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Optimization of Antenna Arrays and Microwave Filters Using Differential Evolution Algorithms

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INTRODUCTION

Several evolutionary algorithms (EAs) have emerged in the past decade that mimic biological entities behavior and evolution. Darwin's theory of evolution is the major inspiration source for EAs. The foundation of Darwin's theory of evolution is natural selection. The study of evolutionary algorithms began in the 1960s. Several researchers independently developed three mainstream evolutionary algorithms, namely, genetic algorithms (Goldberg, 1989), evolutionary programming (Fogel, 1995), and evolution strategies (Beyer & Schwefel, 2002). EAs are widely used for the solution of single and multi-objective optimization problems. Swarm Intelligence (SI) algorithms are also a special type of EAs. SI can be defined as the collective behavior of decentralized and self-organized swarms. SI algorithms among others include Particle Swarm Optimization (PSO) (Kennedy & Eberhart, 1995), Ant Colony Optimization (Dorigo & Stutzle, 2004), and Artificial Bee Colony (ABC) (Karaboga & Basturk, 2007).

An evolutionary algorithm that has recently gained popularity is Differential Evolution (DE) (R. Storn & Price, 1995; R. Storn & Price, 1997). DE is a population-based stochastic global optimization algorithm. DE has been used in several real world engineering problems like fuzzy logic controller design problem (Cheong & Lai, 2007), molecular sequence alignment problem (Kukkonen, Jangam, & Chakraborti, 2007), and automatic image pixel clustering (Das & Konar, 2009). The fact that the DE algorithm can handle efficiently arbitrary optimization problems has made it popular for solving problems in electromagnetics. Therefore, DE has been applied successfully to a variety of constrained or unconstrained design problems in electromagnetics (Goudos, Siakavara, Samaras, Vafiadis, & Sahalos, 2011a; Goudos, Siakavara, Vafiadis, & Sahalos, 2010; Goudos, Zaharis, & Yioultsis, 2010 ; Kurup, Himdi, & Rydberg, 2003).

The purpose of this chapter is to briefly describe the DE algorithm and its variants and present their application to antenna and microwave design problems. This chapter presents results from design cases using self-adaptive DE. The chapter is supported with an adequate number of references. This chapter is subdivided into five sections. The "Background" Section presents the issues, problems and trends with DE for wireless communications. Then we briefly present the different DE algorithms. In the next Section, we describe the design cases and present the numerical results. An outline of future research directions is provided in the following Section while in the "Conclusion" Section we conclude the chapter and discuss the advantages of using a self-adaptive DE-based approach in the design and optimization of microwave systems and antennas. Finally, an "Additional Reading Section" gives a list of readings to provide the interested reader with useful sources in the field.

BACKGROUND

Differential evolution was introduced proposed by KennethV. Price and R. Storn in 1995. It uses

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real operators for mutation and crossover, instead of the binary operators used in the first GAs. That fact has made DE suitable for solving real-valued problems. DE is a very simple but very powerful stochastic global optimizer. It has been used to solve problems in many scientific and engineering fields and proved to be a very efficient and robust technique for global optimization. In 1997, Storn established a website (Rainer Storn) to where DE source code is publically available for several popular programming languages. Since then there is an explosive growth in differential evolution research.

One of the DE advantages is that very few control parameters have to be adjusted in each algorithm run. However, the control parameters involved in DE are highly dependent on the optimization problem. Therefore, one of the major issues with DE is the correct selection of the control parameters. A basic trend in DE research is the control parameter setting, which has been extensively studied in the literature (Eiben, Hinterding, & Michalewicz, 1999). The effect of the population size was reported in (Feoktistov & Janaqi, 2004).

Another issue is the selection of the appropriate strategy for trial vector generation, which requires additional computational time using a trial-and-error search procedure. Therefore, it is not always an easy task to fine-tune the control parameters and strategy. Since finding the suitable control parameter values and strategy in such a way is often very time-consuming, there has been an increasing trend among researchers in designing new adaptive and self-adaptive DE variants. A DE strategy (jDE) that self-adapts the control parameters has been introduced in (Brest, Greiner, Boskovic, Mernik, & Zumer, 2006). This algorithm has been applied successfully to a microwave absorber design problem (Goudos, 2009) and linear array synthesis (Dib, Goudos, & Muhsen, 2010). SaDE, a DE algorithm that self-adapts both control parameters and strategy based on learning experiences from previous generations is presented in (Qin, Huang, & Suganthan, 2009). SaDE has been applied to microwave filter design, (Goudos, Zaharis, et al., 2010), and to linear arrays synthesis (Goudos, Siakavara, Samaras, Vafiadis, & Sahalos, 2011b).

Composite DE (CoDE) (Y. Wang, Cai, & Zhang, 2011) is an adaptive DE variant, which combines three different trial vector generation strategies with three preset control parameter settings. The above combination is performed in a random way in order to generate trial vectors. The main advantage of CoDE is that it has a simple structure and thus it is very easy to be implemented in any programming language.

Most of the DE strategies or variants use the binomial crossover operator, which has been found to produce better results than the exponential crossover operator (Mezura-Montes, Velazquez-Reyes, & Coello Coello, 2006). The authors in (Guo & Yang, 2015) propose an alternative crossover operator, namely the eigenvector-based crossover. This operator utilizes the eigenvector information of the covariance matrix of the population to rotate the coordinate system. Additionally, this crossover operator can be applied to any DE variant. In (Goudos, 2015) the eigenvector-based operator is combined with CoDE to introduce a new algorithm the Composite DE with Eigenvector-Based Crossover (CODE-EIG).

The performance comparison of DE among other popular algorithms is another open issue. DE produced better results than PSO on numerical benchmark problems with low and medium dimensionality (30 and 100 dimensions) (Vesterstrom & Thomsen, 2004). However, on noisy test problems, DE was outperformed by PSO. In (Goudos, 2009) a comparative study between DE and PSO variants is presented for the design of radar absorbing materials (RAM). The number of problem dimensions was 10 and DE outperformed the PSO variants in terms of convergence speed and best values found. In (Panduro, Brizuela, Balderas, & Acosta, 2009) a comparison between DE, PSO and Genetic algorithms (GAs) for circular array design is presented. DE and PSO showed similar performances and both of them had better