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A Multi-Expression Programming Application to the Design of Planar Antennae

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A Multi-Expression Programming Application to the Design of Planar Antennae

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Abstract - A method to determine functional relationships between the variable physical dimensions of an antenna and the antenna performance characteristics is presented. By applying multi-expression programming (MEP) to this data set, optimization with regard to a given criteria can be subsequently performed on the functions instead of performing repeated electromagnetic simulations. The functionals are trained on an initial population of simulation samples and refined using a point-wise error estimate to identify design parameters for subsequent samples. Additionally, the depth of the MEP tree is adjusted for increased accuracy as the data set is deemed sufficient.

1. INTRODUCTION

The design of an antenna system generally involves an attempt to satisfy many objectives, such as impedance characteristics, center frequency, bandwidth, polarization, gain, directivity, etc. Typically, a tradeoff exists where one property is optimized at the expense of another. The optimization process then becomes a twofold challenge, where it becomes necessary to determine which design features correspond to which performance characteristics and to select the optimal combination of output characteristics available within the range of permitted geometries. Parametric post-processing design methods, such as genetic algorithms, offer the advantage in that they are readily integrated into existing software products[1][2]. In this work, the initial step of identifying and mapping the geometric parameters that most affect each output characteristic is considered such that the optimization may be performed on a simplified set of equations.

2. NUMERICAL METHODS

The analysis in this work can be divided into two parts, the first being the electromagnetic simulation itself and the second being the data mining of the simulation results.

2.1 Field Calculation

Since the parameter mapping corresponds to a post-processing application, it can be applied to any numerical method. Due to the differences in formulations, the derived functions will naturally have some dependency on the method used. In this work, the finite difference time domain (FDTD) method was implemented to calculate the electromagnetic parameters of the dual band antenna. Solutions to the FDTD are obtained by solving Maxwell's curl equations[4]:

$$\nabla \times \vec{H} = \frac{\partial \vec{D}}{\partial t} + \vec{J}$$
$$\nabla \times \vec{E} = -\frac{\partial \vec{B}}{\partial t} - \vec{M} \qquad (1)$$

where a fictitious magnetic current is included for symmetry purposes. Both spatial and temporal derivatives of the Maxwell's equations are expanded using the central finite differences. To account for the finite numerical domain in an infinite radiation problem, the UA-PML technique is adopted for treatment of the absorbing boundary condition (ABC).

2.2 Multi-Expression Programming

MEP [3] represents a genetic programming technique where syntactically correct functions are derived from a data set. For a given set of input data and output data, the MEP derives a function that best fits this data set. The function is derived from a combination of possible mathematical expressions. Some examples of MEP genes are provided in Table I. The accuracy of the function is determined by the allowed depth, or number of genes in the chromosome. It has been extensively applied to data mining applications where large amounts of data exist and has recently seen usage as an optimization tool in electromagnetics [4].

<TABLE 1> EXAMPLES OF MEP GENES

MEP Classes	Genes
Arithmetic operations	+, -, /, *, ^
Functions	sin, log, exp
Conditionals	&, |, <

As with any optimization technique, minimizing the number of electromagnetic simulations is very important. In this analysis a similar goal exists, while still obtaining the most accurate functional. To construct the functional, two sets of random variables are chosen and a functional is extracted from each set. An absolute error estimate using the two trial spaces is obtained. When the dominant parameters of each trial space are different, the respective variable space is expanded to include greater interpolation for each set. Variables with minor significance continue to receive random perturbations. It is worth noting that the MEP algorithm is applied twice to the data sets since different functionals will be derived. When developing the fitting functional, the following conditions were applied:

1. A successful run indicates that 90% of the terms have a value within a relative 5% of the fitting function
2. Restart with a new initial set of genomes if 10 generations pass without improvement
3. Restart with a new initial set of genomes if a satisfactory functional is not obtained after 50 generations
4. Increase the data pool if no successful runs have occurred ten consecutive times

3. RESULT

Analysis was performed on two planar antenna structures, a simple rectangular patch antenna and a dual-band slotted antenna.

3.1 Patch Antenna

The first investigation focused on a test structure to evaluate the effectiveness of the MEP functionals. A simple patch element designed for single band radiation at 2.24 [Ghz] was implemented. Only two variables are considered, the length and width of the patch element, $14<W<16$ [mm] and $41<L<45$ [mm]. A single output function, the resonant frequency was chosen as the objective. The derived tree for one of the functionals is shown in Figure 1.

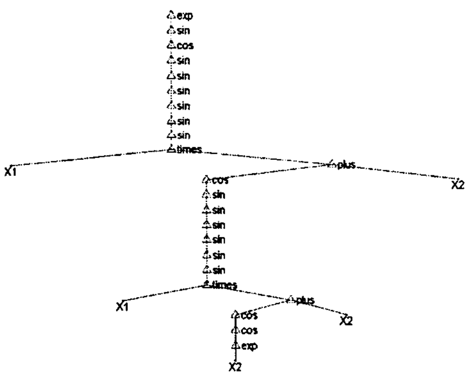
3.2 Dual Band Slotted Patch Antenna

A more thorough analysis was applied to the dual band antenna shown in Figure 2. Many design variables exists, corresponding to overall patch dimensions, slot dimensions, slot locations, and feed position. In order to maintain physical symmetry, the design variables were limited to those indicated in Table II. The patch was fed through the ground plane by a rectangular coaxial feed with a 50 Ohm impedance. The perturbation dimensions of each of the design variables, including slot position, are provided in Table II also. The FDTD algorithm was applied to determine the frequency response characteristics in the range $1 < f < 3$ [GHz]. The output variables corresponded to the resonant frequencies and the return loss.

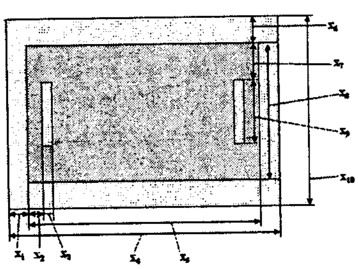
A total of 100 simulations were performed using the FDTD algorithm. Fifty of the samples were used as a training set, with the initial 30 being completely random and the next 20 generated using the algorithm described. The remaining 50 were also generated from a random selection of inputs and were used to test the accuracy of the derived MEP function as a predictor.

With the larger set of input variables, it was much more difficult for the MEP function to obtain a function that mapped the input data to the output data while satisfying the accuracy constraint. A completely naïve selection of random input variables as initial function arguments proved to cause a large number of failed genetic processes. In Figure 3, the correlation between two input variables, the slot length and the patch length are shown relative to the first resonant frequency of the antenna. It is clear that the patch length has a strong correlation to this output characteristic. Therefore a weighted variable selection can be applied to the MEP algorithm, where leaf selection at initialization and mutation is favored toward variables with a strong statistical correlation to a givenset of output data.

As can be seen in Table III, the accuracy of the derived function depends on the amount of training data and can be increased greatly by weighting the selection of variables. The first three rows represents data derived from a purely random selection of data while the last row includes the improved selection process of design variables. As would be expected, the accuracy of the functional improves significantly.



<Fig. 1> Derived tree mapping the patch dimensions to the first resonant frequency. This function fits 90% of the elements to an accuracy of 5%.



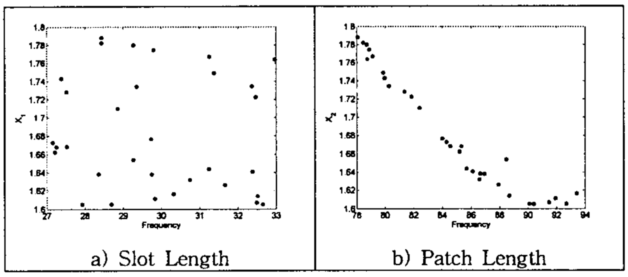
<Fig. 2> Design parameters of the dual ban slot loaded patch antenna

3. CONCLUSION

A MEP algorithm to determine a function mapping antenna design variables to electromagnetic performance was implemented. Training and test data were obtained using FDTD simulations, however any numerical tool would be acceptable. Investigations into MEP behavior revealed several aspects that would improve the likelihood of an acceptable functional. Additionally, statistically preprocessing the correlation between input and output data provided a weighting scheme to improve the performance of the algorithm. This work provides insight into further research regarding a reduction in chromosome length and improved genetic selection in the algorithm.

<TABLE 2> DESIGN PARAMETERS OF THE SLOT-LOADED DUALBAND PATCH ANTENNA

Parameter	Center Value[mm]	Variation[mm]
Patch Length, x1	30	3
Patch Width, x2	86	6
Slot Height	15	1.5
Slot Width	1.5	0.15
Slot Location	7.5	1
Horizontal Feed Position	11	1.5
Vertical Feed Position	0	|1.5|



<Fig. 3> Plots of the slot length and patch length, respectively, against the first resonant frequency of the patch antenna.

<TABLE 3> ACCURACCY OF THE DERIVED MEP FUNCTIONAL BASEDON THE NUMBER OF TRAINING SAMPLES AND A NA□VE OR WEIDGHTED SELECTION OF DESIGN INPUT VARIABLESS

Number of Samples	Predictive Error Percentage, Naïve Variable Selection	Predictive Error Percentage, Weighte d Variable Selection
10	85%	76%
20	65%	47%
30	43%	30%
50	25%	12%

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