Chapter 15
Neuromodeling and Natural Optimization of Nonlinear Devices and Circuits

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ABSTRACT
This chapter describes some/new artificial neural network (ANN) neuromodeling techniques and natural optimization algorithms for electromagnetic modeling and optimization of nonlinear devices and circuits. Neuromodeling techniques presented are based on single hidden layer feedforward neural network configurations, which are trained by the resilient back-propagation algorithm to solve the modeling learning tasks associated with device or circuit under analysis. Modular configurations of these feedforward networks and optimal neural networks are also presented considering new activation functions for artificial neurons. In addition, some natural optimization algorithms are described, such as continuous genetic algorithm (GA), a proposed improved-GA and particle swarm optimization (PSO). These natural optimization algorithms are blended with multilayer perceptrons (MLP) artificial neural network models for fast and accurate resolution of optimization problems. Some examples of applications are presented and include nonlinear RF/microwave devices and circuits, such as transistors, filters and antennas.

INTRODUCTION
Versatility, efficient computation, reduced memory occupation, stability of learning algorithms and generalization from representative data are some characteristics that have motivated the use of neural networks in many areas of microwave engineering (Patnaik & Mishra, 2000; Zhang & Gupta, 2000). In circuit simulation, neuromodeling applications reported in literature to improve
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The harmonic balance method have been used as nonlinear device models for microwave circuit steady-state analysis (Santos, Romariz, & Carvalho, 1997). On the other hand, neuromodeling technique is evaluated in time-domain, in order to improve nonlinear GaAs MESFET logic gate circuit transient and sensitivity analysis (Silva, Melo, & Neto, 2001; Silva, Melo, & Neto, 2002).

Circuit simulators like SPICE (with integrated circuit emphasis) are formed around semiconductor devices like diodes, BJTs, MOSFETs, MESFETs etc. (Raghuram, 1989). In general, the quality of simulation is decided by the accuracy of device models. On the other hand, a very detailed model would naturally slow down the program. A compromise between accuracy and speed of computation has to be struck. Using neural networks enables to overcome this problem.

Generally, the use of circuit simulation packages presents difficulties to the designer in implementing their own nonlinear model applied to a new device (Raghuram, 1989). Numerical simplifications are required. Then, the use of empirical models increases the computational efficiency of numerical simulations. In this context, artificial neural networks trained by accurate electromagnetic (EM) data, are very suitable for developing computer aided design (CAD) tools. Neural models combine the accuracy of EM-simulators with the computational efficiency of empirical models (Silva, 2002). For this reason, ANN models for nonlinear RF/microwave devices and circuits have been widely used (Zhang & Gupta, 2000). Various hybrid neuromodeling techniques incorporate previously EM knowledge to ANN in order to obtain more consistent training, reliability and accuracy for the resulting ANN models. Versatility, stability of learning algorithms and generalization abilities permit us to employ neural models for complex ill-defined input-output mappings in new (not well-known) devices (Santos et al., 1997).

Neuromodeling methodology can be described by two steps: i) neural network model development - that includes selection of representative training data, network configuration and training algorithms; ii) neural model validation - the neural network model is tested and validated according to its interpolation and generalization capacities in a given region of interest.

Natural optimization algorithms, which are stochastic population-based global search methods inspired by nature, such as simulated annealing (SA), genetic algorithm (GA) and particle swarm optimization (PSO) are effective for optimization problems with a large number of design variables and inexpensive cost function evaluation (Haupt & Werner, 2007; Kennedy & Eberhart, 1995). However, the main computational drawback for optimization of nonlinear devices and circuits relies on the repetitive evaluation of numerically expensive cost (or fitness) functions. Finding a way to shorten the optimization cycle is highly desirable. In the case of GA, for example, several schemes are available in order to improve its performance, such as: the use of fast full-wave methods, micro-genetic algorithm, which aims to reduce the population size, and parallel GA associated with parallel computation (R. Haupt & S. Haupt, 2004).

In this chapter, we present neuromodeling techniques based on single hidden layer feedforward neural network configurations − trained by the efficient resilient back-propagation (RPROP) algorithm (Ridmiller & Braun, 1993) - to solve modeling learning tasks associated with device or circuit under analysis. In particular, we focus on the use of new hidden neuron activation functions in order to improve learning, reliability and generalization of neural models. Some optimal neural network activation functions are described. Modular configurations of these feedforward networks, as well as mathematical formulation and implementation details are presented. An overview of the applications of proposed neuromodeling techniques based on previous developed researches are shown.