]. A scale factor K_m is applied to the linear average pattern so that the mean value of $P_{av}(x,y)$ matrix is equal to P_D. In this way, correct comparisons with the other optimisation procedures can be carried out. Equation (7) summarises this procedure:

$$P_{av} = K_m \cdot \sum_k P^{(k)} / N \quad (7)$$

with k being the index for the k^{th} sample position.

B. Gradient Optimisation Algorithm

In this algorithm, each A_k in (6) is updated by computing the direction of the gradient of the quadratic error surface (ε_q) [8]. This iterative method is known as Method of Steepest Descent (MSD). The expression for the A_k update that decreases ε_c in each iteration, t, is given by:

$$A_k[t+1] = A_k[t] - \mu \cdot \nabla_k \varepsilon_q[t] = A_k[t] - \mu \cdot \frac{\partial \varepsilon_q[t]}{\partial A_k} \tag{8}$$

where μ is the convergence parameter that controls the stability of the adaptive algorithm, and $\varepsilon_q[t]$ corresponds to the quadratic error function. In this case, the quadratic error function must be recalculated in each step, which is expressed as:

$$\varepsilon_q[t] = \sum_{i,j} \left(P_D(i,j) - \sum_k A_k^2[t] \cdot P(i,j)^{(k)} \right)^2 \tag{9}$$

with i and j being the element indices for the two-dimensional pattern matrices, $P^{(k)}$ and P_D,

The gradient function of $\varepsilon_q[t]$ in (8) is computed as

$$\frac{\partial \varepsilon_q[t]}{\partial A_k} = \frac{\partial}{\partial A_k} \sum_{i,j} Err(i,j)^2 = -4 \cdot \sum_{i,j,k} A_k[t] \cdot P^{(k)}(i,j) \cdot Err(i,j) \tag{10}$$

where $Err(i,j)$ is one element of the quadratic error matrix Err, i and j represent the element indices for the P and Err 2-D matrices and k is the index for the k^{th} sample position. By modifying (8) with (10), the updating expression for each weight is obtained as:

$$A_k[t+1] = A_k[t] + 4\mu \cdot \sum_{i,j,k} A_k[t] \cdot P^{(k)}(i,j) \cdot Err(i,j) \tag{11}$$

Once the optimisation algorithm reaches the convergence condition, the solution for the estimated uniform pattern is provided by (5).

C. Levenberg-Marquardt Optimisation Algorithm

The main advantage of the LM algorithm is the control of its convergence, because both the learning rate and A_k are updated in each iteration by means of error surface slope estimations [9]. However, LM needs to invert a matrix in each iteration, as indicated in (12). The application of this algorithm permits to reach the optimal solution in terms of quadratic error in few steps. In this case, the design of this optimisation algorithm permits to obtain the next A_k updating equation:

$$A_k[t+1] = A_k[t] - \left(Z^T Z + \lambda[t] I\right)^{-1} Z^T \varepsilon_c[t] \tag{12}$$

where $\lambda[t]$ is the temporal dependent learning rate coefficient, I is the identity matrix and Z vector corresponds to $Z = \nabla \varepsilon_q[t]$, which has been previously indicated in (10) for each A_k.

IV. ***MSD-VC Algorithm***

The goal of this work is to provide a uniform average electric field distribution around a desired value. This implies that the variance of the average pattern must be minimum. A contribution of this MSD-VC (*Method of Steepest Descent with Variance Control*) novel algorithm is to add a function that continuously measures the variance of the electric field spatial distribution to the MSD optimisation equations. In this way, MSC-VC carries out an adaptive reduction of this variance and permits a simultaneous control of quadratic error in order to obtain a uniform final electric field pattern around the desired electric field pattern, P_D. Thus, a new method is proposed in this work to adaptively reduce both the quadratic error $\varepsilon_q[t]$ and the variance $\varepsilon_v[t]$ of the final average electric field distribution. Starting from the MSD algorithm, the general weight update equation (8) is modified by the inclusion of a new term for variance control:

$$\varepsilon_V[t] = \sum_{i,j} \left(P_{av}(i,j) - \overline{P}_{av}(i,j) \right)^2 \tag{13}$$

which results in

$$A_k[t+1] = A_k[t] - \mu\left(\nabla_k \varepsilon_q[t] + \nabla_k \varepsilon_V[t] \right) \tag{14}$$

where $\overline{P}_{av}$ is the mean value of the P_{av} matrix. $\nabla_k \varepsilon_V[t]$ is calculated as:

$$\nabla_k \varepsilon_V[t] = \frac{\partial \varepsilon_V[t]}{\partial A_k} = 2 \cdot \sum_{i,j} \left[\left(P_{av}(i,j) - \overline{P}_{av}(i,j) \right) \cdot \frac{\partial}{\partial A_k} \left(P_{av}(i,j) - \overline{P}_{av}(i,j) \right) \right] \tag{15}$$

By putting (6) into (15) and calculating the derivate of the resulting expression, the $\nabla_k \varepsilon_V[t]$ function is obtained as:

$$\nabla_k \varepsilon_V[t] = 4 \cdot A_k[t] \cdot \sum_{i,j} \left[\left(P_{av}(i,j) - \overline{P}_{av}(i,j) \right) \cdot P(i,j)^{(k)} \cdot \left(1 - \overline{P}^{(k)}(i,j) \right) \right] \tag{16}$$

with $\overline{P}^{(k)}$ being the mean value for the k^{th} pattern. Therefore, the error between the average and the desired electric field pattern handled by this algorithm is defined by taking into account both

ε_q and ε_V:

$$\varepsilon = \sqrt{\varepsilon_q^2 + \varepsilon_v^2} \tag{17}$$

V. RESULTS

In order to provide examples of uniform electric field patterns synthesis, several computations have been carried out by using the microwave cavity in Figure 1 and the Matlab^{TM} PDE Tool described above for different dielectric materials and sample dimensions. A mesh with approximately 14700 points and 29000 triangles has been implemented for solving the 2D EM problem. About one minute was needed to generate each electric field pattern with the employed FEM simulator.

Table I shows the sample permittivity, dimensions and the number of different sample positions used to generate the k = 1…N electric field patterns, which are needed to apply the proposed optimisation algorithms. The N generated sample electric field patterns are evenly spaced along the x-axis.

In all the optimisation procedures, the maximum iteration number to reach the weights convergence was set to 100, while the desired final value for the uniform electric field surface in the considered sample has been fixed to 0.3 V/m (peak value). The initial values for A_k have been randomly generated with normal distributions, The initial values for A_k have been randomly generated with normal distributions, with 0,05 mean and 0,05 variance for MSD and MSD-VC, and 0.025 mean and 0.025 variance for LM.

Table I. Experimental scenarios

Sample Number	**Sample Size** ***L(mm)*** **×** **W*(mm)***	**Relative Permittivity** **(ε'-jε'')**	***N***
1	100 × 50	5-j0.5	344
2	50 × 60	5-j0.5	301
3	80 × 80	5-j0.5	976
4	10 × 150	3-j1.0	300
5	10 × 150	3-j0.2	201

Fig. 2 shows the average electric field spatial distribution within sample 2 for the different algorithms in order to compare their performance. The electric field pattern achieved with the traditional algorithm shows a maximum value at the sample centre which leads to a bad variance indicator and a large quadratic error. On the contrary, all the other optimisation methods achieve a very similar solution much more uniform that the traditional method The optimised patterns in Figure 2 have been generated by considering the N=301 electric field patterns for sample 2. However, one advantage of the application of algorithms based on adaptive techniques is the possibility of analysing the significance of the contribution of each individual pattern in the final solution. Thus, Figure 3 shows the optimised W_k values obtained during sample 2 movement for MSD, LM and MSD-VC algorithms, which provides information about the influence of the k^{th} pattern on the final average electric field spatial distribution.

From Figure 3, one can conclude that some sample positions are more influent on the final optimised average electric field pattern than others. Additionally, as Figure 3 shows, the proposed MSD-VC algorithm presents a great number of irrelevant patterns in comparison with the rest. This implies that only few sample positions could be considered to generate the final solution, without increasing ε_q or ε_v, and permits to eliminate a great percentage of the used patterns, those ones less significant, and in this way to decrease the time for the generation of the final electric field pattern in real microwave-heating cavities. It can also be observed from Figures 2 and 3 that different pattern combinations provide very similar average electric field patterns which indicates that there are several possibilities to obtain an optimised solution.

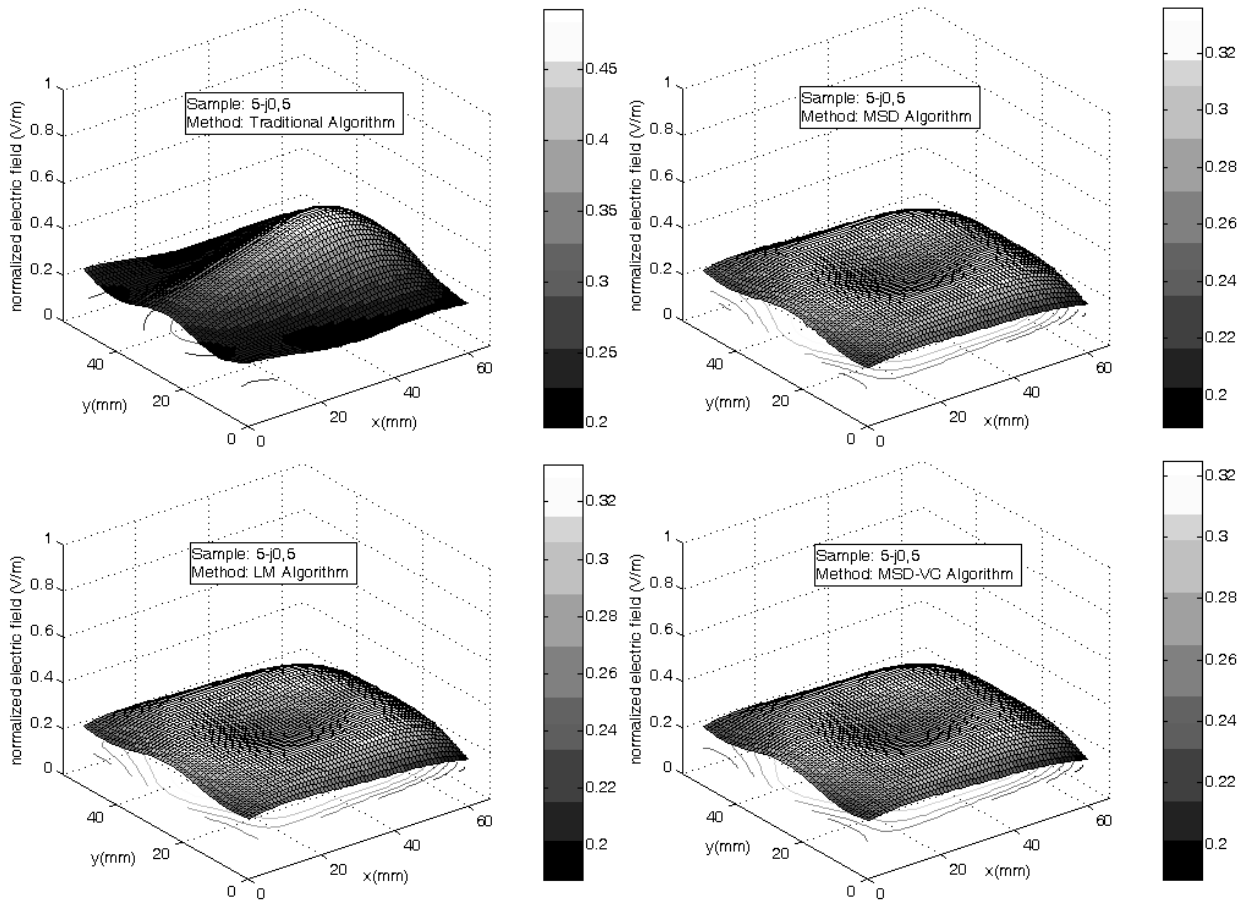


Figure 2. Average electric field distributions within sample 2 for Traditional, MSD, LM and MSD-VC algorithms. μ=0.0005 and λ=0.1 for MSD, LM and MSD-VC.

Figure 4 shows the quadratic error and variance convergence velocity for each adaptive algorithm and sample 2. From Figure 4 it can be concluded that MSD-VC is the fastest algorithm since it needs roughly eight iterations to converge to the optimum solution. By contrast, the LM algorithm is the slowest one since it needs more 30 iterations to converge.

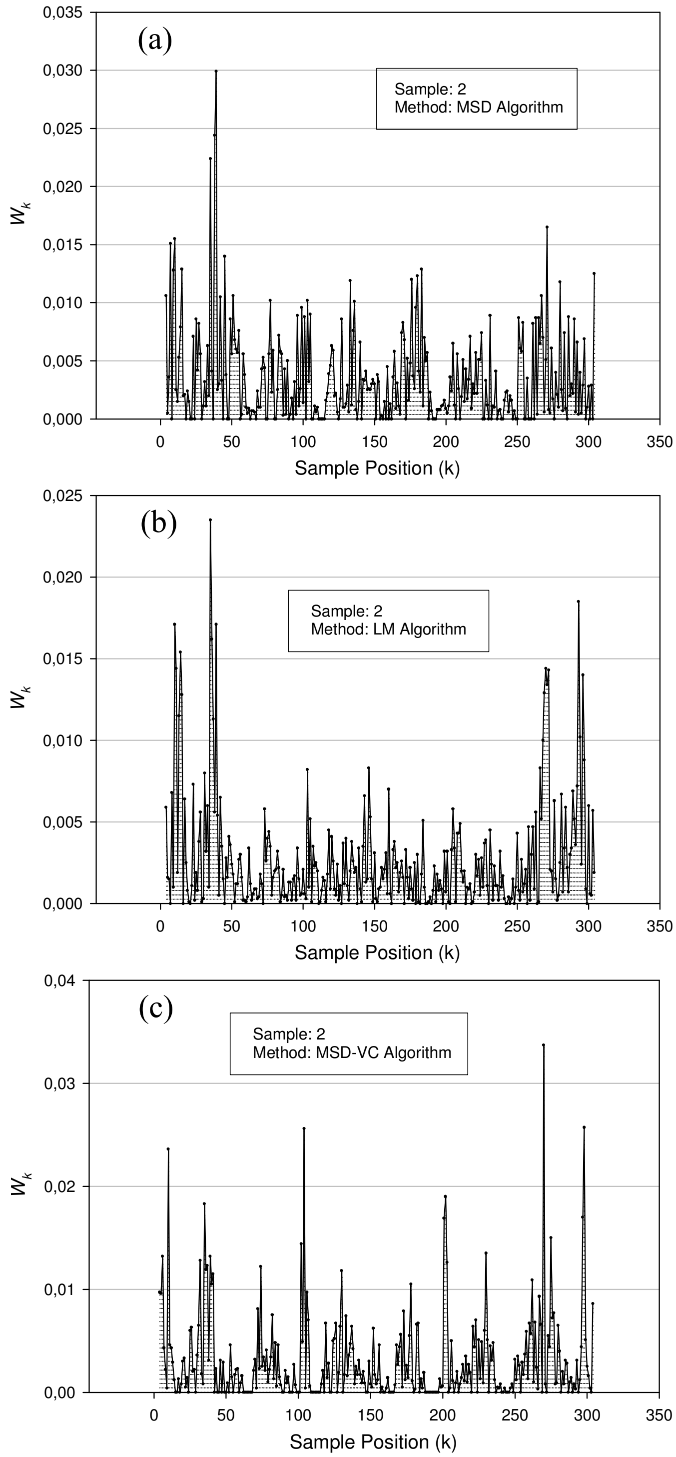


Figure 3. Optimum W_k values for sample 2 and (a) MSD, (b) LM and (c) MSD-VC algorithms.

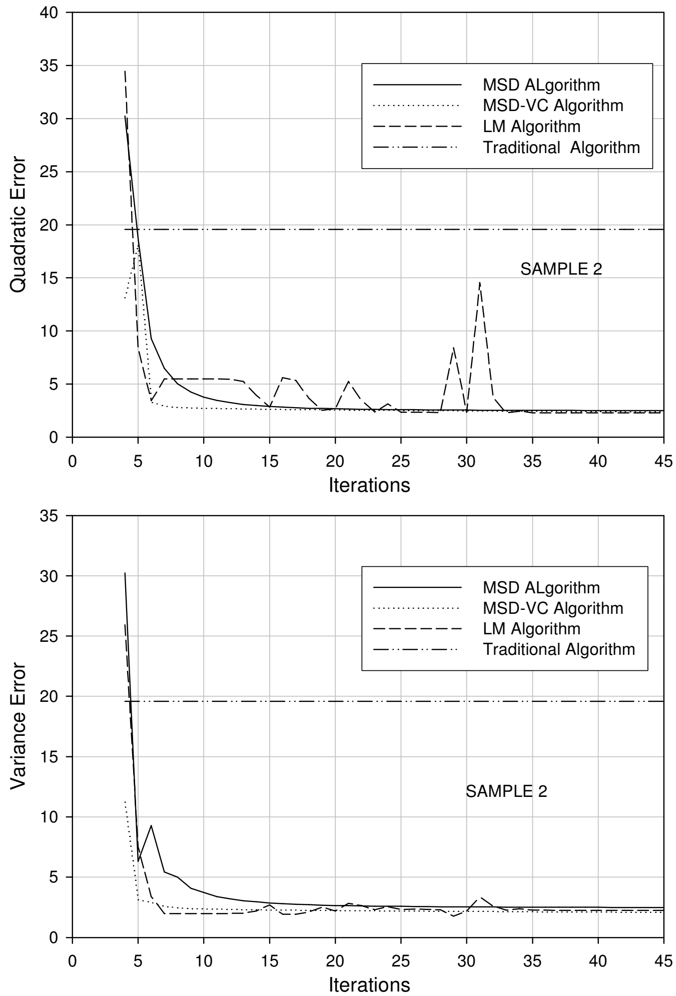


Figure 4. ε_q and ε_v error evolutions for sample 2, by considering the 4 described algorithms

Table II shows the quadratic error and the pattern variance normalized by the pattern electric field average value for the proposed optimisation algorithms: traditional, MSD, LM and MSD-VC and the samples listed in Table 1. From results in Table 2, one can observe that the proposed MSD-VC method based on the adaptive control of the pattern variance presents the best solution in terms of variance for all the considered samples, without significantly incrementing the quadratic error with respect to the other optimisation algorithms. On the other hand, LM algorithm provides the best quadratic error in all cases apart from sample 5. It is also clear from Table II that the traditional method for temperature levelling provides the worst results both for quadratic error and variance values since, in this case, sample movement is not optimised and the algorithm simply carries out a linear averaging.

Table II. Quadratic error and normalized variance for the obtained average electric field patterns

Sample	Quadratic Error (ε_c)				Pattern variance / Pattern Mean Value			
	Traditional	**MSD**	**MSD-VC**	**LM**	**Traditional**	**MSD**	**MSD-VC**	**LM**
1	39.80	20.39	17.03	14.76	0.0258	0.0094	0.0067	0.0087
2	19.57	3.13	2.99	2.21	0.0210	0.0024	0.0022	0.0024
3	72.37	43.88	48.18	32.16	0.0368	0.0162	0.0120	0.0155
4	23.82	8.64	5.11	3.56	0.0478	0.0125	0.0062	0.0072
5	32.05	14.82	4.33	9.85	0.0644	0.0217	0.0049	0.0084

Figure 5 shows the optimum average electric field spatial distribution obtained by the traditional, MSD, LM and MSD-VC algorithms for sample 5. In this case, μ has been set to 0.002 for MSD and MSD-VC whereas λ has been set to 0.1 for LM. Additionally, the initial values for the A_k weights have been randomly generated with normal distributions, with 0.15 mean and 0.15 variance for MSD and MSD-VC, and 0.25 mean and 0.25 variance for LM. From Figure 5 one can conclude again that the MSD-VC algorithm presents the best solution in terms of uniformity for the electric field pattern. Once again, the constant sample movement obtains the worst results providing edge overheating since the electric field concentrates in the sample corners.

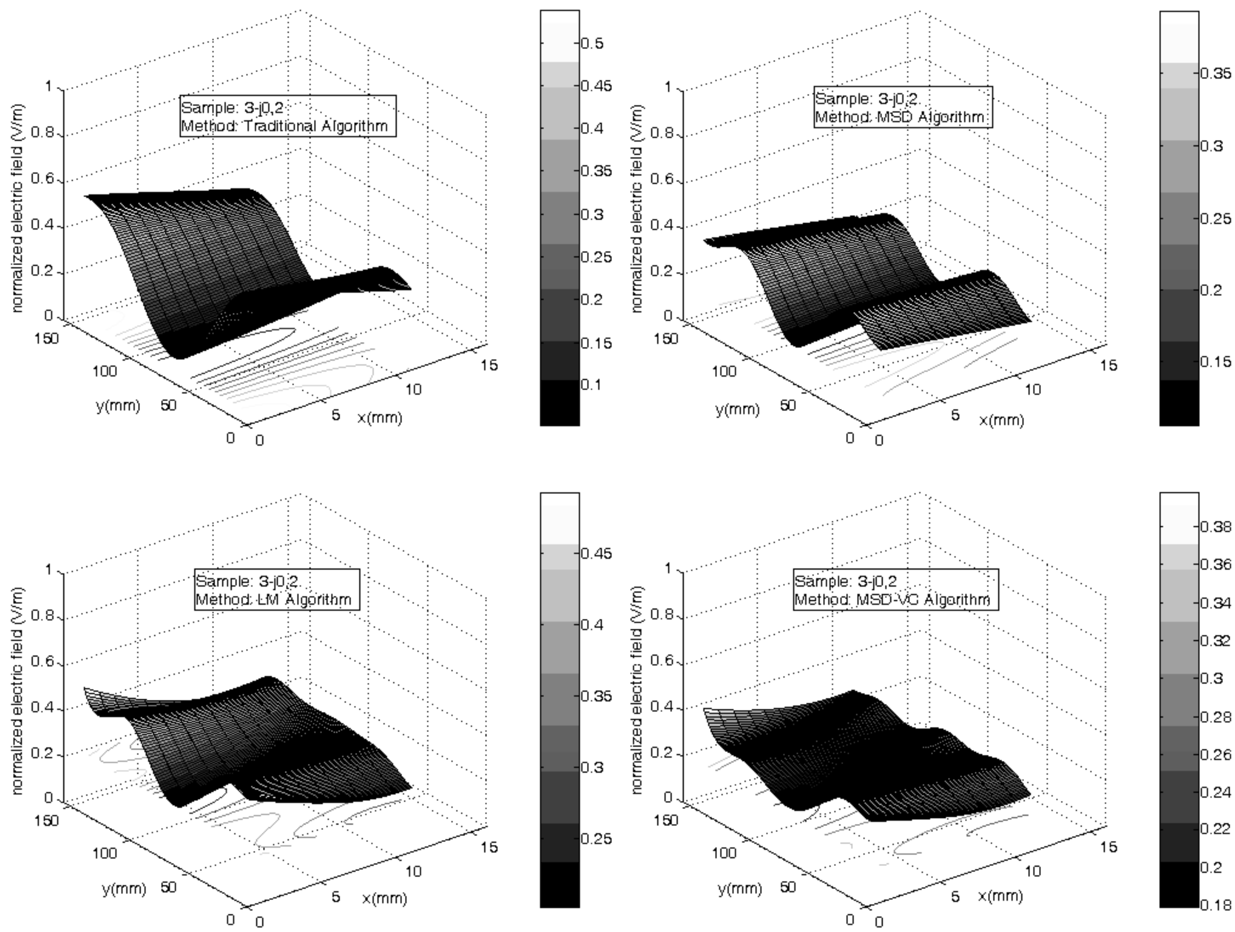


Figure 5. Average electric field distributions within sample 5 for Traditional, MSD, LM and MSD-VC algorithms. μ=0.0005 and λ=0.1 for MSD, LM and MSD-VC.

Figure 6 shows the optimum sample position irradiation intervals (W_k) obtained from MSD, LM, and MSD-VC algorithms when applied to sample 5. From obtained results it can be deduced that MSD-VC needs less sample positions to obtain a more uniform electric field pattern. It can also be observed that, in this case, the sample must stay longer in the cavity centre.

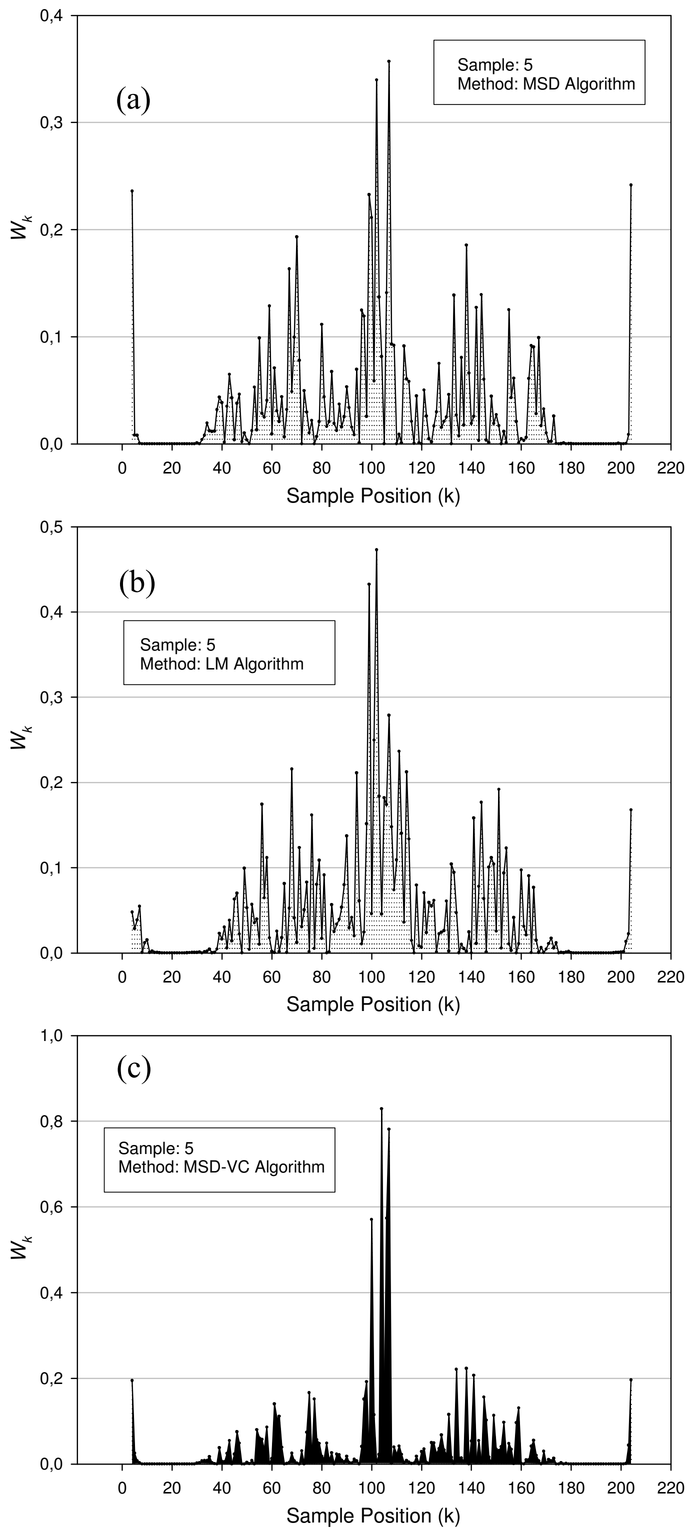


Figure 6. Optimum W_k values for sample 5 and (a) MSD, (b) LM and (c) MSD-VC algorithms.

Figure 7 shows the quadratic error and variance convergence versus the optimisation iteration number. Again, MSD-VC algorithm provides the best convergence speed both for quadratic error and the electric field pattern variance.

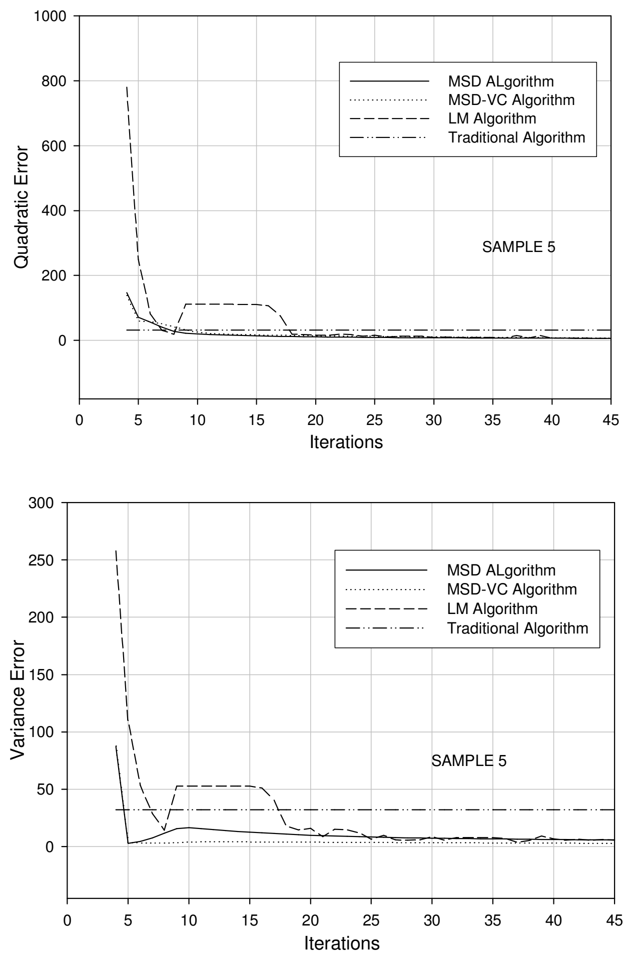
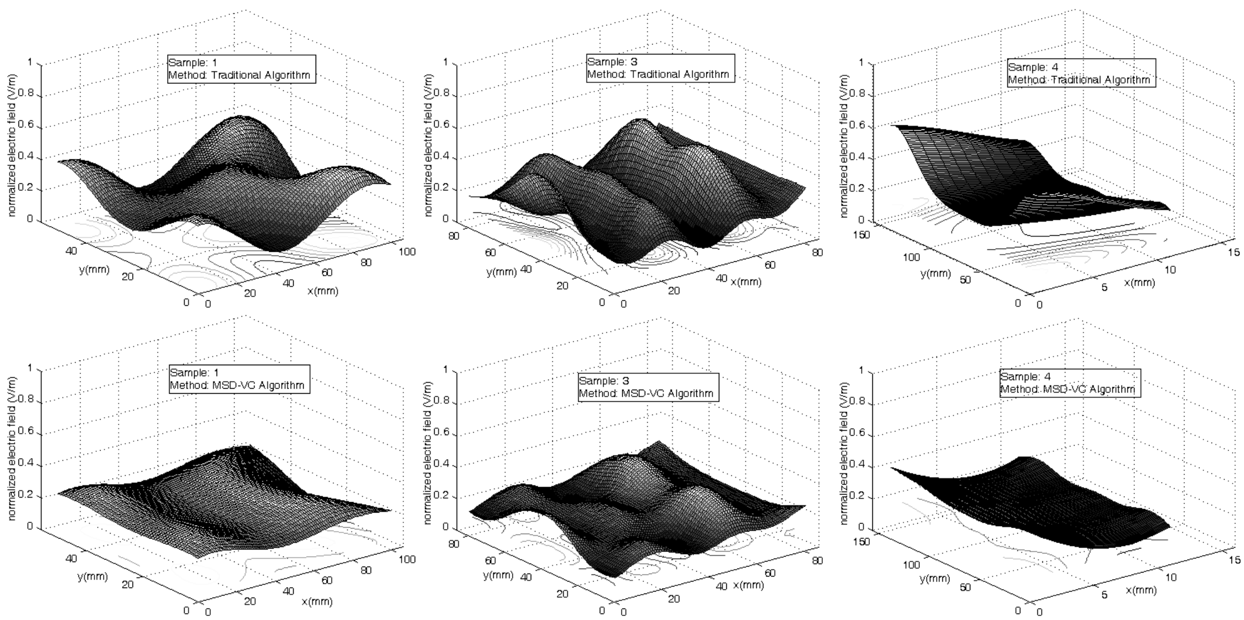


Figure 7. ε_q and ε_v error evolution for sample 5 and Traditional, MSD, LM and MSD-VC algorithms.

The simulation times employed for the computer in each adaptive algorithm have been around 0.1 sec./iteration or 0.05 sec./iteration for samples 2 and 5, approximately.

Figure 8 shows the optimum electric field patterns for samples 1, 3 and 4 when applying the Traditional and MSD-VC algorithms. From this figure, one can conclude that MSD-VC algorithm provides a more uniform average electric field pattern than that obtained from a uniform sample movement that usually provides the so-called ‘hot spots’. It can also be observed that the obtained average electric field patterns depend very much on the sample geometry and its permittivity which agrees with the results obtained in [3-4].



(a) **(b)** **(c)**

Figure 8. Electric field pattern comparison for samples (a) 1, (b) 3 and (c) 4 and Traditional and MSD-VC algorithms. μ=0.0005.

As it has been described before, all the optimisation algorithms have shown that several sample positions can be avoided since their irradiation times are negligible. This was more evident for the MSD-VC than for the rest of optimisation strategies. Thus, it seems interesting to estimate the needed sample positions to achieve a good quadratic error and a low electric field pattern variance. Figure 9 shows the evolution of the error given by (17) for the different samples versus the sample position percentage used to achieve the optimal solution. In Figure 9, the N sample positions within the microwave heating applicator have been sorted as function of the value for W_k. In this way, the sample positions with highest W_k values were used to calculate ε before the ones with lowest W_k values. As Figure 9 shows, the sample position percentage needed to reconstruct the final optimum average electric field pattern, without varying the final error is lower that 40% for all the tests with the MSD-VC method.

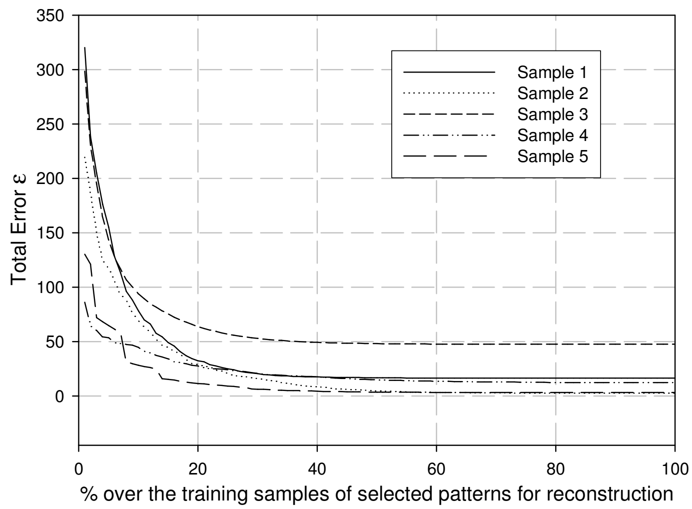


Figure 9. MSD-VC error evolution for different percentages over the sample position number.

In order to compare the number of significant electric field distributions for all the optimisation methods, we have considered as negligible electric field patterns those ones whose W_k is lower than a 10 % of the maximum value for W_k. This estimation permits to detect the behaviour differences of each algorithm in terms of needed electric field patterns to generate the optimum electric field distribution. Additionally, this also indicates the needed sample positions used to synthesize the optimum average electric field distribution. Figure 10 shows the number of the significant sample positions for the different samples and algorithms used in this work. From figure 10 it can be concluded that MSD-VC algorithm provides the lowest number of significant sample positions in most cases. This implies that this algorithm needs less sample positions to be explored than the rest of algorithms when implementing the sample movement in an experimental applicator.

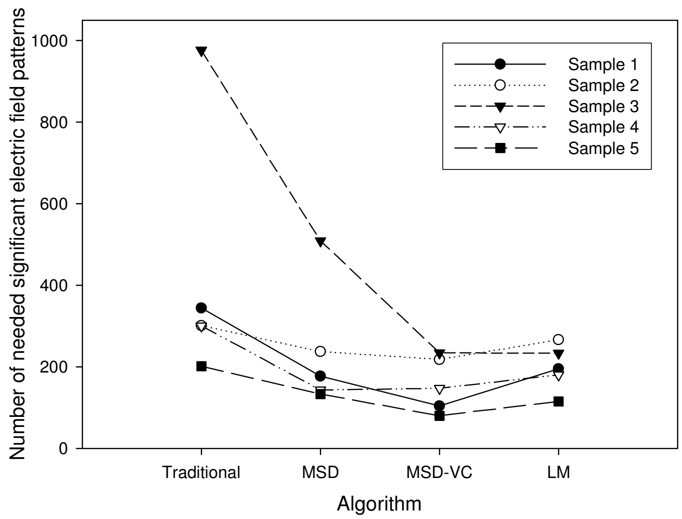


Figure 10. Significant electric field patterns for all the proposed algorithms

Finally, in order to analyze the effect of the needed times to get the final "uniform" electric field distribution, and taking into account that, in this work, the irradiation times are directly related to the sum of the Wk coefficients associated to each 'k' significant pattern, Figure 11 shows the final exposure time to get the solution for each considered method. As it can be observed, the time requirements are similar when MSD or MSD-VC algorithms are applied while for the other ones are significantly greater.

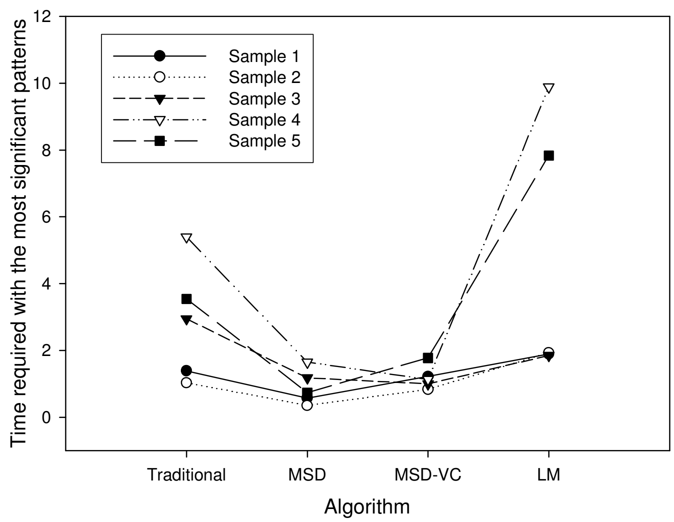


Figure 11. Time required (in seconds) needed to generate the final solution by considering only the obtained most significant patterns

VI. CONCLUSIONS

In this paper we have presented a new strategy for achieving uniform temperature distributions within microwave-heating applicators. This uniform microwave-heating has been accomplished by achieving even average electric field distributions within the dielectric samples. Several traditional optimisation methods such as MSD and LM have been used to optimise the sample movement in order to obtain a constant electric field distribution and their results have been compared to both the traditional constant sample movement and a novel optimisation procedure, MSD-VC, which ensures a minimum variance for the electric field distribution.

The implementation of MSD-VC for uniformity optimisation in this work significantly reduces the variance of the final average electric field pattern and at the same time approaches the desired constant electric field distribution. This new procedure reaches the minimal level of variance in comparison with the most traditional adaptive models, which implies the best solution in terms of electric field uniformity inside the sample to be heated. Additionally, this method provides the lowest number of sample positions and time requirements needed to synthesize the final average electric field distribution which is important in terms of the experimental implementation of this optimisation technique.

The comparison of the electric field patterns provided by both the traditional sample movement and the proposed intelligent and non-uniform sample displacement shows that it is possible to greatly improve microwave-heating uniformity when using the proposed sample-movement optimisation methods.

Finally, future tasks are planned in order to implement the proposed method in real scenarios for microwave heating applicators.

REFERENCES

[1] J. Monzó-Cabrera, A. J. Canós, J.M. Catalá-Civera and E. de los Reyes, Simulation of Temperature Distributions in Pressure-Aided Microwave Rubber Vulcanization Processes, Journal of Microwave Power and Electromagnetic Energy 37 (2002), 73-88.

[2] P. Kopyt and M. Celuch-MarzYsiak, FDTD Modelling and Experimental Verification of Electromagnetic Power Dissipated in Domestic Microwave Ovens, Journal of Telecommunications and Information Technology 1 (2003), 59-65.

[3] P. Plaza-González, J. Monzó-Cabrera, J.M. Catalá-Civera and D. Sánchez-Hernández, A New Approach for the Prediction of the Electric Field in Multimode Microwave Applicators with Mode Stirrers, IEEE Transactions on Magnetics 40 (2004), 1672-1678.

[4] P. Plaza-González, J. Monzó-Cabrera, J.M. Catalá-Civera and D. Sánchez-Hernández, Effect of Mode Stirrer Configurations on Dielectric Heating Performance in Multimode Microwave, IEEE Transactions on Microwave Theory and Techniques 53 (2005), 1699-1706.

[5] J. Pitarch, A.J. Canós, F.L. Peñaranda-Foix, J.M. Catalá-Civera and J. V. Balbastre, Synthesis of Uniform Electric Field Distributions in Microwave Multimode Applicators by multifeed Techniques, 9th International Conference on Microwave and High Frequency Heating, Loughborough, 2003.

[6] M.E. Requena-Pérez, J.L. Pedreño-Molina, J. Monzó-Cabrera and A. Díaz-Morcillo, Multimode Cavity Efficiency Optimization by Optimum Load Location: Experimental Approach, IEEE Transactions on Microwave Theory and Techniques. Vol. 53, No. 6, (2005), 2838-2845.

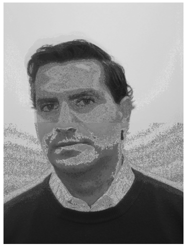
[7] http://www.mathworks.com (available online).

[8] J. Monzó-Cabrera, A. Díaz-Morcillo, J.L. Pedreño-Molina and D. Sánchez-Hernández, A new method for load matching in multimode-microwave heating applicators based on the use of dielectric-layer superposition, Microwave and Optical Technology Letters 32, (2002), 465-469.

[9] S. Haykin, Adaptive Filter Theory 3rd Edition, Prentice Hall, New Jersey, 1996.

[10] D.W. Marquardt, An algorithm for least-squares estimation of nonlinear parameters. Journal of the Society for Industrial and Applied Mathematics 11 (1963), 431-441.

BIOGRAPHIES



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