Analogue Filter Tuning for Antenna Matching with Multiple Objective Particle Swarm Optimization

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***Abstract*— This paper discusses and compares the methods of Multiobjective Genetic Algorithm (MOGA), Multiobjective Simulated Annealing (MOSA) and Divided Range Multiobjective Particle Swarm Optimization (DRMPSO) applied to LC filter tuning. Specifically, the paper is concerned with applying these methods to design an antenna tuning unit, providing the facility to adapt to changes in load impedance, temperature or environmental effects, ensuring maximum power transfer and harmonic rejection. A number of simulations were carried out to evaluate the relative performance of these algorithms. Our results indicate that the DRMPSO provides a substantial improvement over the two other algorithms.**

I. INTRODUCTION

For radio antenna transmission systems it is very important to transmit maximum power to the antenna to achieve maximum transmission efficiency. In many cases, for example the mobile and fixed terminal applications, these systems must deal with changing load and environmental aspects. The goal of obtaining fast antenna tuning systems that are capable of offering impedance matching whilst maintaining good harmonic rejection properties has become increasingly significant. One of the most popular impedance matching configurations used is the Pi-Network, which is simple in structure and can accommodate a wide range of load impedances and offer high harmonic rejection capabilities. The Pi-Network's versatility allows additional criteria to be considered for optimization i.e. harmonic rejection, parasitic effects, component costs. However, the contribution of each component made to the Pi-Network impedance characteristic is complex. Current tuning algorithms in commercially available equipment use a step-by-step approach, where the tuning network is adjusted iteratively until impedance matching is achieved [1-2]. This method is slow and just focuses on impedance matching, rather than optimizing the full capabilities of the Pi-Network. Global optimization techniques have been reported for a range of applications, which consist of multiple objectives and where time constraints are also of importance. Previously, the Genetic Algorithm and Simulated Annealing [3-4] optimization algorithms have been applied to this problem, however an aggregate fitness is used which lead the full capabilities of the system not being realized. Multiobjective evolutionary algorithms have also been applied to this problem [5], however the running time is too long. In this paper, we use the DRMPSO to investigate the characteristics of the system.

Figure1 shows the arrangement of the Pi-Network between load and source impedances, R_s represents the transmitter source impedance, (typically 50 ohms resistive) z_L represents the complex load impedance, while z_1 z_2 and z_3 represent the impedance of the network at each stage from source to load respectively. In order to achieve conjugate impedance matching and hence maximum real power transfer from the transmitter to the load, z_3 must equal the complex conjugate of the load impedance (z_L). We will use this Pi-Network model for further analysis.

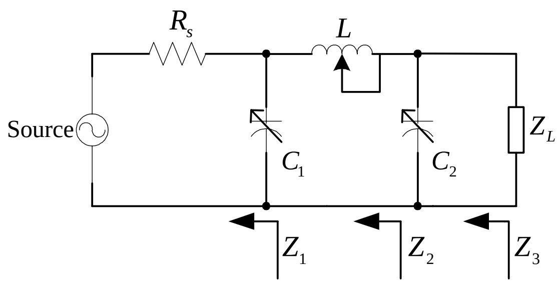

Figure 1 Pi-Network used for Impedance Matching between Source and Load Impedances

The Pi-Network's versatility creates problems when attempting to control it for optimal performance. When multiple objectives are considered, conflicting requirements may occur i.e. for a particular situation impedance matching may be achieved through low inductor values, while maximum harmonic rejection is achieved through maximum inductance. These conflicts between objectives compound the tuning problem by creating more complex error functions, containing greater numbers of local minima in which a search algorithm may become entrapped. By considering the objectives separately using the DRMPSO, this problem may be eliminated and the interaction between objectives can be examined, providing valuable insight into the tradeoffs and leading to efficient optimization.

II. PROBLEM FORMULATION: DIVIDED RANGE MULTIOBJECTIVE PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is a population-based stochastic optimization technique developed by Kennedy and

Eberhart [6]. Through cooperation and competition among the population, population-based optimization approaches often can find good solutions efficiently and effectively. Unlike most of population based search approaches motivated by evolution as seen in nature, e.g. genetic algorithms, evolutionary strategies and genetic programming, PSO is motivated from the simulation of social behavior [7].

In this paper, we present a novel PSO model for distributed computing, which will be referred to as Divided Range Multiobjective Particle Swarm Optimization (DRMPSO). In the DRMPSO, the individuals are divided into sub-populations by the values of their objective functions, which is benefit for local search. This model is suitable for parallel processing. The flow of the DRMPSO algorithm is explained as follows.

Step1. Initial population (population size is N) is produced randomly. The fitness value of each individual is calculated.

Step2. The individuals are sorted by the values of focused objective function f_i. This focused objective function f_i is chosen in turn, and is turned with the loop. Then, the individuals of number N/m are chosen in accordance with the value of this focused objective function f_i. As the result, there are m sub-populations.

Step3. In each sub-population, one multiobjective PSO has been performed for some iterations. The end of each generation, the terminal condition is examined and the process is terminated when the condition is satisfied. When the terminal condition is not satisfied the process progresses into the next step.

Step4. After the multiobjective optimization has been performed for k generations, all of the individuals are gathered. Then the process goes back to Step 2. This generation k is called the *sort interval*.

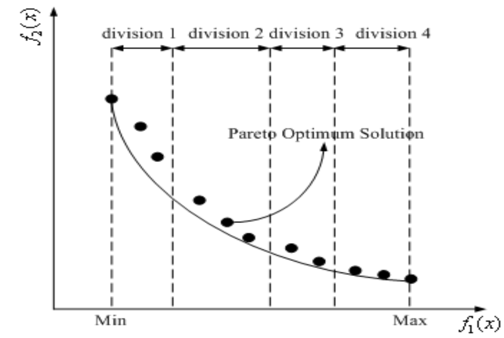

Figure 2 DRMPSO

In this study, the number of distribution m and the sort interval k is determined in advance. In Figure 2, the concept of the DRMPSO is shown and two objective functions are considered. Individuals are divided into four by the value of the focused objective function f_1. The area with respect to the focused objective function determines the sub-populations of the DRMPSO. Therefore, the derived Pareto optimum solutions of the DRMPSO might have the high diversity.

III. Result Analysis

It is demonstrated that the DRMPSO is an efficient and general method to locate the Pareto front of multiobjective optimization problems. The advantage of the PSO method is that it is easy to implement and has few parameters that need to be adjusted. In this paper the DRMPSO used a population of 80 particles. The inertia weight w is gradually decreased from 1.0 towards 0.1; the learning rates c_1 and c_2 are 2.0. Sort interval k is set to 5.

To allow a fair comparison of running times, all the experiments were performed on a PC with a Pentium II processor; the simulations were carried out using MATLAB. The approximate simulation times for each of the algorithms are listed below:

MOGA: (approx. 60 minutes)
EMOGA: (approx. 60 minutes)
MOSA: (approx. 15 minutes)
DRMPSO: (approx. 3 minutes).

The results illustrate that the DRMPSO required lower computational times than any of the three other algorithms tried. The graphical representation of the results obtained by each method also indicate excellent performance of the proposed algorithm (see Figure 3, 4, 5 and 6)

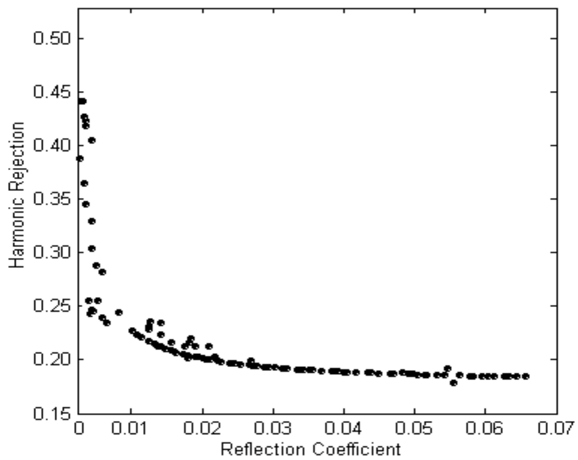

Figure 3 Overall Solutions Set Obtained by MOGA

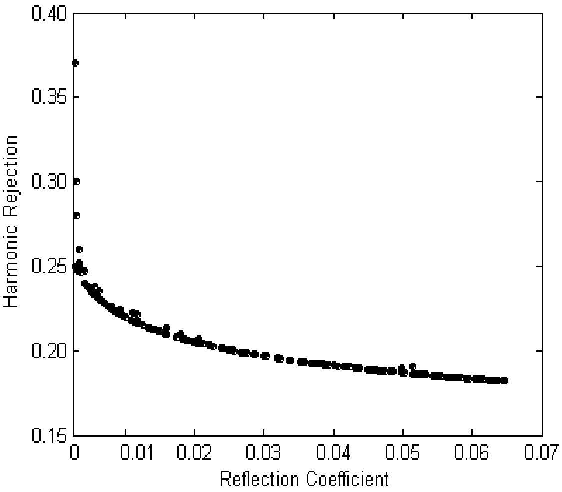

Figure 4 Overall Solutions Set Obtained by EMOGA

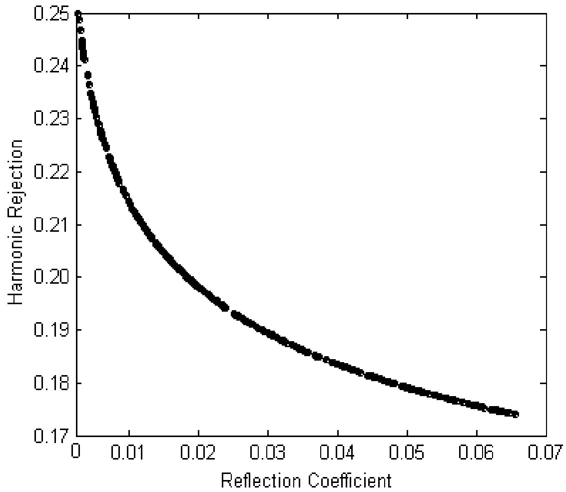

Figure 5 Overall Solutions Set Obtained by MOSA

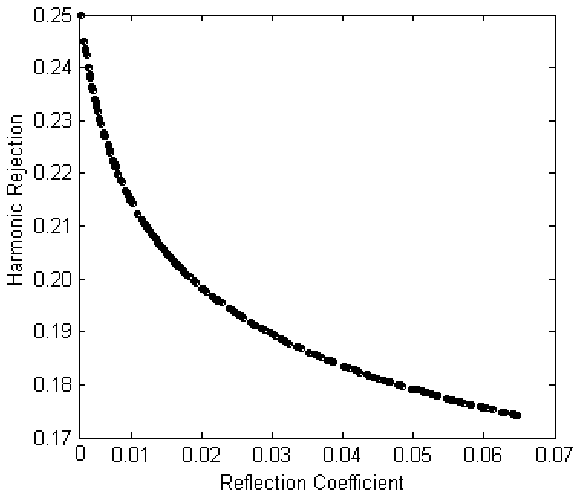

Figure 6 Overall Solutions Set Obtained by DRMOPSO

IV CONCLUSION

A novel particle swarm optimization technique has been presented. It has been applied to the problem of joint optimization of harmonic rejection and reflection coefficient of an antenna in the Pi-Network configuration. Results demonstrate that the proposed method yields the same level of optimization as other methods but with substantial improvement in time of algorithm efficiency. Thus it is useful for real-time optimization of these antenna circuit parameters in a reduced-complexity system.

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