Synthesis of Interdigital Capacitors Based on Particle Swarm Optimization and Artificial Neural Networks

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ABSTRACT: This article reports on the use of the particle swarm optimization (PSO) algorithm in the synthesis of the planar interdigital capacitor (IDC). The PSO algorithm is used to optimize the geometry parameters of the IDC in order to obtain a certain capacitance value. The capacitance value of the IDC is evaluated using an artificial neural network (ANN) model with the geometry parameters of the IDC as its inputs. Several design examples are presented that illustrate the use of the PSO algorithm, and the design goal in each example is easily achieved. Full-wave electromagnetic simulations are also performed for some of the studied IDC structures implemented using coplanar waveguide (CPW) technology. The simulation results are in good agreement with those obtained using the ANN/PSO algorithm.

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I. INTRODUCTION

One of the common elements in microwave integrated circuits (MICs) is the interdigital capacitor (IDC), which was first introduced and analyzed by Alley [1] almost 35 years ago. Since then, it has been the subject of several publications [2–12]. Given the recent developments in wireless telecommunications, a fast, accurate, and effective computer-aided design (CAD) model to design IDCs has become increasingly more important in microwave design [13].

In a recent work [14], we developed an artificial neural network (ANN) model to compute the capacitance of the IDC shown in Figure 1. A closed-form expression for the capacitance was used to generate data for training and testing. The expression was

taken from [8] with few modifications. Using that expression, a CAD model for the coplanar waveguide (CPW) IDC was presented in [14].

The objective of this article is to use the developed ANN model in [14], coupled with the particle swarm optimization (PSO) algorithm [15], to synthesize the IDC shown in Figure 1. That is, given a specific capacitance value, the dimensions of the IDC and the substrate parameters will be obtained. Alternatively, one can fix the substrate parameters and find the corresponding IDC physical dimensions and number of fingers. It should be noted that no ground plane is shown in Figure 1. However, our design works for the series capacitance of the CPW IDCs [14], while the shunt capacitors can be derived using expressions given in [14]. Moreover, our design should work for microstrip IDCs with a ground plane far enough such that it has negligible effect on the series capacitance of the IDC [14].

A brief description of the developed ANN model used in [14] is presented in the next section, while the

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Figure 1. General view of a five-finger interdigital capacitor.

PSO algorithm is described in section III. Several design cases are given in section IV. To support the theory presented in this article, full-wave electromagnetic simulations realized using the commercial software IE3D are also presented for some of the IDC structures, and agreement with the ANN/PSO results is good.

II. ANN MODEL

Recently, ANNs have been widely used in RF and microwave CAD [16–22]. The multilayer feed-forward network is one of the most effective and commonly used ANN architectures [23]. This type of network consists of neurons that are arranged in layers (an input layer, output layer, and a number of hidden layers), as shown in Figure 2.

In [14], a multilayer feed-forward network was developed to model the capacitance of the IDC. The parameters: ϵ_r , h , W , S , t , and G of the IDC are the inputs to the network, while the network outputs three variables from which the value of the IDC capacitance, for some given values of N and L , is obtained directly using a simple expression given in [14]. Table I gives the range of the input parameters used in

Figure 2. Example of a multilayer feed-forward network architecture with an input layer, two hidden layers, and an output layer.

TABLE I. The Range of Input Parameters

ϵ_r	h [μm]	W [μm]	S [μm]	t [μm]	G [μm]
9–13	100–700	10–50	2–50	1–5	2–50

creating the training and testing data. This range covers most practical CPW IDCs used in MMICs.

The network is trained and tested using 1000 and 100 different randomly distributed points of the parameters in the range given in Table I, respectively. A two-hidden layer network with 15 neurons in the first layer and 25 neurons in the second layer successfully models the IDC. The developed ANN can be used to accurately compute the value of the capacitance of the IDC for any given set of input parameters in negligible time. The ANN results given in [14] demonstrate the accuracy and the generalization ability of the trained ANN model. Therefore, the developed network is an accurate and attractive alternative module that can be used in a CAD-based tool to optimize the design of an IDC. The following sections support and demonstrate this conclusion.

III. PARTICLE SWARM OPTIMIZATION

The PSO algorithm is used in this article to optimize the geometry parameters of the IDC in order to obtain a certain capacitance value. The PSO algorithm is an evolutionary algorithm capable of solving general multidimensional optimization problems. The PSO algorithm was introduced in 1995 by Kennedy and Eberhart [24], and since then the PSO has gained an increasing popularity as an efficient alternative to genetic algorithms (GAs) and simulated annealing (SA) in solving optimization design problems. Like other evolutionary algorithms, the PSO algorithm utilizes the social interaction between independent agents, hereafter called particles, during their search for the optimum solution using the concept of fitness. What is attractive about the PSO algorithm over conventional and evolutionary optimization algorithms is its simplicity and generality. It requires the least amount of mathematical preprocessing. It is easy to write a general-purpose computer code for the PSO and in it the fitness evaluation is left for the user to conduct, depending on the problem at hand. The PSO algorithm has been tested on standard optimization problems ranging in difficulty from simple zero-finding of N -dimensional functions to the optimization of the profile of corrugated horn antennas with pre-defined radiation properties [15].

Figure 3. Flowchart diagram showing the main steps of the PSO algorithm. B.T. stands for “better than” and for the current problem it is translated mathematically as “less than.”

It should be mentioned that this article is not intended to be an extensive review of the PSO algorithm, and therefore only the main steps of the algorithm are presented here. The reader is referred to [15, 24–30] and the references mentioned therein for a detailed discussion of the basic concepts of the PSO algorithm, how it works, and its advantages over other optimization techniques. The flowchart diagram shown in Figure 3 summarizes the main steps of the PSO algorithm discussed below.

After defining the solution space and the fitness function, the PSO algorithm starts by randomly initializing the position and velocity of each particle in the swarm. For an N -dimensional problem with M particles, each particle has its own position and velocity in every dimension; therefore, the positions and velocities of the particles can be specified by the following $M \times N$ matrices:

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1N} \\ x_{21} & x_{22} & \dots & x_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ x_{M1} & x_{M2} & \dots & x_{MN} \end{bmatrix}, \quad (1)$$

$$V = \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1N} \\ v_{21} & v_{22} & \dots & v_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ v_{M1} & v_{M2} & \dots & v_{MN} \end{bmatrix}. \quad (2)$$

Any row of the position matrix represents a possible solution to the optimization problem. The velocity of each particle depends on the distance between the current position and the positions that result in good fitness values. To update the velocity matrix, every particle should know, up to the current iteration, its personal-best and the global-best position vectors. The personal-best position vector defines the position at which each particle attained its best fitness value up to the present iteration. The personal best position can be defined by the following matrix:

$$P = \begin{bmatrix} p_{11} & p_{12} & \dots & p_{1N} \\ p_{21} & p_{22} & \dots & p_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ p_{M1} & p_{M2} & \dots & p_{MN} \end{bmatrix}. \quad (3)$$

TABLE II. IDC Design Results (Eight Parameters)

C_{des} [pF]	ε_r	h [μm]	W [μm]	S [μm]	t [μm]	G [μm]	L [μm]	N	C_{ANN} [pF]
0.05	9	303	27	30	1	27	292	4	0.0499
	11	300	35	32	1	34	301	3	0.0498
0.1	9	496	17	22	1	17	250	10	0.099
0.5	12.61	505	35	27	3	28	254	29	0.498
1	12.88	301	19	12	5	18	301	50	1.003
1.5	11	302	17	13	4	16	602	49	1.518
	12	301	21	17	2	17	601	46	1.490

The row of the position matrix X at which the best fitness value is achieved is the global-best position vector in the solution space, given by

$$G = [g_1 \ g_2 \ \dots \ g_N]. \quad (4)$$

All the information needed by the PSO algorithm is contained in X , V , P , and G . The core of the PSO algorithm is how to update these matrices in each iteration of the algorithm. These matrices are updated such that the position vector of each particle is encouraged to move closer to both its personal-best and the global-best positions at every new iteration. For this goal, the velocity matrix is updated according to [25, 26]:

$$v_{mn}^t = w v_{mn}^{t-1} + c_1 \eta_{n1} (p_{mn}' - x_{mn}^{t-1}) + c_2 \eta_{n2} (g_n' - x_{mn}^{t-1}), \quad (5)$$

where the superscripts t and $t - 1$ refer to the time index of the current and the previous iterations, η_{n1} and η_{n2} are two different uniformly-distributed random numbers in the interval $[0, 1]$. The parameters c_1 and c_2 specify the relative weight of the personal-best position versus the global-best position. It has become a common practice to choose a value of 2.0 for both parameters [29]. The parameter w is called the “inertial weight”, and it is a number in the range $[0, 1]$ that specifies the weight by which the particle’s current velocity depends on its previous velocity, and the distance between the particle’s position and its personal-best and global-best positions. Empirical studies [15] have shown that the PSO algorithm converges faster if w is linearly damped with iterations, for

example, starting at 0.9 at the first iteration and finishing at 0.4 in the last iteration. The position matrix is updated according to the simple relation:

$$X^t = X^{t-1} + V^t. \quad (6)$$

The PSO algorithm, like GA and other evolutionary algorithms, uses the concept of fitness to decide how good the position vector of each particle in the swarm is, during the search for the optimum position vector in the N -dimensional space. At each iteration of the algorithm, the particle’s position vector that resulted in the best fitness is chosen as the global-best position vector, and this information is communicated to all other particles to use in updating the velocity and position vectors matrices according to eqs. (5) and (6). In the current problem, we are interested in designing the geometry of the IDC to give us a certain capacitance value. To achieve this goal, the following function is used to evaluate the fitness:

$$\text{Fitness} = \min |C_{des} - C_{ANN}|, \quad (7)$$

where C_{des} is the desired capacitance, and C_{ANN} is the capacitance evaluated from the ANN model as outlined in section II. It is clear from (7) that for the current problem, the particle with the best fitness is the one with the position vector that minimizes the fitness function defined in (7).

IV. RESULTS AND DISCUSSION

The PSO algorithm and the ANN model were used to design the IDC. In designing the IDC, we aim to find

TABLE III. IDC Design Results (Seven Parameters, $\varepsilon_r = 13$)

C_{des} [pF]	h [μm]	W [μm]	S [μm]	t [μm]	G [μm]	L [μm]	N	C_{ANN} [pF]
0.5	310	25	30	4	25	306	27	0.494
	306	32	25	4	25	312	24	0.497
1.5	337	20	19	3	22	601	44	1.492
	302	20	21	3	19	601	45	1.491

TABLE IV. IDC Design Results (Seven Parameters, $\epsilon_r = 9.8$)

C_{des} [pF]	h [μm]	W [μm]	S [μm]	t [μm]	G [μm]	L [μm]	N	C_{ANN} [pF]
0.5	516	19	24	1	17	505	25	0.502
	318	29	13	4	28	509	18	0.496
1.5	411	34	10	4	14	607	42	1.504
	519	37	6	5	27	516	42	1.489

its parameters that will result in a certain capacitance. In Table II, the dimensions of the IDC and the substrate parameters were determined for a given specific capacitance value. That is, starting with a desired value of capacitance C_{des} , the PSO algorithm is used to search the solution space for the dimensions of the IDC and the substrate parameters that will give the desired capacitance with some acceptable error. The designed values of the capacitance using the parameters obtained by the PSO search are either exactly equal or very close to the required values. The difference (if any) between the desired capacitance and the designed capacitance is a result of two factors: (i) the stopping criteria used in the PSO search and (ii) the allowance of only integer parameter values (except for the value of ϵ_r) to be a valid solution. In addition, Table II shows different sets of the dimensions of the IDC and the substrate parameters that give a certain required capacitance value. For example, two sets of parameters are shown for the desired capacitance values of 0.05 and 1.5 pF which would give the designer more freedom in selecting the IDC parameters for a certain capacitance. Furthermore, it also emphasizes the fact that the parameters obtained from the PSO are not unique and depend on the random initialization step for this particular design problem.

In certain situations, some of the design parameters are fixed or given to the designer. For example, one can fix one or more of the IDC parameters and search for the other parameters. In Tables III and IV, the substrate type is fixed and the other parameters are obtained using the PSO algorithm. Table V shows the design results for fixed substrate parameters (the

height and the type of the substrate) and metal thickness.

In all of the results shown in Tables II–V, the objective of the optimization is to find the IDC parameters that result in a capacitance value that is very close to the desired capacitance value. However, during the search process only values that are within the ranges given in Table I (which cover most practical IDCs) are used. Therefore, there are constraints on the values of the parameters that are accepted as a valid solution. In addition, more parameters were set to some desired values as we progress from Table II to Table V. For example, in Tables III and IV the dielectric constant of the substrate is set to some typical values, while in Table V the height, dielectric constant, and metal thickness are set to some fixed values which are assumed to be manufacturing standards. More constraints may be added on the other geometrical parameters, but this action may result in two problems. First, the solution space will be reduced, which in some cases might make the acceptable solution infeasible, especially for a high desired capacitance value. Second, in some other cases, this action could slow the search process dramatically.

In each row in Tables II–V, a nonunique solution that results in an acceptable error between the desired and the obtained capacitance values is given. The nonuniqueness of the solution was demonstrated by giving more than one solution for the same desired capacitance value, as shown in Tables III and IV. Three factors have led into this nonuniqueness of the solution. The fact that a desired capacitance value can be realized by many different parameters sets is the

TABLE V. IDC Design Results (Five Parameters, $\epsilon_r = 12.9$, $h = 400 \mu\text{m}$, $t = 3 \mu\text{m}$)

C_{des} [pF]	W [μm]	S [μm]	G [μm]	L [μm]	N	C_{ANN} [pF]
0.155	46	20	30	534	4	0.154
0.5	21	12	21	403	19	0.499
0.75	34	35	18	319	36	0.750
1	47	10	21	307	37	0.999
1.5	48	6	28	306	50	1.499
1.75	47	9	4	366	50	1.750
2	44	2	7	410	43	2

Figure 4. A general view of a CPW IDC and its equivalent-circuit model. T_1 and T_2 are the reference planes at which the scattering parameters are evaluated. G_f was chosen to obtain 50 Ω feeding lines.

most important one. The other two factors are the random initialization step and the velocity and position update of each particle according to eqs. (5) (which requires two random variables) and (6) in the PSO algorithm. One may argue that the PSO algorithm can be initialized with some desired initial parameters values to remove nonuniqueness of the solution. However, the other two factors are dominant and will again result in a nonunique solution.

During the synthesis process, the PSO algorithm will converge and the search process will be terminated if the difference between the desired capacitance value and the calculated (using the ANN model) capacitance value is less than or equal to an accepted error value. In this particular synthesis problem, an error value of 10^{-2} was used. Therefore, termination of the search process and the output of the PSO algorithm are controlled by the accepted error value. However, this does not mean that any set of parameters will be accepted as long as the termination criterion is achieved, but during the search process only the set of parameters in the solution space is used. As stated above, the solution space is the values of the parameters that are within the ranges given in Table I. It should be emphasized that these ranges cover most practical IDCs. As a result, the designer is not taking any risk by accepting the output of the PSO algorithm. In addition, the designer may obtain another solution simply by running the PSO algorithm one more time. Furthermore, the designer can set some of the parameters to some desired values and run the PSO algorithm to find the remaining parameters. Also, more constraints can be added on the parameters to change

the solution space. However, careful attention to the selection of the parameters to be set or the constraints to be added should be made in order to avoid the possible occurrence of the two problems mentioned above.

To verify our approach, the full-wave electromagnetic simulator IE3D [31] is used to obtain the scattering parameters for some of the IDC designs presented in the above tables. To be able to perform a full-wave analysis, a ground plane needs to be added to the IDC structure shown in Figure 1. We have chosen to analyze a CPW IDC in which the ground planes are placed around the IDC, as shown in Figure 4. In the same figure, a lumped-element equivalent circuit of the CPW IDC is also shown [14]. The values of these capacitances are obtained from the scattering parameters using simple network theory [32]. Although, in this article, we are interested in the series capacitance C , values for the shunt capacitances C_1 and C_2 will be also presented and compared to those obtained using the expression proposed in [14]. It should be mentioned that if N is even, the IDC structure will be symmetric and $C_1 = C_2$, but if N is odd, the structure is asymmetric and $C_1 \neq C_2$.

The simulation results for some examples are shown in Figures 5–7. The results show that up to about 10 GHz there is fair agreement between the value of the series capacitance from full-wave simulation and that obtained from the ANN model. The difference between the two values can be attributed to two reasons. First, the ANN model used is based on data generated from quasi-static expressions for the capacitance obtained using the conformal mapping method. Second, the circuit model used here neglects

Figure 5. CPW IDC series and shunt capacitances vs. frequency. The corresponding geometry is given in the first row of Table II. The desired value of C is 0.05 pF. $G_f = 72 \mu\text{m}$.

the series inductance of the IDC, and that explains why the full-wave simulation results for the series capacitance are larger than the ANN model values in order to account for the neglected inductance.

Regarding the shunt capacitances, it can be seen that the value of this capacitance is almost independent of frequency. As explained in [14], the shunt capacitance can be approximated as the product of the IDC length with the per unit length capacitance of a CPW line having one ground plane only (with slot width S_f and conductor width W). Such a line is a quasi-TEM line, which gives a constant shunt capacitance as a function of frequency. The values obtained using the expression in [14] are $C_1 = C_2 = 0.021$, 0.0142, and 0.046 pF for the IDCs studied in Figures 5, 6, and 7, respectively. These approximate values do not take into account the capacitance between the inner fingers and the ground plane. This explains why these values are less than those obtained from full-wave simulations (especially for the case with $N = 10$, as shown in Fig. 6)

V. CONCLUSION

This article has illustrated the use of the particle swarm optimization (PSO) method in the synthesis of interdigital capacitors (IDCs). The PSO algorithm, in conjunction with an ANN model of the IDC, were successfully used to optimize the geometry parameters of the IDC in order to obtain a desired capacitance value. The validity of the presented design approach was shown through the discussion of several design examples. In each example, the design goal was easily

Figure 6. The CPW IDC series and shunt capacitances vs. frequency. The corresponding geometry is given in the third row of Table II. The desired value of C is 0.1 pF. $G_f = 130 \mu\text{m}$.

Figure 7. The CPW IDC series and shunt capacitances vs. frequency. The corresponding geometry is given in the first row of Table V. The desired value of C is 0.155 pF. $G_f = 152 \mu\text{m}$.

achieved, at least in theory. The full-wave simulation results are also in support of the proposed ANN/PSO model of the IDC. A CAD model for the IDC based on the design methodology presented in this article can be easily incorporated with existing CAD software.

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